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Intangible Assets and Imperfections in Product and Labor Markets

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Intangible Assets and Imperfections in Product and Labor Markets*

Abstract

This paper develops a micro-founded framework linking price-cost and wage markups to intangible assets. Intangible assets, once created, are a source of firm rents. Owing to limits to enforceable ownership and the non-rival nature of knowledge, these rents can be both retained by the origin firm and transferred to a competitor through poaching of workers. Search and matching frictions affect labor mobility and result in bargaining over rents between the firm and the worker. This environment generates hold-up in intangible asset creation and motivates rent sharing. Under non-compete agreements, poached workers face start delays that weaken outside options. Using microdata from the Netherlands, we document higher price-cost and wage markups in more intangible-intensive firms and lower wages for workers with non-compete agreements, consistent with the model.

JEL classification

J41, L10, O30

Keywords

price-cost markups, wage markups, rent sharing, intangibles, non-compete agreements

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1 Introduction

It is widely recognized that product and labor markets are characterized by some degree of imperfect competition.[1] Recent empirical evidence has shown not only the joint occurrence of product and labor market imperfections (Kroft et al., 2025) but also their co-movement (Dobbelaere and Wiersma, 2025). What is lacking is a microfoundation for the co-movement between pricing rules in both markets and empirical evidence to validate this micro-founded mechanism. Establishing such microfoundations is valuable, as it can inform about the origins of the observed market imperfections and guide policy interventions to address them, such as implementing changes in legal restrictions on worker mobility.

We address this gap by developing a micro-founded framework that explains the joint occurrence of price-cost markups and wage markups. The model integrates elements of a dynamic heterogeneous-firm model (Hopenhayn, 1992) and a labor market model with search and mobility frictions (Mortensen and Pissarides, 1994). The central mechanism of the model links intangible assets in the firm with imperfections in the product and labor markets. Intangible assets reduce the marginal cost of production and generate price-cost markups. Because intangible assets are non-rival in their use and ownership is only imperfectly enforceable, the rents that they create can be both retained by the origin firm and transferred to competitors through the poaching of workers. Search and matching frictions affect labor mobility and result in bargaining over these rents between firms and workers. This environment generates hold-up in intangible asset creation, and leads to both price-cost markups and wage markups in intangible-using firms.

In the model, there are two types of intangible-asset-using firms: "innovators" that co-create intangibles with their employees and "poachers" that hire away knowledgeable employees from innovators. An innovative firm's rent increases in its intangible asset stock, which is given by the quality of the worker-firm match. An innovative firm's value falls with the risk that a portion of its intangible assets is transferred to another firm if it poaches a worker. Anticipating this hold-up risk, firms choose whether to operate as innovators or poachers in equilibrium and design rent-sharing contracts to reduce poaching. There are three dimensions of heterogeneity that affect firm and worker choices: the quality of the worker-firm match, worker-specific "leakability" (the share

[1] See e.g. De Loecker et al. (2020), and Dobbelaere and Mairesse (2018) and Manning (2021) for empirical evidence on the pervasiveness of imperfectly competitive product and labor markets, respectively.

of intangibles a worker can transfer to a poacher) and firm-specific “retainability” (the share of intangible assets the origin firm keeps after poaching). Match quality, leakability, and retainability are drawn from known distributions, yielding a tractable characterization of the sorting of firms into innovators or poachers and of the joint distribution of firm intangibles, rents, and rent-sharing contracts.

The model has fairly standard behavior of firms and workers, but provides some novel insights into the evolution of intangible assets. In addition to the choice of opening a vacancy as a prospective innovator or as a poacher, firms optimally choose labor contract terms. Workers optimally choose between an outside option or a wage plus rent-sharing contract with an innovator, and if employed at an innovator, workers can choose to accept a contract offer from a poaching firm. In this paper, we explore how non-rivalry and imperfect contract enforceability of intangibles affect workers' wages and mobility.

The model offers four main theoretical insights that we test in our microdata. *First*, firms characterized by a higher intensity of intangible assets charge higher price-cost markups. On the product side, firms selling their goods in imperfectly competitive markets set output to equate marginal cost and marginal revenue, where the price-cost mark-up is determined by the demand elasticity at that output level. If demand is sub-convex (Mrázová and Neary, 2017), the price-cost markup increases with optimal output, which in turn rises with the stock of intangibles that reduce the marginal cost of production. *Second*, on the labor side, rent sharing generates wage premia (markups) that generally increase in intangible intensity and poaching risk. At high levels of intangible intensity, roughly the top ten percent of firms or double the mean intangible intensity, wage markups decline with the level of intangibles because the proportional profit loss from poaching shrinks, reducing rent-sharing incentives. *Third*, wage markups fall with retainability. The larger the share of intangibles the innovating firm keeps when a worker is poached, the less it needs to share rents. *Fourth*, non-compete agreements reduce wage markups and limit worker mobility from innovators to poachers by imposing a waiting period before starting at the poacher. This delay reduces the flow profits of waiting poachers and makes acceptable poaching offers less likely. As a result, the equilibrium share of poaching firms falls, poaching risk declines, rent sharing by innovators diminishes, and innovator-to-poacher worker transitions become less frequent.

Using linked survey and administrative data on Dutch firms' annual accounts, technology adoption, and innovation, merged with matched employer-employee data on jobs, worker characteristics, and the presence of non-compete clauses, we present different pieces of descriptive evidence consistent with the model's qualitative predictions. We show that most employers in manufacturing and services set prices above the marginal cost of production and pay workers above their marginal revenue product. Both price-cost markups and wage markups are positively related to intangible intensity at the firm level. To proxy intangible assets, we use a firm's "automation expenditure", capturing 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. For firms in the upper tail of the intangible intensity distribution and firms with intellectual property protection (which we interpret as firms with high retainability), the positive relationship between wage markups and intangibles weakens, and even disappears for the former group. Workers bound by non-compete agreements in intangible-intensive firms are paid less.

Contribution to related literature. Our paper connects to three strands of literature that are typically studied separately. The first and foremost is the literature on modeling product and labor market imperfections. On the product market side, price-cost markups are recovered using the demand-conduct approach (Berry, 1994; Berry et al., 1995; Nevo, 2001; Berry et al., 2004), the production function approach (De Loecker and Warzynski, 2012; De Loecker et al., 2016), or combining both (De Loecker and Scott, 2026). Several mechanisms provide the microeconomic foundations of price-cost markups. On the demand side, product differentiation or customer switching costs can result in a monopolistically competitive or oligopolistic market structure with less than perfectly elastic demand. On the supply side, heterogeneous firms with entry frictions or abusive firms that limit competition can prevent cost dispersion across firms from being competed away, even with perfectly elastic demand. On the labor market side, empirical labor economists have traditionally resorted to estimating the responsiveness of workers' wages to firms' profitability to assess the extent of rent sharing, interpreting the wage-profitability link as evidence of labor market imperfections (wage markups) (Booth, 1995; Card et al., 2018). Wage markups can be rationalized through bargaining (individual or collective), risk-sharing arrangements, or fair wage considerations. In recent years, there has been a resurge of interest in monopsony, with firms' labor supply elasticities (and wage markdowns) estimated using either the turnover-based approach (Manning, 2011, 2021) or the production function approach (Yeh et al., 2022). Alternative microfoundations of wage markdowns include search frictions, mobility costs, job differentiation, or oligopsonistic conduct. Most recently, empirical researchers have used the production function approach to estimate product- and labor-market imperfections jointly (Dobbelaere and Mairesse, 2013; Caselli et al., 2021; Dobbelaere et al., 2026). This approach does not only allow the data to determine whether wage-markup or wage-markdown pricing is a better approximation of firms' wage determination process in a specific environment, it also accounts for a possible interdependency between product and labor market imperfections, which would otherwise contaminate estimates of either market imperfection. However, a proper microfoundation of the joint occurrence of product and labor market imperfections is missing. We contribute to this literature by developing a microfounded partial equilibrium model that links both market imperfections to intangible assets, responding to Van Reenen (2024)'s call to modeling imperfections in the two markets jointly and to carefully examine the origin of the resulting market power.

The second is the literature on intangible capital and their impact on firm performance and market structure. Models emphasizing non-rivalry and scalability demonstrate how intangibles can increase market power by reducing marginal costs or increasing demand elasticity. In particular, Eeckhout and Veldkamp (2022) and De Ridder (2024) show how data, software, and organizational capital allow firms to expand output at low marginal cost, amplifying market power. More broadly, the rise of intangible capital has been argued to reshape production technologies and growth dynamics (Corrado et al., 2013; Haskel and Westlake, 2018; Crouzet et al., 2024). These contributions focus primarily on how intangible capital affects firm growth and price-cost markups. Research in the related innovation literature studies ex-ante incentive problems in the joint creation of knowledge (Peters et al., 2017; Mezzanotti and Simcoe, 2023). We contribute to this literature by modeling how imperfect enforceability of match-specific knowledge affects bargaining over rents between firms and workers and how this ex-post bargaining, in turn, influences innovation. We further demonstrate how incorporating search frictions, following the tradition of Burdett and Mortensen (1998) and Mortensen and Pissarides (1994), can shed light on the origins of firms' and workers' market power in the wake of technological change.

The third is the recent literature on non-compete agreements (NCAs). One set of papers studies how legal restrictions affect wages and worker mobility (Lipsitz and Starr, 2022; Young, 2024; Johnson et al., 2025). Another set of papers examines the impact of NCAs on firms' innovation and investment decisions (Conti, 2014; Johnson et al., 2023; Jeffers, 2024). A third set of papers calibrates general equilibrium models to assess the joint impact of NCAs on firm-level investment and knowledge diffusion, and provides a framework for the optimal regulation of such clauses (Liu, 2023; Shi, 2023). We contribute to this literature by embedding NCAs in a framework where mobility constraints alter the equilibrium allocation of rents arising from intangible assets through changing workers' outside options, which in turn affect firm-level market imperfections. Methodologically, integrating heterogeneous-firm dynamics with search and matching frictions generates endogenous sorting between innovators and poachers and makes mobility constraints quantitatively relevant for the allocation of rents.

The remainder of this paper proceeds as follows. Section 2 presents a theoretical framework with innovative firms that co-create intangible assets jointly with heterogeneous workers. Section 3 empirically verifies the model's main predictions about quantitative relationships between product and labor market imperfections and intangible intensity, and between non-compete agreements and labor compensation. Section 4 concludes.

2 A model of intangible assets and market imperfections

Section 2.1 presents the product demand and production technology of our model as well as consumption and labor/leisure decisions of households, and production and pricing decisions of firms. Section 2.2 describes the discovery and evolution of intangibles at the firm level, and the dimensions of heterogeneity of firms and workers related to intangibles. Section 2.3 presents the incentives and optimal rent-sharing conditions of innovators and poachers. All the above model features are described independently of frequency and horizon of the model. We present the model in a two-period discrete-time version in Section 2.4, but in principle the model could be solved and analyzed in other configurations. In Section 2.5, we discuss some key modeling choices, illustrate the model's key theoretical insights and summarize the qualitative findings that can be brought to the data.

2.1 Taste and technology

Households. The demand side of the market assumes that household utility depends on consumption of an "outside" good, y_0, consumption of differentiated goods, y_f, and leisure. The outside good, y_0, is produced by firms in the "safe" sector using a fixed technology and frictionlessly hired labor. The differentiated good, y_f, is produced by monopolistically competitive firms in the intangible-using sector with a stock of intangible assets and labor hours, l. Workers are assumed to be indifferent between the marginal utility of leisure and the marginal utility of goods they can buy with their marginal earnings at the outside wage, ω, at any level of total income including their rent-sharing component.

We follow Mrázová and Neary (2017) in choosing a sub-convex demand system where the elasticity of demand for the differentiated good decreases in its sales. In other words, we assume a positive relationship between sales and the price-cost markup. Below we discuss the results for a constant proportional pass-through demand system (CPPT).[2]

In the utility function underlying the CPPT demand system, we wrap the constant-elasiticity-of-substitution (CES) aggregator for differentiated products in a concave transformation to generate a choke price for each monopolistically competitive firm's output. Although we analyze our model in a partial equilibrium setting, our specification with an outside good would allow the framework to be extended and embedded in a general equilibrium macro model, as in Atkeson and Burstein (2008).

$$U = y_o + A\bar{Y} + \frac{\gamma B}{\gamma + 1}\bar{Y}^{\frac{\gamma+1}{\gamma}} + \omega(T - l), \quad \text{with} \quad \bar{Y} = \left(\int_{\mathcal{F}} y_f^{\frac{\sigma-1}{\sigma}}\, df\right)^{\frac{\sigma}{\sigma-1}},$$

where A and B are parameters, T is available hours, γ gives the curvature of valuing differentiated goods versus the outside good, and σ is the substitution elasticity between the differentiated goods.

Utility maximization ensures that each differentiated product firm faces a Bulow and Pfleiderer (1983)-demand curve:[3]

$$p = D_0 - D_1 y^{\frac{1}{\gamma}} \tag{1}$$

We now move to considering the optimizing behavior of workers. Workers can be either unemployed or employed, and in the model extension with non-compete agreements, can be in a waiting period between jobs. Unemployed workers receive an unemployment benefit. Unemployed workers stochastically meet with an innovative firm that has a vacancy. In equilibrium, unemployed workers are indifferent between choosing a labor contract with an innovator or with a firm in an outside,

[2]Similar comparative statics can be derived for a constant revenue elasticity of marginal revenue demand system. These results are available upon request.

[3]It can be shown that $D_o = |\mathcal{F}|^{\frac{1}{\sigma-1}} A$ and $D_1 = B|\mathcal{F}|^{\frac{1}{\sigma-1}} + \frac{\sigma}{\gamma(\sigma-1)}$, where $\mathcal{F}$ is the mass of intangible-using firms.

safe sector, where firms produce with a known technology. Utility-maximizing workers supply labor hours elastically at the outside wage, adjusted for unemployment hazard, regardless of their level of total wage and rent-share income.

Workers evaluate contract offers from an intangible-using firm, either an innovator, or once matched with an innovator, a poacher, that consist of a real wage ω and a share of rents $\beta\pi(z)$. Because our model has no stochastic evolution of z after a contract is offered, the wage offer could be rewritten as $w = \frac{\omega l(\bar{z})+\beta\pi(\bar{z})}{l(\bar{z})}$, where $\bar{z}$ is the fixed productivity draw. The aligns well with the wage measures that are available in the data.

Firm production and pricing. Firm production takes place with a constant-returns-to-scale Cobb-Douglas technology, where the intangible assets generate a Hicks-neutral shift in technology:

$$y = zx^{\alpha}l^{1-\alpha} \tag{2}$$

where x is intermediate input, l is labor input and z is the measure of intangible assets. For firms in the safe sector, $z = 1$, and for intangible-using firms $z > 1$.

Marginal costs are then given by:

$$MC(y) = \frac{dC}{dy} = \left(\frac{p_x}{\alpha}\right)^{\alpha}\left(\frac{\omega}{1-\alpha}\right)^{1-\alpha} z^{-1} = \bar{C}z^{-1},$$

with p_x the price of intermediate input.

Conditional on the level of intangible assets, we can compute the profit-maximizing output, price, and flow profit for each firm, as well as their markup of price over marginal cost by setting output where marginal revenue equals marginal cost (see Appendix A.1).

- **Output:** $y^*(z) = \left(\frac{\gamma(D_0-\bar{C}z^{-1})}{D_1(\gamma+1)}\right)^{\gamma}$
- **Price:** $p^*(z) = \frac{D_0+\gamma\bar{C}z^{-1}}{\gamma+1}$
- **Profits:** $\pi^*(z) = \left(\frac{D_0-\bar{C}z^{-1}}{\gamma+1}\right)^{\gamma+1}\left(\frac{\gamma}{D_1}\right)^{\gamma}$
- **Price-cost markup(z):** $\frac{p(y^*)}{MC} = \frac{\gamma}{\gamma+1} + \frac{D_0}{(\gamma+1)\bar{C}}z$

We see that optimal output and profits increase in z, while optimal price decreases in z. Optimal profit is concave in z. A first result of the model is that price-cost markups increase in firms' use of intangibles:

Proposition 1. *Consider a firm facing a demand curve as in (1) and operating with a production technology summarized by (2). Then, its price-cost markup $\mu(z)$ is increasing in the value of intangible capital z: $\frac{\partial \mu(z)}{\partial z} \geq 0$.*

2.2 Intangible assets

It is difficult to overemphasize the importance of the non-rival nature of intangible assets in an economy (Romer, 1990; Jones, 2019). In the Romer endogenous growth model, a small market failure, namely price-cost markups for "blue prints", provides resources to pay an endogenously chosen level of research that, owing to intertemporal knowledge spillovers, generates steady-state intangible asset- and output growth. We share with the endogenous growth literature the non-rival nature of intangible assets that lower the marginal cost of production at any scale. We differ from much of the growth literature because we simplify the intricacies in the path from innovative investment to intangible asset stock. In our model, additions to the aggregate stock of intangibles take place at the extensive margin and are determined by the number of firms that choose to become innovators.

Once a firm chooses to be an innovator, pays an entry fee, c_f, and matches with a worker, intangible assets, z, appear as manna-from-heaven, with the magnitude given by a draw from an exogenous Pareto distribution with scale parameter z_m and shape parameter a.[4]

$$z \sim \text{Pareto}(z_m, a)$$

In this setup, for example, there is no role for incentives to spur researchers, no R&D races between competitors and no intertemporal knowledge spillovers in the innovation process. Further, there are no marginal contributions of workers or firms to the resulting intangible asset to guide the distribution of the proceeds. Instead, innovation generates a match surplus and our attention is

[4]The entry fee can be interpreted as a search cost for labor but also as an investment in innovative discovery. Without loss of generality, we could also assume that intangible investment occurs during period of paid employment before the intangible asset is discovered and production starts. Nonetheless, the investment is sunk and not related to the magnitude of the post-innovation rent.

focused on the division of rents, depending on optimal choices made by heterogeneous firms and workers.

Besides non-rivalry in use, intangible assets may also feature imperfect enforceability of ownership. Non-rivalry makes it possible for a firm to use an intangible asset in its production process without reducing the ability of another firm to use it at the same time. Imperfect enforceability of ownership makes it hard for the co-creators of the asset and the resulting match surplus to contract for rights to the asset, either ex-ante or ex-post. We model this by allowing a worker who co-developed the intangible asset to take a portion of the asset to another job. At the same time, the ability of the firm to operate an intangible asset might be impaired once a worker departs, such that the firm *de facto* only retains a portion of the intangible asset.

We introduce heterogeneity on both sides of the labor market. Firms differ in asset retainability, ξ_f, the share of intangible assets remaining at a firm after a worker is poached. Workers differ in asset leakability, ξ_w, the share of intangible assets they take with them to the poaching firm. The retainability parameter, drawn from a uniform distribution, is known to the firm before choosing whether to become a poacher or an innovator.

$$\xi_f \sim \text{Uniform}(0, 1)$$

The worker's leakability parameter, drawn from a uniform distribution, is not known to an innovating or poaching firm prior to giving a contract offer:

$$\xi_w \sim \text{Uniform}(0, 1)$$

The nature of intangibles allows the possibility that the sum of assets retained by the innovating firm, $z_r = \xi_f z$, and the assets available to the poacher after poaching the worker, $z_p = \xi_w z$ is higher or lower than the initial asset level: $0 < \xi_f z + \xi_w z < 2z$. Although the distributions of ξ_w and ξ_f are independent, so that $\mathbb{E}[\xi_f + \xi_w] = 1$, aggregate z may change as a result of poaching. What matters for the total amount of aggregate z after poaching is the sum of the parameters of the joint distribution (ξ_f, ξ_w) of the co-creators of the transferred asset.

Aggregate intangible assets thus depend on the original distribution of z, on the mass of innovators that are never poached with their conditional distribution of z, on the mass of poachers with their conditional distribution of $\xi_w z$ transferred by the poached worker, and on the mass of poached firms with replacement hires and the conditional distribution of their retained intangibles $\xi_f z$. Finally, in the model there is a flow of z that is destroyed by the exogenous exit of firms, and a flow of z from new innovators drawn from the original distribution of z.

2.3 Rent-sharing contracts

To prevent losing intangible assets to poachers or to induce workers to leave innovators, innovating and poaching firms offer rent-sharing contracts. In this section, we look at optimal rent sharing of innovators and poachers, and at the joint distribution of jobs –in terms of $z, \xi_f, \text{and } \xi_w$– that are poached, by considering the optimization problems and participation constraints of innovators, poachers, and poachees.

We start with the optimal contract offered by a poacher. Upon meeting a worker at an innovating firm, poachers make a take-it-or-leave-it offer, so there is no wage negotiation. An offer consists of a wage ω and a share of profits β, but since hourly wages are exogenous, a worker's decision only depends on a comparison of the rent-sharing components of compensation. We denote by β_f the share of innovator rents that a potential poachee is receiving and by β_p the share of poacher rents offered to the worker by the poacher. The worker will be willing to accept any poacher's offer when:

$$\omega + \beta_p \pi(\xi_w z) \geq \omega + \beta_f \pi(z)$$
$$\Leftrightarrow \beta_p \geq \frac{\beta_f \pi(z)}{\pi(\xi_w z)} = \beta_p^m.$$

The poaching firm does not gain by giving an offer above the minimally acceptable offer, β_p^m. The poaching firm will give the offer as long as its resulting flow profits are non-negative.[5] The poacher's flow profits are non-negative when $(1 - \beta_p^m)\pi(\xi_w z) \geq 0 \Leftrightarrow \pi(\xi_w z) - \beta_f \pi(z) \geq 0$. Below it will be shown that the optimal rent-sharing offer of the innovator, β_f depends on z and ξ_f of the innovator.

The innovating firm, with a given z and conditional on β_f, can compute the probability that

[5] In equilibrium with endogenous choice between types of firms, the expected flow profits of poachers need to be just enough to equate returns between different choices. Since entry fees or investments are sunk, a poacher will choose to operate with non-negative profits conditional on having paid the fee.

their worker will receive an acceptable offer without knowing their worker's leakability parameter ξ_w: if we denote by $\Xi(\beta_f, z)$ the value of ξ_w that solves $\pi(\xi_w z) = \beta_f \pi(z)$, then the probability of matching with a worker who will accept a poaching offer given β_f and z is equal to the probability of matching with a worker with leakability $\xi_w \geq \Xi(\beta_f, z)$. Since ξ_w is uniformly distributed, this is simply given by:

$$\mathcal{P}(\beta_f, z) = 1 - \Xi(\beta_f, z).$$

With the functional form for $\pi(z)$ given in Section 2.1, we can derive $\Xi(\beta_f, z)$:

$$\Xi(\beta_f, z) = \frac{\bar{C}}{\bar{C}\beta_f^{\frac{1}{\gamma+1}} + zD_0\left(1 - \beta_f^{\frac{1}{\gamma+1}}\right)} \tag{3}$$

where $\bar{C} = \frac{p_x^{\alpha}\,\omega^{1-\alpha}}{\alpha^{\alpha}(1-\alpha)^{1-\alpha}}$.

Complete deterrence, $\Xi(1, z) = 1$, occurs when $\beta_f = 1$, but then the firm leaves all rents to the worker. When $\beta_f = 0$, workers with a leakability higher than $\Xi(0, z) = \frac{C}{D0} z^{-1}$ are poachable.[6]

The meeting of poachers and innovators is modeled with a standard matching function (Mortensen and Pissarides, 1994), where a meeting between the two takes place with frequency: $m = \lambda s_p^{\eta} s_f^{1-\eta}$, where $\eta \in (0, 1)$, λ is the arrival rate of a chance to meet, s_p is the mass of poachers and s_f is the mass of innovators. Then, the arrival rate per poacher of a meeting with an innovator is:

$$\lambda_p = \lambda \left(\frac{s_f}{s_p}\right)^{\eta}.$$

and the arrival rate per innovator of a meeting with a poacher is:

$$\lambda_f = \lambda \left(\frac{s_p}{s_f}\right)^{\eta}.$$

In the next section, we characterize the solution to the equilibrium rent-sharing rule of innovators that emerges in a two-period discrete time setting.

[6]When z is at its lowest possible value, $z = z_m$, then the restrictive assumption $D_0 > CZ_m^{-1}$ ensures that $\Xi(0, z_m) < 1$.

2.4 Two-period discrete-time model

We present the model as discussed in a two-period discrete time setting $\{t_0, t_1\}$.

Here is a summary of the timing of firm actions, information revelation, and payoffs.

1. **At start of t_0.**
   - All workers receive their private leakability parameter ξ_w
   - An entering firm can choose between the safe sector and the intangible-using sector.
   - Safe-sector firms frictionlessly attract a worker, pay outside wage ω, and get zero value.
   - Intangible-using firms get a draw of their retainability parameter ξ_f.
   - Intangible-using firms choose to become a poacher or an innovator and pay fee c_p or c_f (or $c_f + c_\nu$ for the latter, in case the innovator imposes a non-compete contract).
2. **At end of t_0.**
   - The innovator and worker "discover" $z \sim \text{Pareto}(z_m, a)$, and sign an optimal rent-sharing contract, β_f.
3. **At beginning of t_1.**
   - The poacher meets, at hazard rate λ_p, an innovator's employee with state (ξ_w, z, β_f); the poacher makes an acceptable offer when $\pi(\xi_w z) > \beta_f \pi(z)$.
   - The innovator has a hazard of being poached of $\lambda_f \mathcal{P}(z, \beta_f)$, which is the hazard of meeting a poacher times the probability that the poacher can make an acceptable offer.
4. **During period t_1.**
   - The poacher with an accepted offer receives $\pi(\xi_w z) - \beta_f \pi(z)$.
   - An innovator that has not been poached makes optimal output and price decisions and receives $(1 - \beta_f)\pi(z)$; a poached innovator retains $\pi(\xi_f z)$.

We start with a short description of the general equilibrium environment. The discount rate, ρ, the price of intermediate goods, p_x, and the total number of workers are given exogenously. The outside benefit for the unemployed, b_0, frictionless hiring in the safe sector, and our assumed utility function, pin down the wage in the safe sector, $\omega = \frac{b_0}{T}$. The entry fee and profits for firms in the safe sector equal zero. Each safe-sector firm will have one worker. These assumptions, along with the distribution of draws of z and job finding rates that decline log-linearly with the share of intangible-using firms, determine the wage, ω and total employment in the intangible-using sector. In equilibrium, the expected utility of workers is equalized between unemployment, employment in the safe sector, and employment at either innovator or poacher firms in the intangible-using sector. In equilibrium, the value of being a firm in the intangible-using sector equals that in the safe sector, $V^0 = 0$.

Entrants that have chosen to be intangible-using firms receive their retainability draw, ξ_f. Because the only source of heterogeneity between firms at entry is ξ_f, we define the values of being a poacher (p) or an innovator (f) as a function of ξ_f. We start by assuming an exogenous share of entrants that are poachers, s_p, or innovators, $s_f = 1 - s_p$. Later, we will show that there will be a unique equilibrium cutoff level of ξ_f that makes the entrant indifferent between becoming a poacher or an innovator such that $s_p = \underline{\xi_f}$ and the expected value of being a poacher with $\xi_f < \underline{\xi_f}$ equals the expected value of being an innovator with retainability above the threshold value.

Value of Poacher. Upon entering and paying c_p at the start of t_0, a poaching firm has a hazard of meeting with an employee of an innovating firm at rate λ_p at the start of $t = 1$. The worker reveals the amount of transferrable intangibles, $\xi_w z$, the non-wage compensation $\beta_f \pi(z)$ and the intangibles of the poachee, z.[7] With an offer acceptance probability $\mathcal{P}(\beta_f, z) = 1 - \Xi(\beta_f, z)$, the firm p will employ the worker from f in period t_1, and will receive $\pi(\xi_w z) - \beta_f \pi(z)$, whenever $\xi_w > \Xi$.[8]

The value of an entering poacher equals:

$$V^p(\xi_f) = -c_p + \rho \lambda_p \mathbb{E}_{(z, \beta_f(z, \xi_f^f), \xi_w)}[I(\beta, z, \xi_w)(\pi(\xi_w z) - \beta_f \pi(z))], \quad (4)$$

[7] Alternatively, with qualitatively equal results, the worker does not reveal z. The poaching firm can construct a conditional expectation of ξ_w that is more informative than assuming a uniform distribution of ξ_w. This turns the acceptance probability of an offer from a cutoff in ξ_w to a cutoff in ($\xi_w z$).

[8] Note that the poachers rents, $\pi(\xi_w z) - \beta_f \pi(z)$, reflects the optimal rent-sharing of the poacher, $\beta_p^* \pi(\xi_w z) = \beta_f \pi(z)$.

where $I(\beta, z, \xi_w) = 1$ when $\pi(\xi_w z) - \beta_f \pi(z) > 0$, else $I(\cdot) = 0$. Note that for a poacher the value does not vary directly with ξ_f, but it does vary with the retainability of the poachee, ξ_f, that determines the poachee rent sharing, β_f. In equilibrium, the hazard λ_p will depend on the cutoff $\underline{\xi_f}$.

Value of Innovator. Upon entering and paying a search/investment fee c_f at the beginning of t_0, an innovator meets and attracts a worker with probability $\lambda = 1$ and draws the level of intangible capital $z > z_m$ from a Pareto distribution with lower bound $z_m > 0$ at the end of period t_0.[9] After receiving the draw of z, at the end of period t_0, the innovator determines the optimal rent-sharing contract β_f to offer for period t_1. During period t_1, the firm either produces using its employee and intangibles z, or the innovator's worker is poached at the beginning of t_1, and it produces with retained assets $\xi_f z$ and with a replacement worker who arrives frictionlessly with probability $\lambda = 1$ and receives the outside wage.

The value of an innovator with retainability ξ_f can be stated as:

$$V^f(\xi_f) = -c_f + \rho \mathbb{E}_{(z)}[(1 - \lambda_f \mathcal{P}(\beta_f, z))(1 - \beta_f)\pi(z) + \lambda_f \mathcal{P}(\beta_f,\, z)\pi(\xi_f\, z)], \tag{5}$$

Optimal rent sharing for innovator. What remains is to find the equilibrium value of the optimal rent sharing β_f conditional on z and ξ_f. The value to be maximized in t_1 by choosing $\beta_f \in [0, 1]$ is:

$$V_{t_1}(\beta_f | \xi_f, z) = (1 - \lambda_f \mathcal{P}(\beta_f, z, \xi_w))(1 - \beta_f)\pi(z) + \lambda_f \mathcal{P} \pi(\xi_f z))$$

So, we are looking for an optimal rent-sharing policy $\beta^*_f(\xi_f, z)$ s.t. $\frac{dV_{t_1}(\beta_f|\xi_f,z)}{d\beta_f} = 0$.

A more intuitive way to understand the solution is to rewrite the value by normalizing the flow profit for a non-poached innovator to one, and make the post-poach retained profit relative to full profit, namely $R(z, \xi_f) = \pi(\xi_f z)/\pi(z) \leq 1$. Moreover, to make the notation lighter we replace β_f with β, and make the dependence on (ξ_f, z) implicit.

[9] Equivalently, we could explicitly model intangible investment by considering c_f to include base compensation at the outside wage ω to attract a worker at the beginning of t_0, leading to the discovery of z at the end of period t_0.

$$\tilde{V}(\beta) = (1 - \lambda_f \mathcal{P}(\beta))(1 - \beta) + \lambda_f \mathcal{P}(\beta) R$$

The first-order condition $\frac{d\tilde{V}(\beta)}{d\beta} = 0$ can be written as:

$$-\lambda_f \mathcal{P}_\beta(\beta)(1 - \beta - R) - (1 - \lambda_f \mathcal{P}(\beta)) = 0 \tag{6}$$

Consider β to be "poach protection intensity", because the accepted offer probability $\mathcal{P}(\beta)$ falls with β (a higher rent-share of the worker at an innovator makes acceptance rarer). Raising β has two effects. First, it reduces exposure to poaching. This increases the probability of not being poached and receiving $(1 - \beta)$ versus being poached and receiving $R < 1$, where at low levels of β the former is larger. Second, increasing β directly reduces the share of surplus gained by a non-poached innovator. At very low protection levels, the marginal benefit of increasing β is large because $(1 - \beta)$ remains larger than R. The marginal cost of increase β is still low, because the chance of retaining unpoached rents is still high. At very high protection, the opposite holds: increasing β further reduces $P(\beta)$, but because the post-poach rents R are now higher than $(1-\beta)$, the benefits of protection become negative. The costs of protection become higher because the extra rents given away are weighted with $1-\mathcal{P}(\beta)$. Decreasing marginal benefit crossing increasing marginal cost once delivers a single interior optimum, β^*.[10]

Next, we characterize two main properties of the optimal sharing rule, $\beta^*_f(z, \xi_f)$. First, the equilibrium rent–sharing schedule is hump–shaped in intangible intensity z: for low z the innovator increases rent sharing to contain poaching risk, whereas for high z rent sharing declines because profits grow more slowly than the induced poaching hazard. Second, higher retainability ξ_f reduces the incentives to share rents, shifting the entire β–schedule downward. We establish these two properties more formally in the next two propositions.

Proposition 2 (Hump-shaped rent sharing)**.** *Suppose z lies in the concavity region characterized in Appendix A.1.4, i.e. $z \geq z_*$. For any retainability $\xi_f \in (0, 1)$, the optimal rent–sharing policy $\beta^*(z, \xi_f)$ defined by (6) is interior and continuously differentiable in z. Moreover, there exists a*

[10]See Appendix A.2, for the proof.

threshold $\bar{z} \in (z_*, \infty)$ *such that*

$$\frac{\partial \beta^*(z, \xi_f)}{\partial z} > 0 \quad \textit{for } z < \bar{z}, \qquad \frac{\partial \beta^*(z, \xi_f)}{\partial z} < 0 \quad \textit{for } z > \bar{z}.$$

Hence $\beta^*(z, \xi_f)$ *is hump-shaped in intangible intensity* z*.*

The proof is relegated to Appendix A.2.

The intuition behind Proposition 2 is that a higher intangible draw generates higher rents, because both price-cost markups and market size are strictly non-decreasing in z. However, due to the concavity of the relationship between rents and intangibles, the rent-protection motive of rent sharing gradually decreases with higher z, implying that for very high value of intangibles the sharing rule becomes less generous towards workers.

Proposition 3 (Higher retainability reduces rent sharing)**.** *For any value of intangibles* z *in the concavity region* $z \geq z_*$*, the optimal rent-sharing rule* $\beta^*(z, \xi_f)$ *obtained from* (6) *is strictly decreasing in the firm's retainability* ξ_f*:*

$$\frac{\partial \beta^*(z, \xi_f)}{\partial \xi_f} < 0 \qquad \textit{for all } z \geq z_* \textit{ and } \xi_f \in (0, 1).$$

The proof is relegated to Appendix A.2.

For innovators, a higher draw of retainability, ξ_f, will decrease the relative rent R at risk from poaching. This reduces the marginal benefits of the protection motive for β^*, which implies a less generous rent-sharing policy.

2.4.1 Entry choice: Innovator versus poacher and sorting

Finally, we consider the endogenous decision of firms to become poachers or innovators. We start the analysis with fixed shares of poachers and innovators, s_p and $s_f = 1 - s_p$. It is easy to verify from (5) that the value of being an innovator increases with ξ_f, because the retained intangibles increase with retainability and profit is strictly increasing in intangibles. Also, we know that the value of being a poacher is unaffected by the poacher's own ξ_f, because a poacher cannot be poached in our setting. If the shares are fixed, and the meeting rates λ_p and λ_f are fixed, there exists a threshold that will equate the values of the two types of firms (with appropriate choice of c_p and c_f). We formalize this argument in Proposition 4.

Proposition 4 (Sorting on retainability)**.** *Consider an environment with fixed masses of innovators and poachers, and hence fixed meeting rates* (λ_f, λ_p)*. Let* $V^f(\xi_f)$ *and* V^p *denote the values of entering as an innovator and as a poacher, respectively. Then:*

1. *The value of becoming an innovator is strictly increasing in retainability* ξ_f*, whereas the value of becoming a poacher does not depend on its own* ξ_f*.*

2. *For any pair of entry costs* (c_f, c_p) *such that*

$$V^f(\underline{\xi}) < V^p < V^f(\overline{\xi}),$$

where $0 < \underline{\xi} < \overline{\xi} \leq 1$ *are the lower and upper bounds of the support of* ξ_f*, there exists a unique cutoff* $\underline{\xi_f} \in (\underline{\xi}, \overline{\xi})$ *such that*

$$V^f(\xi_f) \begin{cases} < V^p & \text{if } \xi_f < \underline{\xi_f}, \\ = V^p & \text{if } \xi_f = \underline{\xi_f}, \\ > V^p & \text{if } \xi_f > \underline{\xi_f}. \end{cases}$$

In equilibrium, firms with $\xi_f > \underline{\xi_f}$ *optimally choose to become innovators, while firms with* $\xi_f < \underline{\xi_f}$ *choose to become poachers.*

The proof is relegated to Appendix A.4.

Now we consider endogenous shares s_p and s_f. With $\xi_f \sim \text{Uniform}(0,1)$, it follows that $s_p = \underline{\xi_f}$ and $s_f = 1 - \underline{\xi_f}$. The hazard of an innovator meeting a poacher, $\lambda_f = \lambda \left(\frac{\underline{\xi_f}}{1-\underline{\xi_f}}\right)^{\eta}$, is increasing in the cutoff $\underline{\xi_f}$. A higher chance of being poached reduces the value of being an innovator at any ξ_f. The value of being a poacher does not depend directly on ξ_f of the poaching firm, but it depends on the distributions of ξ_f at innovators, with β_f^* declining as the retainability cutoff at innovators increases. This increases the chance of making an acceptable offer and increases the value of each poached worker. The effect of these two channels on the value of being a poacher is ambiguous. Appendix A.4 shows that when including the effects of the cutoff on meeting hazards and the values of poachers and innovators, there exists at least one equilibrium cutoff $\underline{\xi_f}$ with sorting as in

Proposition 4. Under a mild monotonicity condition on the effect of the cutoff on poacher values, this cutoff is unique.

Moreover, in Appendix A.4 we show formally that a higher ξ_f raises the innovator's continuation value in case of poaching and reduces the marginal benefit of deterrence, so optimal $\beta^*(z;\xi_f)$ falls. This raises retained profits and increases V^f. On the poacher side, a higher threshold $\bar{\xi}_f$ shifts the innovator pool toward higher ξ_f types who choose lower β^*, which increases poachable surplus and hence V^P, unless the meeting rate changes in the opposite direction, reducing V^p. We formally posit a regularity condition, which requires that, once this feedback is accounted for, the net advantage of becoming an innovator, $V^f - V^p$, still varies monotonically with the cutoff, ruling out multiple equilibria exclusively driven by changes in the meeting rate. Economically, this rules out knife-edge cases where changes in the composition of types and matching probabilities generate multiple intersections between the two value schedules. Firms that are effective at retaining intangible capital are better suited to innovate, as they face a lower loss from poaching.

2.4.2 Non-compete agreements

Now consider a change to the environment, where the innovator inserts a non-compete agreement into the worker's contract. The innovator's entry fee increases to $c_f + c_\nu$, where $c_\nu > 0$ are contract costs. Now, on arrival of an acceptable poaching offer, at hazard $\lambda_f \mathcal{P}$, poachers will see a waiting time before they can receive their flow profit, such that it becomes $\nu\pi(\xi_w z) - \beta_f \pi(z)$, with $0 < \nu < 1$. The reduction in rents reflects the higher rent sharing the poacher must offer to attract the worker. The poacher now must make an offer such that $\beta_p \nu \pi(\xi_w z) \geq \beta_f \pi(z)$. The new cutoff function Ξ^N becomes:

$$\Xi^N(\beta, z) = \frac{\bar{C}}{\bar{C}(\beta/\nu)^{\frac{1}{\gamma+1}} + zD_0\left(1 - (\beta/\nu)^{\frac{1}{\gamma+1}}\right)} \tag{7}$$

Effectively, the NCA reduces $\mathcal{P}$ at any β_f and z, thus reducing the value of poaching, but also reducing the optimal β_f that innovators need to offer to deter poaching. Further, with the value of poaching decreased and the value of innovating increased at the previous retainability cutoff, $\underline{\xi_f}$ will decline and the share of poachers will decrease.[11]

[11] At least, this holds for an appropriately small contract fee. If the extra fee is set to exactly offset the benefit to the innovator, the reduction in poacher value will still reduce the threshold.

Thus, an NCA should reduce worker transitions from innovators to poachers, and reduce compensation for workers for both types.

We formalize this in the next proposition:

Proposition 5 (Non-competes, rent sharing, and poaching)**.** *Consider the introduction of a non–compete agreement as described in Section 2.4.2, with contract cost* $c_\nu > 0$ *for innovators and parameter* $\nu \in (0,1)$ *capturing the reduction in the effective flow payoff from poaching. Let* $\beta^*(z, \xi_f)$ *denote the equilibrium rent–sharing policy in the baseline environment for innovators, and let* $\beta^N(z, \xi_f)$ *denote the optimal policy under non-competes. Then, for any value of intangibles* z *in the concavity region and any retainability* $\xi_f \in (0,1)$*:*

1. *For every* $\beta \in (0,1)$*, the probability of poaching is strictly lower with non–competes:*

$$\mathcal{P}^N(\beta, z) < \mathcal{P}(\beta, z).$$

2. *The optimal rent–sharing policy is weakly lower under non–competes:*

$$\beta^N(z, \xi_f) \leq \beta^*(z, \xi_f),$$

with strict inequality whenever $\beta^*(z, \xi_f) \in (0,1)$*.*

3. *Consequently, the equilibrium probability that an innovator is poached is lower under non–competes:*

$$\mathcal{P}^N\big(\beta^N(z, \xi_f), z\big) < \mathcal{P}\big(\beta^*(z, \xi_f), z\big).$$

Thus, under our assumptions, non–compete agreements reduce both the generosity of rent sharing and the likelihood of poaching (and hence innovator–to–poacher mobility).

The proofs can be found in Appendix A.3.

2.5 Modeling choices, model illustration and testable predictions

Modeling choices. Before summarizing the model's testable predictions and turning to the empirical section, we discuss two modeling choices and their implications.

The first modeling choice concerns the demand system. The choice is motivated by tractability reasons. In our setting, we focus on the relationship between one firm and one worker, with a production function defined in (2). The distribution of z is unbounded from the right, which implies that the firm can potentially grow its labor demand to infinity. This conflicts with the finite time endowment of the single worker employed, therefore, we adopt a demand system that ensures that labor demand remains bounded. In particular, we use the demand system proposed by Bulow and Pfleiderer (1983), which guarantees that optimal output remains finite even when marginal costs converge to zero at high levels of z. Any alternative demand system featuring both a choke price and a choke quantity would preserve the model's properties, provided it also ensures concavity of the profit function in z. If the firm could employ a mass of workers rather than a single employee, a convex inverse demand curve would be sufficient. Examples include demand systems used in models of oligopolistic competition and CES demand (Atkeson and Burstein, 2008; Mayer et al., 2014), as well as more general non-constant-elasticity specifications (Kimball, 1995).

The second modeling choice concerns the assumed distributions of the leakability and retainability parameters (ξ_w and ξ_f, respectively). We adopt uniform distributions primarily for tractability and transparency, as they yield closed-form expressions for poaching probabilities and acceptance thresholds. This allows us to highlight the economic mechanisms linking appropriability, rent sharing, and price-cost markups without imposing additional parametric structure. Importantly, the uniform assumption is not essential for the qualitative forces at work. What matters for the model's logic is that leakability and retainability are heterogeneous, continuously distributed, and independent, so that innovators face ex-ante uncertainty about a worker's ability to transfer intangibles, poachers draw workers with sufficiently high leakability to make poaching profitable, and firms with higher retainability have weaker incentives to share rents.

While these features do not rely on uniformity, alternative functional forms may affect the model's quantitative implications. For instance, a right-skewed distribution of ξ_w would reduce equilibrium poaching risk, lower rent sharing, and weaken worker mobility, as fewer workers can transfer intangibles to poaching firms. Conversely, a distribution with more mass near one would increase poaching pressure and increase rent sharing. Similarly, a distribution of ξ_f with more mass shifted to the right would allow more firms to sort into innovating rather than poaching, thereby reducing overall rent sharing. These changes are relevant for the model's quantitative predictions but do not alter its fundamental comparative statics: higher average leakability increases poaching and rent sharing, higher average retainability reduces rent sharing, and non-compete agreements dampen poaching incentives. The uniform assumption therefore serves as a parsimonious benchmark, which can also be interpreted as a flat Bayesian prior that can be informed by future empirical work.

Model illustration. Based on these modeling choices and the choice of model parameters[12], reported in Table 1, we illustrate the model's main theoretical insights in Figures 1 and 2. Figure 1 shows the positive relationship between the price-cost markup and intangible intensity z, implied by Proposition 1. Figure 2 illustrates the hump-shaped relationship between the optimal rent-sharing policy β^* and intangible intensity z, with the relationship being positive for about 90 percent of the mass of firms, implied by Proposition 2. The $\beta - z$ relationship is plotted for different levels of retainability ξ_f. A higher level of intangibles initially increases optimal rent sharing, up to a point at which the opportunity cost of more rent sharing tilts in favor of a less generous policy. This occurs because profits grow more slowly than the poaching hazard, making it less attractive to give up rents in order to retain a worker in the event of a potential poaching attempt. Finally, as implied by Proposition 3, for any given level of intangible intensity, the relationship between optimal rent sharing and retainability is negative, since worker separation becomes less costly in terms of forgone profits.

Testable predictions. In general, our model yields the following qualitative predictions:

- *Qualitative prediction 1, following from Proposition 1.* There is a positive relationship between the level of intangibles z and price-cost markups (μ), by choice of demand curve.
- *Qualitative prediction 2, following from Proposition 2.* There is a hump-shaped relationship between the level of intangibles z and the extent of rent sharing (β), but in simulations the relationship is positive for about 90 percent of the mass of firms.
- *Qualitative prediction 3, following from Proposition 3.* The level of β and the positive relationship between z and β weakens at high values of retainability (ξ_f).
- *Qualitative prediction 4, following from Proposition 5.* A non-compete agreement (a) reduces the extent of rent sharing for innovators and (b) limits worker transitions from innovators to

[12] The parameter values are either imposed to satisfy technical targets, bounded to loosely meet some stylized facts in the data, or calibrated based on values commonly used in the existing literature.

poachers.

3 Model meets data

This section empirically tests the model's main predictions through a series of descriptive analyses. Section 3.1 introduces our microdata for the Netherlands. Section 3.2 examines the co-movement between product and labor market imperfections, showing that most Dutch employers in manufacturing and services charge prices above marginal cost and compensate workers above their marginal revenue product. Section 3.3 presents evidence on the positive relationship between product and labor market imperfections (price-cost markups and wage markups) and intangible intensity, including some heterogeneity checks. Section 3.4 presents descriptive evidence on the relationship between NCAs and worker-level outcomes. Section 3.5 discusses the empirical mapping of our novel model features and directions for future research.

3.1 Data

To test the model's predictions about qualitative relationships, we use several micro data sets collected by Statistics Netherlands (CBS).

The first is the "Production Statistics Survey" (*Productiestatistiek, PS*). This source provides enterprise-level (business unit) data on production value, factor inputs and factor costs. It also includes automation expenditure, a specific item encompassing any expenses allocated to third-party services geared towards automating business processes. 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 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 second is the"Use of ICT by Companies Survey" (*ICT*). This source contains annual data on the use of information and communication technology (ICT) in enterprises. 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 third is the "Community Innovation Survey" (*CIS*). This a biennial enterprise survey that asks enterprises about their innovation activities over a three-year reference period. It follows the Oslo Manual and the EU harmonized questionnaire. We match this source with the PS via unique firm identifiers.

The fourth is the administrative matched employer-employee dataset (*Banen en lonen volgens Polisadministratie, POLIS*). It records every monthly employment spell with earnings, hours, and contract type, covering all employees in the Netherlands who work for domestic firms and pay social security contributions. We use it to extract labor income, tenure, contract type, whether workers' wages are negotiated through collective bargaining at the firm level, and demographic characteristics.

The fifth is the education database (*Hoogsteopltab, EDUC*). It provides the highest level of education attained by an individual on October 1 of the year. The education level is based on a 2-digit SOI-code (Dutch education classification, "Standaard Onderwijsindeling") and is converted to the ISCED classification (International Standard Classification of Education). Using the ISCED-codes, we classify employees as low-, medium-, or high-skilled, following O'Mahony et al. (2008).[13]

The final is the "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 in workers' contracts, which is available from 2015 until 2018. We also retrieve information on workers' occupation type which is based on the ISCO code ("International Standard Classification of Occupations"). We only retain workers

[13]Low-skilled refers to workers who have up to and including low (junior) secondary education. Medium-skilled refers to workers with upper-secondary or post-secondary education excluding tertiary education. The latter includes higher levels of vocational education ("middelbaar beroepsonderwijs", MBO), which is post-secondary but not classified as higher education. High-skilled workers have tertiary education, which falls under higher education, and is divided into two types: higher professional education ("hoger beroepsonderwijs", HBO) and research-oriented higher education ("wetenschappelijk onderwijs", WO). Both universities of applied sciences (HBO institutions) and research universities (WO institutions) offer bachelor's, master's, and doctoral programs. Doctoral programs include professional doctorates, awarded by universities of applied sciences and PhDs, awarded by research universities.

who provide non-missing information on the survey questions related to NCAs. We match this source with the firm data via unique employee identifiers in the POLIS and EBB.

3.2 Co-movement between product and labor market imperfections

Production function approach. In essence, our model offers a framework for analyzing how product and labor market imperfections jointly arise. To let the model meet the data, we start by measuring product market imperfections (price-cost markups) and labor market imperfections (rent sharing) at the firm level. To do so, we follow the production function approach introduced in Dobbelaere and Mairesse (2013), which is widely applied in empirical research. The authors 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 versus 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 versus wage markup) and size (deviation of wages from the marginal revenue product of labor) of labor market imperfections that allows the researcher to be agnostic about market structure. 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 $\Omega_{H,it}$ 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:

$$Q_{it} = \Omega_{H,it} Q(L_{it}, M_{it}, K_{it}) \tag{8}$$

In terms of the firm's input choices, we assume that (i) labor and intermediate inputs are free of adjustment 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}:

$$\mu_{it} = \frac{P_{it}}{(C_Q)_{it}} = \left(1 + \frac{s_{it}\bar{C}_{it}}{e_t}\right)^{-1} \tag{9}$$

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 $\bar{C}_{it} = \partial Q_t/\partial Q_{it}$ 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 by:

$$\mu_{it} = \frac{(\varepsilon_M^Q)_{it}}{\alpha_{Mit}} \tag{10}$$

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, which is our model-consistent measure of product market imperfections ($\frac{p(y)}{MC}$ in Section 2).

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:

$$\psi_{it} = \frac{(\varepsilon^Q_M)_{it}/\alpha_{Mit}}{(\varepsilon^Q_L)_{it}/\alpha_{Lit}} = \frac{\mu_{it}}{\frac{(Q_L)_{it}L_{it}}{Q_{it}}\frac{P_{it}Q_{it}}{W_{it}L_{it}}} = \frac{W_{it}}{P_{it}(Q_L)_{it}/\mu_{it}} = \frac{W_{it}}{(R_L)_{it}} \tag{11}$$

that gives the ratio of the firm's wage to the marginal revenue product of labor. The intuition behind (11) 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. Wage markups paid by firms can be rationalized by a rent-sharing mechanism and serves as our model-consistent measure of rent sharing (β in Section 2). To validate this rent-sharing interpretation, we examined the predictive power of ψ_{it} for employer wage premia, that is, employers' wage levels adjusted for worker sorting (see infra). Such premia are typically interpreted as representing rent sharing (Card et al., 2016).

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 shares in total revenue 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 survey, we implement the production function approach and estimate production functions using Ackerberg et al. (2015)'s control function estimator (see Appendix B for details on the estimation and variable definitions).

Co-movement between product and labor market imperfections. The majority of Dutch employers set prices above marginal cost and pay workers above their marginal revenue product. This evidence is shown in the left panel of Figure 3, presenting median estimates of product and labor market imperfections for manufacturing and services industries over the period 2000-2020 in the Dutch economy.[14] Each circle represents a 3-digit NACE Rev. 2 industry. The size of each circle

[14]These industry medians of price-cost markups should be interpreted as descriptive patterns in product market imperfections rather than as precise estimates of price-cost markup levels, given that output is proxied by revenue

is proportional to the real value-added share of the industry and presents an average over time. We observe that the majority of firm-year observations involve a price-cost markup ($\mu_{it} = \frac{(\varepsilon_M^Q)_{it}}{\alpha_{Mit}} > 1$) and a wage markup ($\psi_{it} = \frac{(\varepsilon_M^Q)_{it}/\alpha_{Mit}}{(\varepsilon_L^Q)_{it}/\alpha_{Lit}} = \frac{W_{it}}{(R_L)_{it}} > 1$). To corroborate our model-consistent rent-sharing interpretation of our measure of labor market imperfections (ψ), we estimated a standard AKM model (Abowd et al., 1999) that decomposes a worker's wage into a worker-specific and a firm-specific component, following Card et al. (2018), Hirsch and Mueller (2020) and Dobbelaere et al. (2024). The firm-specific component reflects the percentage wage premium paid by a firm to all its employees and is typically interpreted as rent sharing. As predicted by theory, we find a statistically significant positive association between the mean employer wage premium and the log of ψ.[15]

The bottom-right panel of Figure 3 shows the proportion of each of the four possible combinations of product (μ_{it}) and labor (ψ_{it}) market imperfection parameter estimates, broken down by 1-digit NACE Rev. 2 industries.[16] This panel highlights that price-cost markups and wage markups are particularly prevalent in the professional, scientific and technical activity industry, as well as the wholesale trade industry, both highly technology-driven industries in the Netherlands. Appendix Figure C1 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 from US manufacturing (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 (SMEs) and exporters, characterized by high productivity, innovativeness (filing more than seven patents per firm on average) and average wages (see Appendix Table C2).

deflated with industry price indices. See Appendix B for a discussion.

[15]More specifically, we regressed the standardized AKM firm-specific wage component on the log ratio of wages to the marginal revenue product of labor (ψ), controlling for firm surplus measured by gross operating profit per worker, firm size measured by the number of full-time equivalent employees, firm age, the share of medium- and high-skilled workers, 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. We find that a one standard deviation larger log ratio (ψ), 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. A standard deviation in firm wage premia amounts to 29 log points in our sample, so this partial correlation is sizeable. The regression uses the universe of workers and firms in the Netherlands. These estimates are not shown but are available on request.

[16]The share of firms for each combination of labor and product market imperfection parameters by 1-digit industry is reported in Appendix Table C1.

3.3 Correlation between product and labor market imperfections and intangible intensity

From Section 3.2, 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 workers' monopoly/bargaining power. While we do not rule out these mechanisms, they are not able to explain the joint occurrence of price-cost markups and wage markup across firms on their own. Our model in Section 2 show how innovative firms that co-create intangible assets jointly with their workers can rationalize the observed joint occurrence.

Measuring intangibles. Our model's first two qualitative predictions (see Section 2.5) invite regressions that relate firms' price-cost markups (μ) and wage markups (ψ) to their level of intangibles (z), with a positive relationship predicted. Testing these predictions involves the challenge of measuring the unobservable z. To proxy intangible assets, we use a firm's "automation expenditure". This variable is reported in the Production Statistics 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.

Automation expenditure has been used in existing work to assess the impact of automation on firm and worker outcomes (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 intangible-driven productivity potential because part of their value is specific to the firm (Corrado et al., 2013; Calligaris et al., 2018; Tambe et al., 2019). 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 poaching, primarily due to its reliance on tacit knowledge.

Additional proxies. To assess whether our automation-expenditure proxy serves as a useful (albeit imperfect) measure for intangibles, we leverage a detailed firm-level survey on the use of information and communication technologies, which we link to the Production Statistics Survey. We compare the average automation expenditure per worker between adopters and non-adopters of Artificial Intelligence, industrial robots, Automated Data Exchange and Enterprise Resource Planning, and by whether firms employ ICT personnel and allow employees to access emails remotely. Appendix Figure C2 shows that automation expenditure per worker is positively correlated with all technologies, except for industrial robots, supporting its use as a proxy for intangibles. To exploit continuous rather than binary ICT measures, we regress log automation expenditure per worker on the share of employees with remote access to company files and, alternatively, on the share with access to telework, controlling for industry and year fixed effects. As shown in Appendix Figure C3, we confirm a positive relationship between both continuous variables and our proxy of intangibles. Finally, we exploit information on firms' implementation of process, product and organizational innovations from the CIS Survey, which we link to the Production Statistics Survey. These measures are self-reported indicators, unlike automation expenditure which is sourced from firms' official accounts. Appendix Table C3 reports correlations between firms' (standardized) automation expenditure per worker and their self-reported implementation of process, product, and organizational innovations, controlling for industry fixed effects and firm size. Automation expenditure per worker is significantly positively associated with all three innovation types, with the strongest association for process innovation. These results suggest that intangible-intensive firms are more innovative across the board.

Correlations between price-cost markups, wage markups, and intangibles. We now test in the micro data the model's prediction of a positive firm-level relationship between price-cost markups (μ), wage markups (ψ) and intangibles (z). To do so, we employ a within (fixed-effects) estimator to uncover the predicted positive correlation, thereby exploiting within-firm changes over time in intangibles and the corresponding within-firm changes in price–cost and wage markups for identification.[17] We start by estimating fixed-effects panel data models covering the years 2000-2020 period using the Production Statistics Survey. 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, as well as industry-level characteristics (market concentration measured by the Herfindahl-Hirschman Index (HHI) and share of patenting firms). Table 2 presents the results. In specifications (2), (4) and (6), we restrict the set of firms to exporting firms only. Consistent with the model's first two qualitative predictions, we find a statistically significant positive correlation between automation expenditure per worker and both market imperfection parameters. We interpret these findings as suggestive evidence of intangible assets driving both labor and product market imperfections.[18]

Figure 4 provides complementary evidence in line with the model's implied patterns. It plots average automation expenditure per worker along with 95% confidence intervals for each possible combination of labor and product market imperfection parameters. Firms that set price-cost markups ($\mu_{it} > 1$) and pay wage markups ($\psi_{it} > 1$) are characterized by a higher intensity in intangible assets (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). Appendix Table C4 presents a robustness check using binary indicators for either process, product, or organizational innovation to proxy intangibles. Consistent with our main proxy for intangibles, price–cost and wage markups are significantly positively associated with any of the three innovation types.

Heterogeneity. To further assess the model's qualitative predictions, we test whether the positive relationship between wage markups and intangibles weakens for firms with either high intangible intensity or high retainability. These heterogeneity analyses are reported in Table 3 and Table 4. The first two columns of Table 3 present estimates by intangible intensity, with high-intangible

[17] This design reduces reliance on cross-sectional differences in price–cost markup levels, which are a concern when markups are measured using the production function approach with revenue data and firm-level prices are unobserved. See Appendix B for a discussion.

[18] 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).

firms defined as those in the upper tail of the intangible-intensity distribution. Column (1) uses the top 25% cutoff and column (2) the top 10%. Consistent with the model's second qualitative prediction, the positive correlation between wage markups and intangibles is weaker for firms in the upper tail of the intangible-intensity distribution. For firms in the top 10% of this distribution, the relationship becomes even negative. In column (3) of Table 3, we proxy firms' ability to retain intangibles by an indicator for patent filing. We do not observe a significant difference in the correlation between wage markups and intangibles for patenting versus non-patenting firms. Since patent filing is only a coarse measure of retainability, we turn to firm-level variation in IP protection (i.e. filings for trademarks, patents, or other IP) from the CIS survey as our preferred measure of retainability. The resulting estimates are reported in Table 4. Using CIS innovation-type indicators to proxy intangibles, we find a weaker relationship between wage markups and intangibles among firms with IP protection, consistent with the model's third qualitative prediction.

3.4 Non-compete agreements and worker-level outcomes

NCAs are becoming increasingly widespread in advanced economies and the literature has shown evidence of their effects on 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.[19] Furthermore, firms indicate that NCAs provide a key tool to protect their knowledge assets (Thomä and Bizer, 2013; Mezzanotti and Simcoe, 2023).

To assess the model's qualitative relationships on non-compete agreements, we turn to regressions at the worker level, exploiting information on NCAs from the Labor Force Survey. We construct a sample of workers matched with their employers using linked employer-employee data (POLIS-PS sample). We match workers from the POLIS-PS panel with workers in the Labor Force Survey, with the latter reporting at the monthly frequency whether workers had an NCA in their contract.[20] Our "treatment" group is composed of workers having an NCA in their contract, our "control" group workers without an NCA. To reduce concerns due to potential selection into treatment, we

[19] 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., 2025).

[20] 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).

do not just compare the two groups but we match treated units to control units via propensity score matching. The propensity score is estimated using a Logit model including tenure, gender, age and age squared, average compensation, education and occupation type. We match each treated unit to up to three control units based on nearest neighbor matching.

We run a simple regression using labor income and job mobility measured by the number of future employees as worker-level outcomes. The estimates are reported in Table 5. Columns (1) and (3) report the baseline results, while columns (2) and (4) restrict the sample to a stronger overlap in terms of propensity score, i.e. where the amount of control units for each decile of the score is at least 50% of the amount of treated units. The overlap is weakest at the right tail of the score, with relatively more treated than control units.

On average, NCA workers earn higher wages, which can be interpreted as a compensating differential: workers receive higher current pay in exchange for signing non-compete agreements, which limit their ability to move to better jobs. However, in intangible-using firms (defined by positive automation expenditure per worker), their labor compensation is lower (see columns (1) and (2)). We interpret the latter as suggestive evidence consistent with the first part of the model's fourth qualitative prediction, stating that NCAs reduce rent sharing for innovators. While these results are descriptive, they are in line with existing evidence –largely from the US– showing that the use and enforceability of NCAs have adverse effects on wages by reducing workers' outside options and shifting bargaining power away from employees (Garnero and Andrews, 2025).

We also examine whether NCAs are associated with lower subsequent worker mobility, measured by the number of future employers (see columns (3) and (4)). Although the estimated average coefficient is negative, it is statistically non-significant. At first glance, this descriptive result appears to be at odds with existing quasi-experimental evidence (Young, 2024; Johnson et al., 2025). However, the average null effect may reflect heterogeneity in how NCAs affect mobility across different types of job transitions. Rather than reducing overall mobility, NCAs may primarily constrain transitions to competitors, which we attempt to capture by moves within the set of intangible-using firms. The estimated coefficient on the interaction between NCAs and intangible-using firms is, however, not statistically significant, and we, therefore, cannot corroborate the second part of the model's fourth qualitative prediction at conventional significance levels. Through the lens of our model, mobility within the pool of competitors corresponds to moves from innovators to poachers, transitions that are difficult to identify with the data at hand. We discuss this measurement limitation in the next section.

3.5 Discussion and directions for future research

Empirical mapping of novel model features. A first point of discussion concerns the nature of the retainability and leakability parameters, ξ_f and ξ_w, respectively. As we are not aware of other studies that examine comparable parameters, it is useful to consider their potential empirical counterparts. By construction, these parameters are time-invariant characteristics of firms and workers and are not directly observable in standard datasets. In empirical work, they can therefore be interpreted as fixed effects capturing persistent heterogeneity in the ability of firms to retain knowledge and in workers' ability to transfer knowledge across employers and need to be measured indirectly.

A high value of ξ_f characterizes an organization that can codify, store, and deploy knowledge independently of specific employees. Empirically, this can be proxied by the adoption of digital technologies and data-management systems, standardized management practices, and investments in information infrastructure that reduce reliance on specific workers. Similarly, firms' retainability might be higher if they are embedded in production networks where such technologies and practices are shared among firms along the value chain. In addition, intellectual property protection –such as trademark or patent filings– provides formal mechanisms for codifying intangible assets and ensuring firm access. We use these measures as proxies for retainability in our heterogeneity analyses (see Section 3.3).

Finding empirical proxies for ξ_w is particularly challenging. A high value of this parameter corresponds to the share of a firm's intangible assets that a worker can carry to another firm, independent of how well the origin firm can retain that knowledge, and thus determines the worker's value to a poacher. Workers may, for example, hold detailed product specifications or operational know-how that enables the poaching firm to exploit part of the origin firm's intangible capital. Education and experience are, however, imperfect proxies because leakability concerns the portability of match-specific intangible assets rather than general productivity. Nor does a simple tacit-versus-codified distinction map cleanly into leakability: codification (e.g. through patents or procedure manuals) may facilitate transfer, but it can also make legal verification and prohibition easier. More informative measures may instead draw on exposure to professional networks and workers' career histories, such as whether job moves are systematically associated with transfers of clients, collaborators, and wage premia at destination firms. One approach is to focus on moves from intangible-using origin firms (innovators) to relevant competitors (i.e. technologically similar destination firms), and then examine whether the poacher's inferred intangible stock and profits increase after the hire.[21] Exploiting repeated moves by the same worker, a first-pass measure could be constructed from the share of transitions to technologically close firms, allowing workers to be grouped into leakability bins.

Implementing such an approach based on innovator-to-poacher transitions entails key econometric challenges related to measurement error, attribution, and selection. First, identifying competitor-to-competitor moves requires credible measures of technological proximity, not only across product or patent spaces but also along harder-to-observe dimensions such as customer relationships and organizational practices. Second, changes in destination-firm outcomes after a hire may reflect contemporaneous investments, demand shocks, or reorganization rather than the contribution of a single worker. Third, selection is central: firms that poach and workers who are poached are systematically different, so measured leakability may partly reflect sorting rather than a transferable knowledge component.

Role of non-compete agreements. A final point of discussion concerns the role of non-compete agreements in the model. While part of the literature has focused on their optimal regulation (Shi, 2023), in our setting the natural question is whether NCAs alleviate the hold-up problem associated with the adoption of intangible assets. It is important to emphasize that, in our framework, NCAs are not necessary to attenuate the hold-up problem between firms and workers. The model already features an endogenous mechanism –rent sharing– that enables innovators to retain workers with sufficiently high probability to make entry into the intangible-using sector privately profitable. By adjusting the share of rents offered to workers, firms can reduce poaching risk even in the absence of contractual mobility restrictions. Therefore, NCAs are not a prerequisite for innovation in the model. Instead, they reshape bargaining conditions in favor of firms by weakening workers' outside

[21] Jointly analyzing destination-firm outcomes and wage premium dynamics would allow the researcher to test whether high-leakability workers generate higher profits and therefore receive better offers. Additional identification might come from institutional variation that alters the feasibility or returns to poaching, e.g. changes in the enforceability of non-compete agreements, which should have the strongest effects on mobility and wage gains for high-leakability workers.

options, reducing equilibrium rent sharing, and lowering mobility. At the same time, NCAs increase the relative attractiveness of innovating over poaching for firms operating in the intangible-using sector, since innovating becomes ex ante less costly. Depending on the joint distribution of firm retainability (ξ_f) and worker leakability (ξ_w) at innovating and poaching firms, this sorting can lead to a higher or a lower level of aggregate value of intangibles z. While the net effect is theoretically ambiguous, empirical calibration could shed light on overall welfare effects of NCAs.

That said, there are environments beyond the scope of our current framework in which NCAs may play a more fundamental role. If worker leakability were sufficiently high and firm retainability sufficiently low, rent sharing alone might not prevent rapid dissipation of intangible rents, potentially deterring firms from entering as innovators. In addition, the present model abstracts from the intensive margin of intangible investment. Integrating an ex-ante innovation function, with incentives for firms and workers would make it possible to study whether NCAs could boost the intensive margin of innovation and affect welfare. We view such an extension as a promising direction for future work.

4 Conclusion

Recent empirical evidence has shown that product and labor market imperfections are related. From a policy perspective, it is important to understand the underlying drivers of such co-movement. In this paper, we provide a microfoundation linked to intangible assets. Intuitively, match-specific intangibles lower the marginal cost of production. Therefore, price-cost markups rise with intangible intensity under imperfect competition. Imperfect appropriability of rents, shaped by worker-specific leakability and firm-specific retainability, together with poaching risk incentivize firms to share rents to increase worker retention, generating wage markups. Through the lens of our model, non-compete agreements impose a start delay at the poacher, making outside offers less attractive. Hence, our framework addresses both market-based remedies (rent sharing) and regulatory interventions (such as non-compete agreements) for the hold-up problem created by knowledge leakability and poaching risk.

Using linked data that merge firms' annual accounts, technology use, and innovation surveys with employer–employee microdata (jobs, worker characteristics, and non-compete agreement clauses), we test the model's main qualitative predictions. Consistent with the theory, both price–cost and wage markups increase with firms' intangible intensity. However, the positive association between wage markups and intangibles disappears for firms in the upper tail of the intangible-intensity distribution and weakens for firms with intellectual property protection. Finally, labor compensation is lower for workers with non-compete agreements employed in intangible-using firms.

Our model and descriptive evidence highlight the challenges in tracing the effects of new, intangible, technologies on the co-movement of product and labor market imperfections. Before attempting to calculate the welfare effects of lowering barriers to worker mobility, for example by reducing stringency of non-compete agreements, one should formulate a framework to understand and quantify the myriad mechanisms between policy and economic outcomes. We hope this paper provides an early step. Our traditional toolkit with constant-return technologies and perfectly competitive spot markets is becoming less relevant, while fixed costs, and bargaining with uncertain outcomes are growing in importance along with new technology. In addition, our current data and the model classifications are hard to match. For example, it is difficult to find an empirical counterpart for technology and worker types used in the model. In the future, we plan to cluster firms by type of technology and features of demand, and cluster workers by traditional characteristics but also by observed labor market trajectories.

Figures and Tables

Figure 1: Price-cost markup by value of intangibles

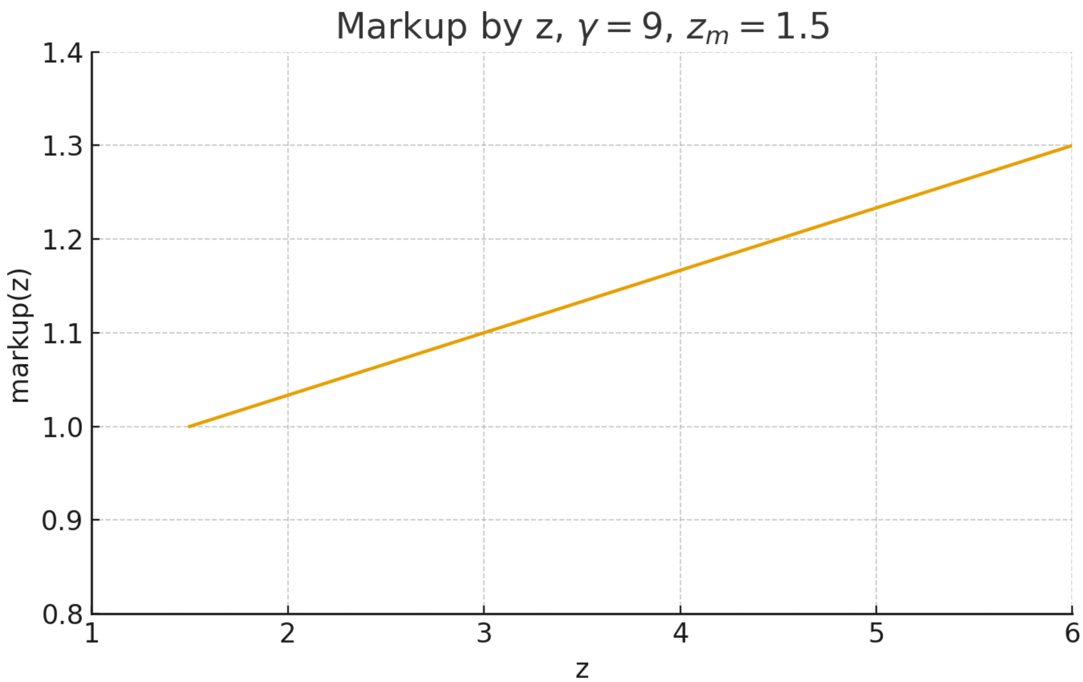


Figure 2: Optimal rent sharing for different values of retainability

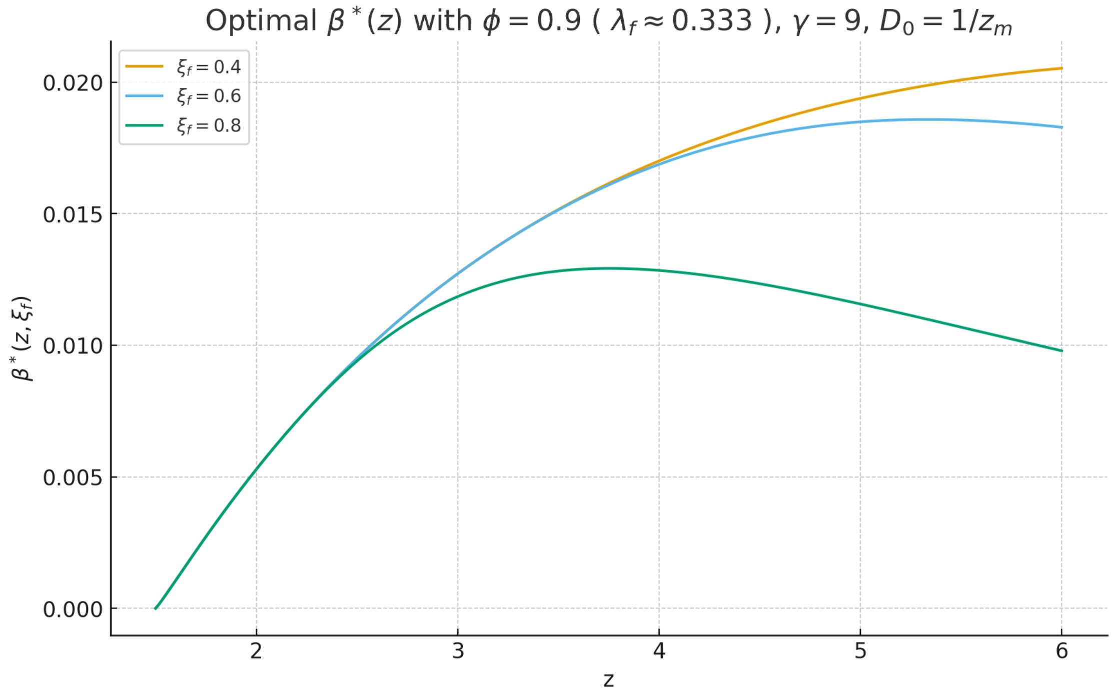
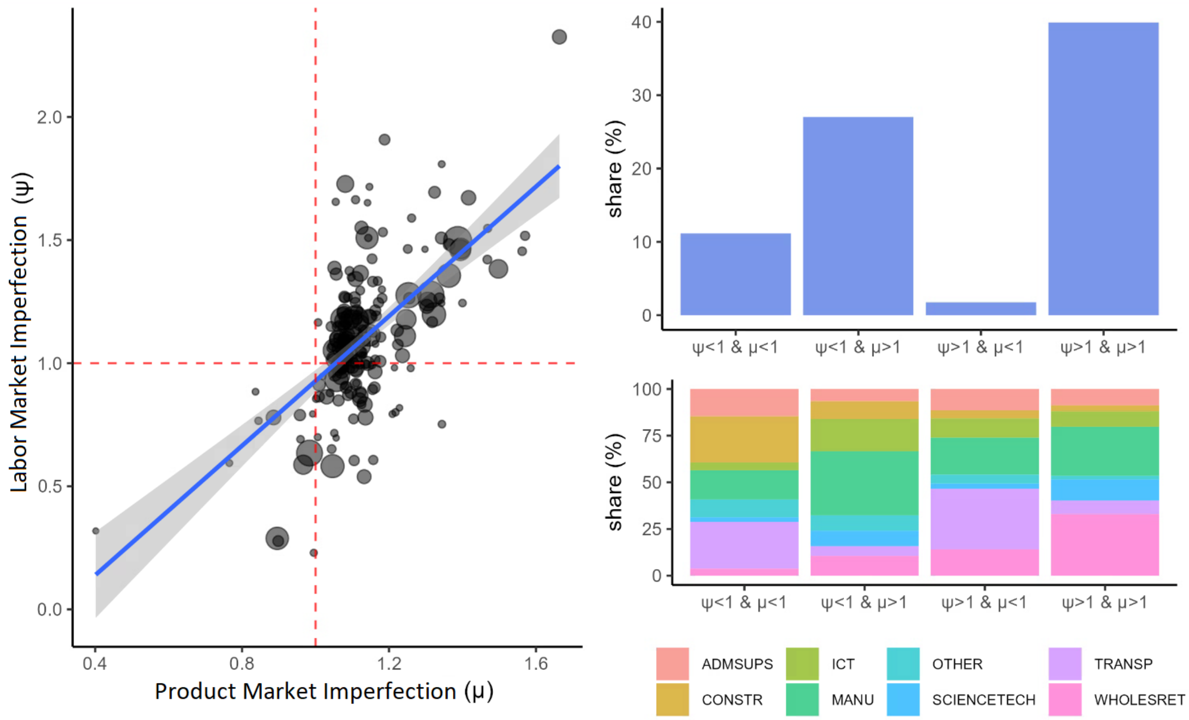
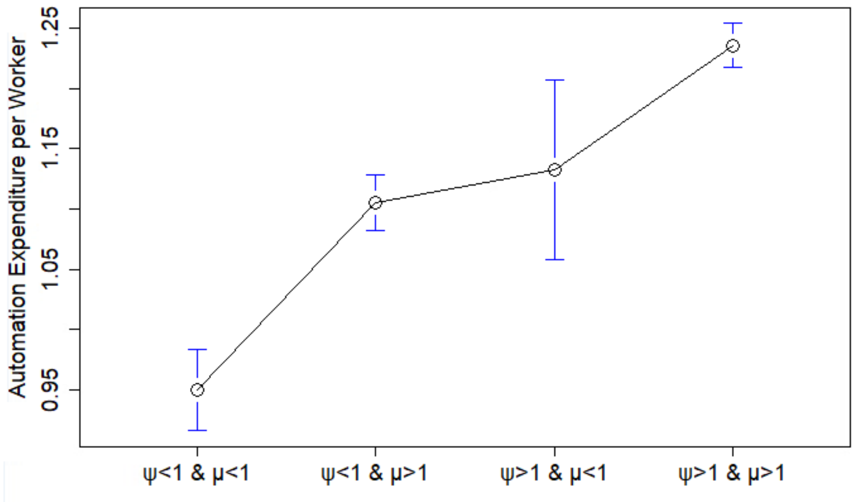


Figure 3: Labor and product market imperfection parameters by industry



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 4: 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.

Table 1: Choice of model parameters

Parameter	Description	Value	Source
z^0	Intangibles in safe sector	1	normalization
z_m	Lower support of intangibles draw	$1.5z_0$	mean$(z) = 2.5$
a	Pareto shape parameter	3	mean of draw is $3z^0$
γ	Exponent on y in demand curve	9	pass-through 0.9
D_1	Demand curve parameter	1	affects price-cost markup
D_0	Demand choke price	$= \bar{C}/z_m$	$\pi(z_m) = 0$
$\bar{C}$	Marginal cost constant	1	normalization
λ	Arrival rate of meeting	1	P(meeting)=1
η	Matching function parameter	0.5	literature
ρ	Discount rate	0.96	good value for a year
c_p, c_f	Entry fees	1, 6	set to allow innovator share of 0.8

Table 2: 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	0.024***	0.020***	0.006***	0.005***	0.018***	0.017***
	(0.003)	(0.004)	(0.002)	(0.002)	(0.003)	(0.003)
Firm size	-0.211***	-0.210***	-0.020***	-0.022***	-0.196***	-0.204***
	(0.010)	(0.012)	(0.004)	(0.005)	(0.008)	(0.011)
Firm age	0.025***	0.014	0.030***	0.028***	0.020**	0.009
	(0.008)	(0.010)	(0.005)	(0.006)	(0.008)	(0.009)
Labor productivity	0.008	-0.001	0.049***	0.035***	0.043***	0.043***
	(0.006)	(0.008)	(0.003)	(0.004)	(0.006)	(0.007)
Average wage	0.001***	0.001***	-0.000***	-0.000***	0.001***	0.001***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Firm-level CBA (0-1)	0.001	-0.002	0.000	-0.002	0.002	-0.007
	(0.008)	(0.008)	(0.005)	(0.005)	(0.007)	(0.008)
Foreign-owned (0-1)		0.025**		0.002		0.032***
		(0.012)		(0.006)		(0.011)
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	-0.010	0.229	-0.282***	-0.193*	0.063	0.237
	(0.194)	(0.234)	(0.098)	(0.109)	(0.182)	(0.224)
Constant	0.779***	0.864***	-0.063**	0.020	0.659***	0.734***
	(0.055)	(0.076)	(0.025)	(0.031)	(0.048)	(0.064)
Number of observations	75,850	51,281	75,850	51,281	66,625	45,953
Number of firms	19,024	14,755	19,024	14,755	17,664	13,689

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. Additional controls include firm fixed effects and year fixed effects. 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 reported in parentheses. ***/**/* denotes statistical significance at the 1%/5%/10% level.

Table 3: Partial correlations between labor market imperfections and intangibles: Heterogeneity by high intangible intensity and retainability

	(1)	(2)	(3)
Automation exp. per worker	0.025***	0.025***	0.024***
	(0.004)	(0.003)	(0.003)
$\mathcal{I}$\{top 25% of autom. exp. per worker\}	0.029**		
	(0.013)		
Automation exp. per worker × $\mathcal{I}$	-0.020**		
	(0.010)		
$\mathcal{I}$\{top 10% of autom. exp. per worker\}		0.065***	
		(0.025)	
Automation exp. per worker × $\mathcal{I}$		-0.036**	
		(0.014)	
$\mathcal{I}$\{Any patents\}			0.003
			(0.013)
Automation exp. per worker × $\mathcal{I}$			0.000
			(0.011)
Number of observations	75,850	75,850	75,850
Number of firms	19,024	19,024	19,024

Note: Fixed-effects regressions of reduced-form firm-level measure of labor market imperfections (ψ) on intangibles measured by automation expenditure per worker. In columns (1)–(2), the average coefficient on intangibles is interacted with an indicator for firms in the upper tail of the intangible-intensity distribution (defined as either the top 25% in column (1) or top 10% in column (2)). In column (3), the average coefficient on intangibles is interacted with an indicator for patent filing, which we use to proxy firms' ability to retain intangible assets. Additional controls include firm fixed effects and year fixed effects, firm size, firm age, average wage bill and labor productivity. Standard errors are clustered at the firm level and reported in parentheses. ***/**/* denotes statistical significance at the 1%/5%/10% level.

Table 4: Partial correlations between labor market imperfections and intangibles: Heterogeneity by retainability based on IP protection

	(1)	(2)	(3)
Process innovator × No IP protection	0.012*		
	(0.007)		
Process innovator × IP protection	0.011		
	(0.010)		
Product innovator × No IP protection		0.015**	
		(0.007)	
Product innovator × IP protection		0.009	
		(0.009)	
Organizational innovator × No IP protection			0.015**
			(0.006)
Organizational innovator × IP protection			0.010
			(0.009)
Number of observation	14,361	14,361	14,361
Number of firms	7,118	7,118	7,118

Note: Fixed-effects regressions of reduced-form firm-level measure of labor market imperfections (ψ) on intangibles proxied by binary indicators for either process, product, or organizational innovation, interacted with a binary indicator for intellectual property (IP) protection (i.e. whether the firm files for trademarks, patents or other forms of IP protection). The average coefficient of intangibles is interacted with this IP binary indicator, a proxy for higher ability to retain intangible assets. Additional controls include firm fixed effects and year fixed effects, firm size, firm age, average wage bill and labor productivity. Standard errors are reported in parentheses. ***/**/* denotes statistical significance at the 1%/5%/10% level.

Table 5: Descriptive evidence on non-compete agreements and worker-level outcomes

Variables	(1) log hourly wage	(2) log hourly wage	(3) future mobility	(4) future mobility
Any NCA	0.225*	0.268*	-0.079	-0.093
	(0.122)	(0.154)	(0.099)	(0.109)
$\mathcal{I}$\{Pos. autom. exp. per worker\}	0.023	0.018	-0.009	-0.008
	(0.021)	(0.023)	(0.008)	(0.008)
Any NCA $\times$ $\mathcal{I}$\{Pos. autom. exp. per worker\}	-0.065**	-0.085*	0.003	-0.001
	(0.032)	(0.048)	(0.014)	(0.025)
Full-time contract (0-1)	-0.034**	-0.033	0.004	0.001
	(0.014)	(0.017)	(0.003)	(0.004)
Medium-skilled	0.114***	0.110***	-0.001	0.002
	(0.020)	(0.020)	(0.005)	(0.004)
High-skilled	0.131***	0.118***	-0.005	0.001
	(0.037)	(0.039)	(0.010)	(0.010)
Overtime work (0-1)	-0.030	0.000	-0.001	-0.005
	(0.019)	(0.022)	(0.004)	(0.004)
Tenure	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Age	-0.005	0.001	-0.004	-0.005
	(0.024)	(0.024)	(0.004)	(0.004)
Age squared	-0.001***	-0.001***	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Number of observations	384,169	319,534	272,762	225,307
Number of individuals	17,886	15,959	13,292	11,855

Note: This table shows two separate OLS regressions using labor compensation (measured by log net hourly wages) and future mobility (measured by the number of future employers) as worker-level outcome variable, respectively. Additional controls include individual, quarter and year fixed effects, and occupation type. Columns (2) and (4) restrict the sample to individuals with a propensity score below 0.4, ensuring large overlap between treated and control individuals. Standard errors are clustered at the individual level and are reported in parentheses. ***/**/* denotes statistical significance at the 1%/5%/10% level.

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Appendix for Intangible Assets and Imperfections in Product and Labor Markets

A Derivations of the theoretical model

A.1 Derivation of static profits and markups

A.1.1 Cost function and marginal cost

Define

$$\bar{C} \;=\; \frac{p_x^{\alpha}\,\omega^{\,1-\alpha}}{\alpha^{\alpha}(1-\alpha)^{\,1-\alpha}}.$$

Then

$$C(y,z) = p_x\,x(y,z) + \omega\,l(y,z) = \bar{C}\,y\,z^{-1}, \tag{A.1}$$

$$MC(y) = \frac{\partial C}{\partial y} = \bar{C}\,z^{-1}. \tag{A.2}$$

A.1.2 Equilibrium output y^*

Recall

$$MC = \bar{C}\,z^{-1}.$$

Marginal revenue

$$MR(y) = p(y) + y\,p'(y) = D_0 \;-\; D_1\Big(1+\tfrac{1}{\gamma}\Big)\,y^{1/\gamma}.$$

Set $MR(y) = MC$ and solve:

$$y^{1/\gamma} = \frac{D_0 - MC}{D_1\big(1+\frac{1}{\gamma}\big)},$$

$$y^*(z) = \left[\frac{D_0 - \bar{C}\,z^{-1}}{D_1\big(1+\frac{1}{\gamma}\big)}\right]^{\gamma}.$$

A.1.3 Equilibrium profits π^*

Profit at optimum:

$$\pi^* = \big(p(y^*) - MC\big)\, y^*.$$

Using $p(y^*) - MC = (D_0 - MC)/(\gamma + 1)$ and $1 + 1/\gamma = (\gamma + 1)/\gamma$ yields

$$\pi^*(z) = \frac{\gamma^\gamma}{(\gamma+1)^{\gamma+1}} \, \frac{\big(D_0 - \bar{C} z^{-1}\big)^{\gamma+1}}{D_1^\gamma}. \tag{A.3}$$

A.1.4 Markup over marginal cost

Applying the definition of markup over total marginal cost:

$$\frac{p(y)}{MC} = \frac{D_0 - D_1\, y^{1/\gamma}}{\bar{C}\, z^{-1}} = \frac{\gamma}{\gamma+1} + \frac{D_0\, z}{(\gamma+1)\, \bar{C}} \tag{A.4}$$

To allow for existence and uniqueness of profit maximizing z^*, we restrict the support of z_f to be bounded by z_*: $\frac{(2+\gamma)\bar{C}}{2D_0}$. It is possible to verify that the profit equation is positive and concave for all $z \in [z_*, \infty)$.

A.2 Analysis of $d\beta^*/dz$

Setup To simplify algebra, we make some substitutions in the function for the cutoff of acceptable offers from poacher:

$$\Xi(\beta, z) = \frac{\bar{C}}{\bar{C}\beta^{\frac{1}{\gamma+1}} + zD_0(1 - \beta^{\frac{1}{\gamma+1}})}$$

Let $b \equiv \beta^{1/(\gamma+1)} \in (0, 1)$ and

$$D(b; z) = A_z + (\bar{C} - A_z)b, \qquad A_z = zD_0, \qquad P(b, z) = 1 - \frac{\bar{C}}{D(b; z)}.$$

Let $R(z, \xi_f) \equiv \pi(\xi_f z)/\pi(z)$ with $\pi(z) > 0$. Normalizing pre- and post-poach rents by dividing by $\pi(z)$, the objective in b is

$$v(b; z, \xi_f) = \big(1 - \lambda P(b, z)\big)\big(1 - b^{\gamma+1}\big) + \lambda P(b, z)\, R(z, \xi_f).$$

An interior optimum $b^*(z, \xi_f) \in (0, 1)$ solves the first-order condition

$$G(b, z, \xi_f) = 0, \qquad G(b, z, \xi_f) = (\gamma + 1)b^{\gamma}(\lambda P - 1) + \lambda P_t\,(b^{\gamma+1} + R - 1), \tag{FOC}$$

where on the support of z defined in A.1:

$$P_b = \frac{\partial P}{\partial b} = \frac{\bar{C}(\bar{C} - A_z)}{D^2} < 0, \qquad P_{bb} = -\frac{2\bar{C}(\bar{C} - A_z)^2}{D^3} < 0,$$

$$P_z = \frac{\partial P}{\partial z} = \frac{\bar{C}D_0(1 - b)}{D^2} > 0, \quad P_{zb} = \frac{\partial^2 P}{\partial z\, \partial t} = \frac{-\bar{C}[D_0 D + 2(\bar{C} - zD_0)\bar{C}(1 - b)]}{D^3}.$$

where the sign of P_{zb} varies with z (see below).

At any interior solution one has $b^{\gamma+1} + R - 1 < 0$ (from $P_b < 0$ and the first-order condition).

Slope formulas (implicit function theorem) Let $G_b \equiv \partial G/\partial b$, $G_z \equiv \partial G/\partial z$, $G_R \equiv \partial G/\partial R$. With $G_b < 0$ (SOC), the comparative statics are

$$\frac{\partial b^*}{\partial \theta} = -\frac{G_\theta}{G_b}, \qquad \theta \in \{z, R\}, \qquad \frac{\partial \beta^*}{\partial \theta} = (\gamma + 1)\,(b^*)^{\gamma}\,\frac{\partial b^*}{\partial \theta}. \tag{CS}$$

Useful derivatives

$$G_z = (\gamma + 1)\, b^{\gamma}\, \lambda P_z \;+\; \lambda P_{zb}\, (b^{\gamma+1} + R - 1) \;+\; \lambda P_b\, R_z, \qquad R_z = \frac{\partial R}{\partial z},$$

$$G_R = \lambda P_b \;<\; 0.$$

Effect of R and of ξ_f (Proof of Proposition 3) From (CS) and $G_R, G_b < 0$,

$$\frac{\partial t^*}{\partial R} = -\frac{G_R}{G_b} < 0, \qquad \frac{\partial \beta^*}{\partial R} < 0.$$

Since $R(z, \xi_f) = \pi(\xi_f z)/\pi(z)$ with z fixed,

$$\frac{\partial R}{\partial \xi_f} = \frac{z\,\pi'(\xi_f z)}{\pi(z)}.$$

Hence, whenever $\pi'(\cdot) > 0$ on the relevant support (profits increasing in productivity),

$$\frac{\partial R}{\partial \xi_f} > 0 \quad \Longrightarrow \quad \frac{\partial \beta^*}{\partial \xi_f} < 0.$$

Interpretation: improving the "alternative state" (larger ξ_f) raises R, which reduces the incentive to raise β; thus β^* falls with ξ_f.

Effect of z. (Proof of Proposition 2) By (CS) and the sign of G_b, $\text{sign}(\partial b^*/\partial z) = \text{sign}(G_z)$. Using $b^{\gamma+1} + R - 1 < 0$ at the optimum,

$$G_z = \underbrace{(\gamma+1)\, b^{\gamma}\, \lambda P_z}_{>0} + \underbrace{\lambda P_{zb}}_{\text{sign varies}} \underbrace{(b^{\gamma+1} + R - 1)}_{<0} + \underbrace{\lambda P_b}_{<0} \underbrace{R_z}_{\text{typically } \geq 0}. \qquad (\star)$$

Near the feasibility bound $z \downarrow \bar{z} = \bar{C}/D_0$: one has $A_z = zD_0 \to \bar{C}$ so $P_b \to 0^-$ and $P_{zb} < 0$. Then the second term in $(\star)$ is ≥ 0 (product of a negative and a negative), the third term is negligible, and the first is > 0; hence

$$\frac{\partial \beta^*}{\partial z} > 0 \quad \text{for } z \text{ close to } \bar{z}.$$

For large z: typically $R_z \geq 0$ (e.g., under $\pi(z) = z^s L(z)$ with $0 < s < 1$ and slowly varying L), while $P_b < 0$. The last term in $(\star)$ is then strictly negative and eventually dominates, with $P_{zb} \geq 0$ for large z (so the middle term is ≤ 0). Thus

$$\frac{\partial \beta^*}{\partial z} < 0 \quad \text{for sufficiently large } z.$$

Combining both regions yields the robust *hump shape*:

$$\exists\, \tilde{z} : \quad \frac{\partial \beta^*}{\partial z} > 0 \text{ for } z < \tilde{z}, \qquad \frac{\partial \beta^*}{\partial z} < 0 \text{ for } z > \tilde{z}.$$

A.3 Proof of Proposition 5

Step 1: Non-competes reduce poaching for given β Using the explicit expressions for Ξ and Ξ^ν we can write

$$\Xi^\nu(\beta, z) = \Xi(\beta/\nu, z).$$

From (3), for $zD_0 > \bar{C}$ (the feasible region), $\Xi(\beta, z)$ is strictly increasing in β; differentiating yields

$$\Xi_\beta(\beta, z) = \frac{\partial \Xi(\beta, z)}{\partial \beta} > 0 \quad \text{for all } \beta \in (0,1),\ zD_0 > \bar{C}.$$

Since $\Xi^\nu(\beta, z) = \Xi(\beta/\nu, z)$ and $\nu \in (0,1)$ implies $\beta/\nu > \beta$, it follows that

$$\Xi^\nu(\beta, z) = \Xi(\beta/\nu, z) > \Xi(\beta, z) \quad \text{for all } \beta \in (0,1).$$

Under the assumed uniform distribution of ξ_w, the probability of a successful poach at (β, z) is

$$\mathcal{P}(\beta, z) = 1 - \Xi(\beta, z), \quad \mathcal{P}^N(\beta, z) = 1 - \Xi^\nu(\beta, z).$$

Hence, for every (β, z),

$$\mathcal{P}^N(\beta, z) = 1 - \Xi^\nu(\beta, z) < 1 - \Xi(\beta, z) = \mathcal{P}(\beta, z),$$

which proves part (i).

Step 2: Non–competes and the optimal β We now compare the innovator's optimal rent–sharing choices. The baseline and NCA objectives can be written as

$$\tilde{V}(\beta) = (1 - \lambda_f \mathcal{P}(\beta))(1 - \beta) + \lambda_f \mathcal{P}(\beta) R,$$

$$\tilde{V}^N(\beta) = (1 - \lambda_f \mathcal{P}^N(\beta))(1 - \beta) + \lambda_f \mathcal{P}^N(\beta) R,$$

suppressing the dependence on (z, ξ_f) for notational convenience.

Differentiating, we obtain

$$\tilde{V}_\beta(\beta) = -(1 - \lambda_f \mathcal{P}(\beta)) - \lambda_f \mathcal{P}_\beta(\beta)(1 - R - \beta),$$

$$\tilde{V}_\beta^N(\beta) = -(1 - \lambda_f \mathcal{P}^N(\beta)) - \lambda_f \mathcal{P}_\beta^N(\beta)(1 - R - \beta).$$

By construction, the baseline interior optimum $\beta^*(z, \xi_f)$ solves $\tilde{V}_\beta(\beta^*) = 0$, i.e.

$$-(1 - \lambda_f \mathcal{P}(\beta^*)) = \lambda_f \mathcal{P}_\beta(\beta^*)(1 - R - \beta^*). \tag{A.5}$$

Since $\mathcal{P}_\beta < 0$ and $1 - \lambda_f \mathcal{P}(\beta^*) > 0$, it follows from (A.5) that

$$1 - R - \beta^* > 0. \tag{A.6}$$

Next, by Step 1 we have, for all β,

$$\mathcal{P}^N(\beta) < \mathcal{P}(\beta).$$

Using $\Xi^\nu(\beta) = \Xi(\beta/\nu)$ and the representation $\mathcal{P} = 1 - \Xi$, we also obtain

$$\mathcal{P}_\beta(\beta) = -\Xi_\beta(\beta), \qquad \mathcal{P}_\beta^N(\beta) = -\Xi_\beta(\beta/\nu)\frac{1}{\nu}.$$

Since Ξ_β is strictly increasing in β over $(0, 1)$, and $\beta/\nu > \beta$ for $\nu \in (0, 1)$, we have

$$\Xi_\beta(\beta/\nu) > \Xi_\beta(\beta) \quad \Longrightarrow \quad \mathcal{P}_\beta^N(\beta) = -\frac{1}{\nu}\Xi_\beta(\beta/\nu) < -\Xi_\beta(\beta) = \mathcal{P}_\beta(\beta),$$

so that for every β,

$$\mathcal{P}_\beta^N(\beta) < \mathcal{P}_\beta(\beta) < 0. \tag{A.7}$$

We now evaluate $\tilde{V}_\beta^N$ at the baseline optimum $\beta^* = \beta^*(z, \xi_f)$. Combining (A.5), (A.6), and

(A.7), we get

$$
\begin{aligned}
\tilde{V}^N_\beta(\beta^*) &= -(1-\lambda_f \mathcal{P}^N(\beta^*)) - \lambda_f \mathcal{P}^N_\beta(\beta^*)(1-R-\beta^*) \\
&= -(1-\lambda_f \mathcal{P}(\beta^*)) - \lambda_f \mathcal{P}_\beta(\beta^*)(1-R-\beta^*) \\
&\quad - \lambda_f \big[\mathcal{P}^N(\beta^*) - \mathcal{P}(\beta^*)\big] - \lambda_f \big[\mathcal{P}^N_\beta(\beta^*) - \mathcal{P}_\beta(\beta^*)\big](1-R-\beta^*) \\
&= 0 - \lambda_f \big[\mathcal{P}^N(\beta^*) - \mathcal{P}(\beta^*)\big] - \lambda_f \big[\mathcal{P}^N_\beta(\beta^*) - \mathcal{P}_\beta(\beta^*)\big](1-R-\beta^*).
\end{aligned}
$$

By Step 1, $\mathcal{P}^N(\beta^*) < \mathcal{P}(\beta^*)$, so the first difference in square brackets is negative. Likewise, from (A.7) and (A.6), $\mathcal{P}^N_\beta(\beta^*) - \mathcal{P}_\beta(\beta^*) < 0$ and $1-R-\beta^* > 0$, so the second bracketed term is also negative. Hence both corrections on the last line are strictly positive:

$$
-\lambda_f \big[\mathcal{P}^N(\beta^*) - \mathcal{P}(\beta^*)\big] > 0, \qquad -\lambda_f \big[\mathcal{P}^N_\beta(\beta^*) - \mathcal{P}_\beta(\beta^*)\big](1-R-\beta^*) > 0,
$$

which jointly imply

$$
\tilde{V}^N_\beta(\beta^*) < 0.
$$

Since $\tilde{V}^N(\beta)$ is strictly concave in β (by the same arguments used in Appendix A.2, proof of Proposition 2), the inequality $\tilde{V}^N_\beta(\beta^*) < 0$ implies that the unique maximizer $\beta^N(z, \xi_f)$ must satisfy

$$
\beta^N(z, \xi_f) < \beta^*(z, \xi_f),
$$

whenever $\beta^*(z, \xi_f) \in (0, 1)$. This proves part (ii).

Step 3: Poaching probability at the optimum Finally, part (iii) follows immediately by combining parts (i) and (ii). For any (z, ξ_f) with interior solutions,

$$
\mathcal{P}^N\big(\beta^N(z, \xi_f), z\big) < \mathcal{P}\big(\beta^N(z, \xi_f), z\big) \leq \mathcal{P}\big(\beta^*(z, \xi_f), z\big),
$$

where the first inequality is part (i), and the second inequality holds because $\mathcal{P}(\beta, z)$ is strictly decreasing in β and $\beta^N(z, \xi_f) < \beta^*(z, \xi_f)$ by part (ii).

This completes the proof of Proposition 5. $\square$

A.4 Sorting on retainability: value functions and thresholds

Lemma 1. *Fix meeting rates* (λ_f, λ_p) *and consider the value of entering as an innovator with retainability* ξ_f*,*

$$V^f(\xi_f) = -c_f + \rho\,\mathbb{E}_z\Big[(1-\lambda_f\mathcal{P}(\beta_f^*(z,\xi_f),z))\,\pi(z) + \lambda_f\mathcal{P}(\beta_f^*(z,\xi_f),z)\,\pi(\xi_f z)\Big],$$

where $\beta_f^*(z,\xi_f)$ *is the optimal rent–sharing rule from Proposition 2 and* $\mathcal{P}(\beta,z)$ *is the poaching probability. Then:*

1. $V^f(\xi_f)$ *is continuously differentiable and strictly increasing in* ξ_f*.*
2. *The value of entering as a poacher,*

$$V^p = -c_p + \rho\,\lambda_p\,\mathbb{E}_{(z,\beta_f^*(z,\xi_f),\xi_w)}\big[I(\beta,z,\xi_w)\big(\pi(\xi_w z) - \beta_f^*(z,\xi_f)\pi(z)\big)\big],$$

does not depend on the poacher's own ξ_f*.*

Proof. (i) For each z, the innovator chooses β to maximize the static objective

$$\tilde{V}(\beta; z, \xi_f) = (1-\lambda_f\mathcal{P}(\beta,z))(1-\beta)\pi(z) + \lambda_f\mathcal{P}(\beta,z)\pi(\xi_f z),$$

whose first–order condition is given by (6). By the envelope theorem, the derivative of the optimized value with respect to ξ_f ignores the indirect effect via β_f^* and is

$$\frac{\partial}{\partial\xi_f}\tilde{V}(\beta_f^*(z,\xi_f); z, \xi_f) = \lambda_f\mathcal{P}(\beta_f^*(z,\xi_f),z)\,\pi'(\xi_f z)\,z.$$

By construction, $\lambda_f > 0$, $\mathcal{P}(\beta_f^*(z,\xi_f),z) \in (0,1)$, and the profit function $\pi(\cdot)$ is increasing in its argument on the concavity region (Appendix A.1), so $\pi'(\xi_f z) > 0$. Hence the derivative above is strictly positive for all (z,ξ_f) in the support. Taking expectations over z yields

$$\frac{\mathrm{d}V^f(\xi_f)}{\mathrm{d}\xi_f} = \rho\,\mathbb{E}_z\Big[\lambda_f\mathcal{P}(\beta_f^*(z,\xi_f),z)\,\pi'(\xi_f z)\,z\Big] > 0,$$

so $V^f(\xi_f)$ is strictly increasing and continuous in ξ_f.

(ii) The expression for V^p in (4) depends on the distribution of innovators' retainabilities and on the policy $\beta_f^*(z, \xi_f)$, but not on the retainability of the poaching firm itself. Formally, the ξ_f entering inside the expectation is that of the innovator being poached, which is drawn from the exogenous distribution; holding this distribution fixed, the poacher's own parameter does not appear in V^p. Thus V^p is constant as a function of the poacher's type. $\square$

Proof of Proposition 4. Part (i) is exactly Lemma 1. For part (ii), fix (λ_f, λ_p) and entry costs (c_f, c_p) satisfying

$$V^f(\underline{\xi}) < V^p < V^f(\overline{\xi}),$$

where $0 < \underline{\xi} < \overline{\xi} \leq 1$ are the bounds of the support of ξ_f. By Lemma 1, $V^f(\xi_f)$ is continuous and strictly increasing on $[\underline{\xi}, \overline{\xi}]$, whereas V^p is constant in ξ_f. Define the difference

$$\Delta(\xi_f) \equiv V^f(\xi_f) - V^p.$$

Then $\Delta(\xi_f)$ is continuous and strictly increasing and satisfies $\Delta(\underline{\xi}) < 0$ and $\Delta(\overline{\xi}) > 0$. By the intermediate value theorem there exists a unique $\underline{\xi_f} \in (\underline{\xi}, \overline{\xi})$ such that $\Delta(\underline{\xi_f}) = 0$, i.e. $V^f(\underline{\xi_f}) = V^p$. Strict monotonicity of Δ implies $\Delta(\xi_f) < 0$ for $\xi_f < \underline{\xi_f}$ and $\Delta(\xi_f) > 0$ for $\xi_f > \underline{\xi_f}$, which yields the stated ordering of values and therefore the equilibrium sorting pattern in entry choices. $\square$

Lemma 2 (Threshold equilibrium with endogenous meeting rates)**.** *Let G denote the continuous distribution of retainability ξ_f on $[\underline{\xi}, \overline{\xi}]$ and suppose that meeting rates are determined by the cutoff $\underline{\xi_f}$ according to*

$$\lambda_f(\underline{\xi_f}) = \lambda \left(\frac{s_p(\underline{\xi_f})}{s_f(\underline{\xi_f})} \right)^\eta, \qquad \lambda_p(\underline{\xi_f}) = \lambda \left(\frac{s_f(\underline{\xi_f})}{s_p(\underline{\xi_f})} \right)^\eta,$$

where $s_f(\underline{\xi_f}) = 1 - G(\underline{\xi_f})$ and $s_p(\underline{\xi_f}) = G(\underline{\xi_f})$. Then:

1. *For every $\underline{\xi_f} \in [\underline{\xi}, \overline{\xi}]$, there exists a unique* best–response *cutoff $T(\underline{\xi_f}) \in [\underline{\xi}, \overline{\xi}]$ such that, given $(\lambda_f(\underline{\xi_f}), \lambda_p(\underline{\xi_f}))$, firms optimally sort according to $\xi_f \geq T(\underline{\xi_f})$ as in Proposition 4.*

2. *The mapping $T : [\underline{\xi}, \overline{\xi}] \to [\underline{\xi}, \overline{\xi}]$ is continuous. Hence there exists at least one fixed point $\underline{\xi_f}^* \in [\underline{\xi}, \overline{\xi}]$ satisfying $T(\underline{\xi_f}^*) = \underline{\xi_f}^*$, i.e. at least one threshold equilibrium with endogenous meeting rates.*

3. (Uniqueness under a monotonicity assumption). *Suppose in addition that the composite value difference*

$$\Phi(\underline{\xi_f}) \equiv V^f(\underline{\xi_f}; \lambda_f(\underline{\xi_f})) - V^p(\lambda_p(\underline{\xi_f}))$$

is strictly monotone in $\underline{\xi_f}$. *Then the fixed point* $\underline{\xi_f}^*$ *is unique.*

Proof. (i) For any given $\underline{\xi_f}$, the induced meeting rates $(\lambda_f(\underline{\xi_f}), \lambda_p(\underline{\xi_f}))$ are just constants. By Proposition 4, there exists a unique cutoff $T(\underline{\xi_f})$ at which firms are indifferent and such that all firms with ξ_f above (below) this threshold strictly prefer to be innovators (poachers).

(ii) The distribution G is continuous, hence $s_f(\underline{\xi_f})$ and $s_p(\underline{\xi_f})$ vary continuously with $\underline{\xi_f}$, and so do $\lambda_f(\underline{\xi_f})$ and $\lambda_p(\underline{\xi_f})$. By Lemma 1, $V^f(\xi_f; \lambda_f)$ is continuous in both arguments, and similarly for $V^p(\lambda_p)$. The implicit definition of $T(\underline{\xi_f})$ through

$$V^f\big(T(\underline{\xi_f}); \lambda_f(\underline{\xi_f})\big) = V^p\big(\lambda_p(\underline{\xi_f})\big)$$

then yields a continuous T by the implicit function theorem. Since T maps the compact interval $[\underline{\xi}, \overline{\xi}]$ into itself and is continuous, the Brouwer fixed point theorem implies the existence of at least one fixed point $\underline{\xi_f}^*$ satisfying $T(\underline{\xi_f}^*) = \underline{\xi_f}^*$.

(iii) If $\Phi(\underline{\xi_f})$ is strictly monotone, then the equation $\Phi(\underline{\xi_f}) = 0$ has at most one solution. But $\Phi(\underline{\xi_f}) = 0$ is exactly the fixed-point condition $T(\underline{\xi_f}) = \underline{\xi_f}$. Hence there is at most one fixed point; combined with existence from part (ii), this yields uniqueness. □

B Estimation of firm-level product and labor market imperfection measures

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 ((8) in the main text) results in:

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

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 $\omega_{H,it}$ 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:

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

with $y_{it} = q_{it} + \epsilon_{it} = f_{it} + \omega_{H,it} + \epsilon_{it}$, 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:

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

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 ($\omega_{H,it}$) to avoid bias from the endogeneity of input decisions to unobservable productivity $\omega_{H,it}$ (Marschak and Andrews, 1944). With respect to unobservable productivity, we assume that $\omega_{H,it}$ 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 $\omega_{H,it}$ 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}:

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

In (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 3.2, 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 $\omega_{H,it}$, 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 $\omega_{H,it}$:

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

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

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

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 (B.6) into (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 $\omega_{H,it}$ from the idiosyncratic ϵ_{it}. This first stage uses (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 $\varphi_t(l_{it}, m_{it}, k_{it}, EXP_{it}) = f_{it} + \omega_{H,it}$. After the first stage, we get an estimate of $\omega_{H,it}$ (up to a constant) for a given coefficient vector $\boldsymbol{\beta}$:

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

We use the law of motion of productivity, (B.4), in combination with (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 $\mathbb{E}[\omega_{H,it}|\omega_{H,it-1}, EXP_{it-1}]$ by taking the predicted value of a non-parametric (second-order polynomial) regression of $\widehat{\omega}_{H,it}(\boldsymbol{\beta})$ on $\widehat{\omega}_{H,it-1}(\boldsymbol{\beta})$ 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:

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

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

Data. Firm-level data on nominal sales (revenue) PQ, employment L measured by the number of employees in September of a given year, intermediate consumption M, capital K proxied by depreciation of fixed assets and factor costs (the wage bill WL) is sourced from the Production Statistics Survey. Export status (EXP) is obtained from customs records. Nominal variables are deflated using two-digit industry price deflators for output, intermediate inputs, and capital from the OECD STAN database. We estimate production functions at the two-digit industry level, assigning firms to industries according to the NACE Rev. 2 classification.

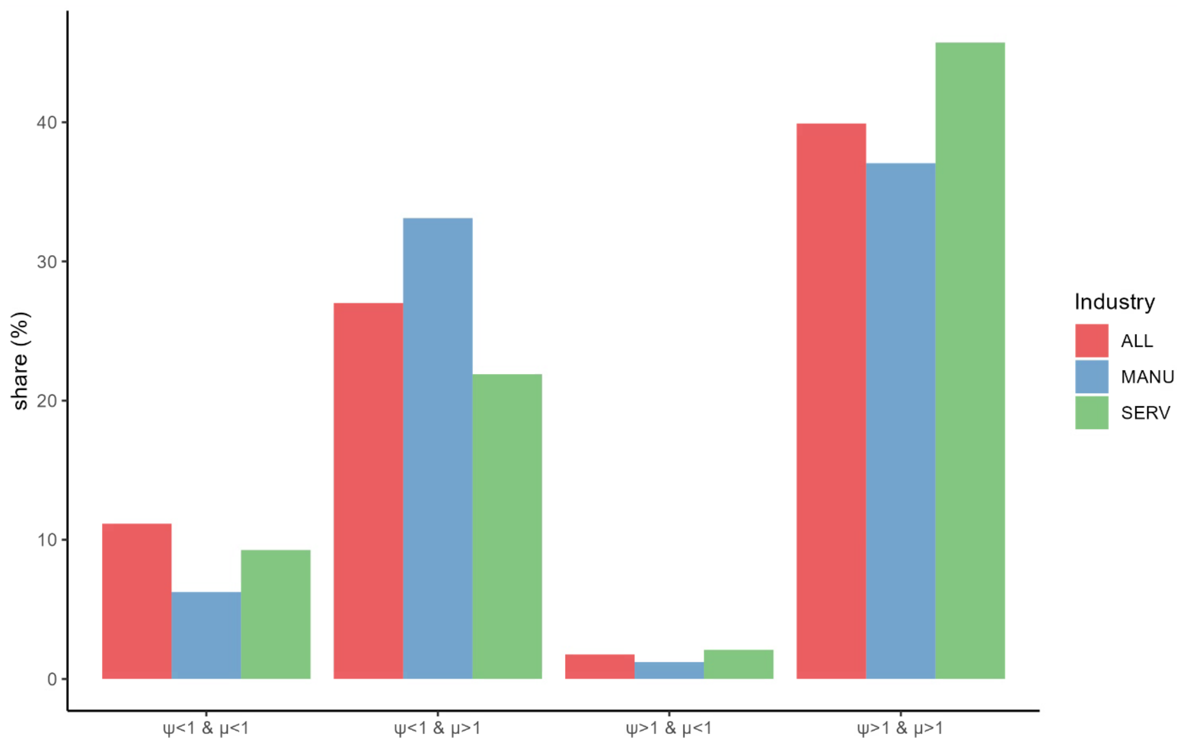
Measurement of product and labor market imperfections with revenue data. Estimating production functions proxying physical output with deflated sales causes a downward bias in the revenue elasticities of variable inputs in an environment with price-setting firms. Such firms must lower prices when raising output, whereas for price takers revenue is proportional to output. Hence, revenue elasticities are generally lower than output elasticities (Klette and Griliches, 1996; Bond et al., 2021; Jaumandreu and Doraszelski, 2021), with the bias depending on the price elasticity of demand. This causes the average revenue-based market imperfection parameters, estimated using the production function approach, to be uninformative of true averages under static profit maximization (De Ridder et al., 2026).

In terms of measurement, the ratio estimator of product market imperfections (see (B.14)) may be uninformative about the true level of price–cost markups. By contrast, the estimator of labor market imperfections is a ratio of two ratio estimators (see (B.15)), so the revenue-versus-quantity measurement problem does not apply. This is because the revenue-versus-quantity distortion (see Equation (3) in Bond et al. (2021)) enters the revenue elasticities of intermediate inputs and labor through a common multiplicative factor and therefore cancels out (see online Appendix O.6.1 of Yeh et al. (2022)).

That said, our model offers a framework for analyzing the co-movement of product and labor market imperfections. Accordingly, what matters for our main analysis is the positive relationship between firms' price-cost markups (μ) and wage markups (ψ) and their levels of intangibles (z), a relationship that we uncover using regression analysis exploiting within-firm variation over time for identification (see Tables (2)-(4) in the main text). In such empirical setting, revenue-based markups retain information content, as shown by De Ridder et al. (2026) who demonstrate that variation in revenue-based market imperfections is well measured.

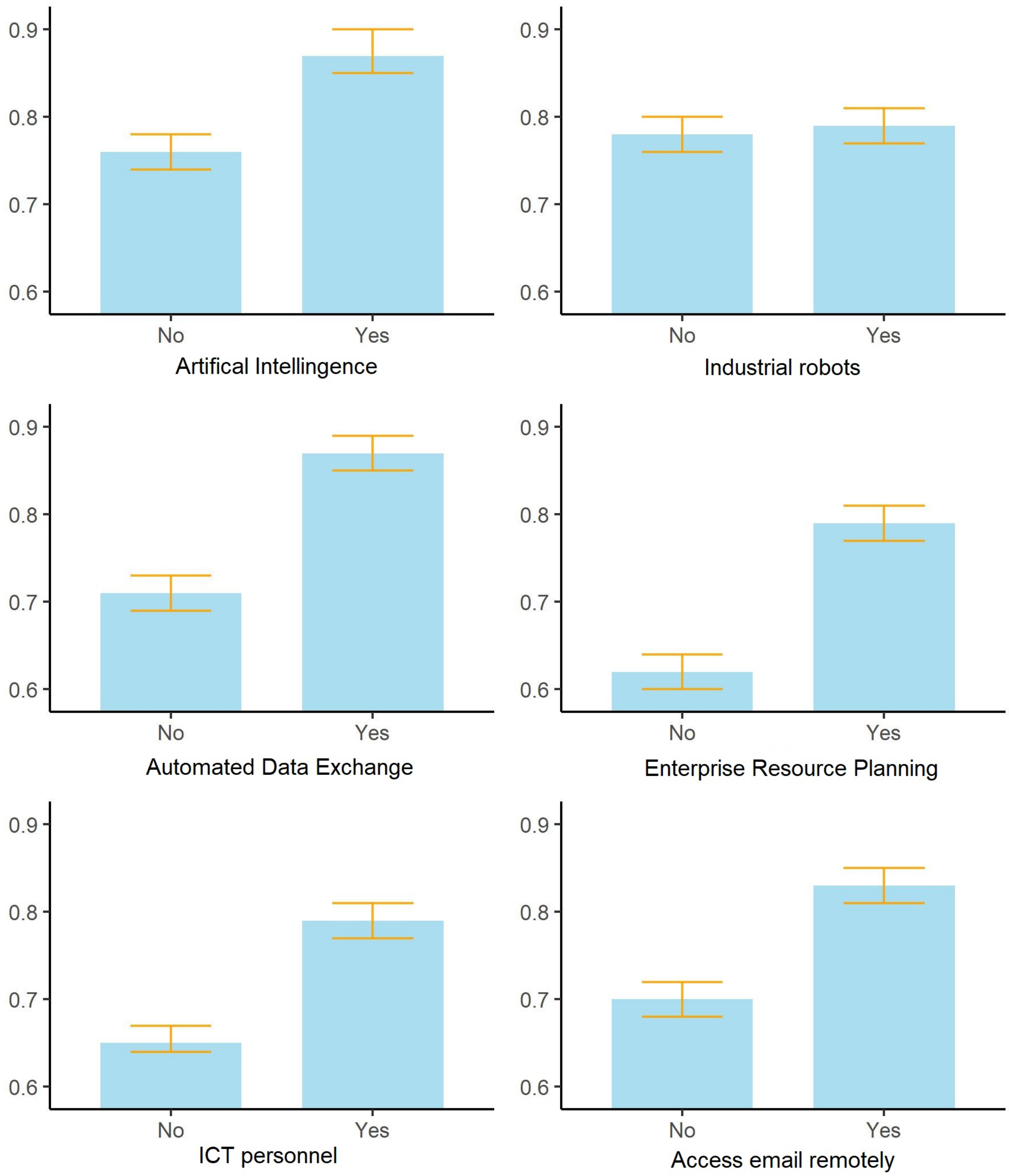
C Additional figures and tables

Appendix Figure C1: Value-added share of each combination of labor and product market imperfection parameters within manufacturing and services



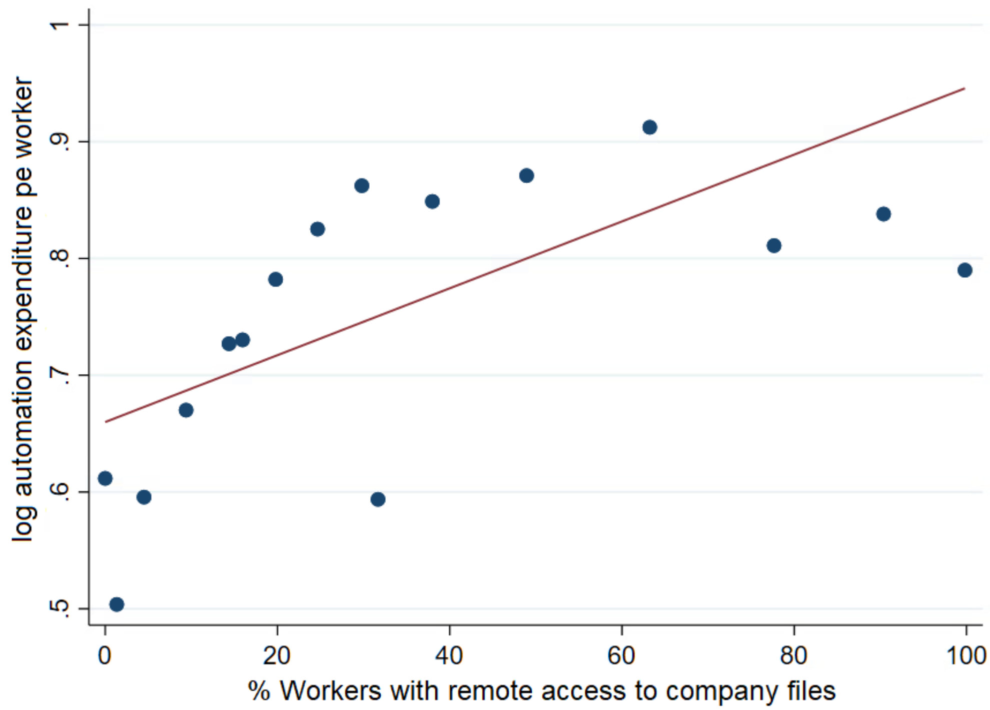
Note: Real value-added share of each combination of labor (ψ) and product (μ) market imperfection parameters for the total economy (ALL) and broken down by manufacturing (MANU) and services (SERV). Combinations are defined based on whether the reduced-form labor market imperfection parameter ψ_{it} or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

Appendix Figure C2: Automation expenditure per worker in firms that adopt specific technologies and those that do not

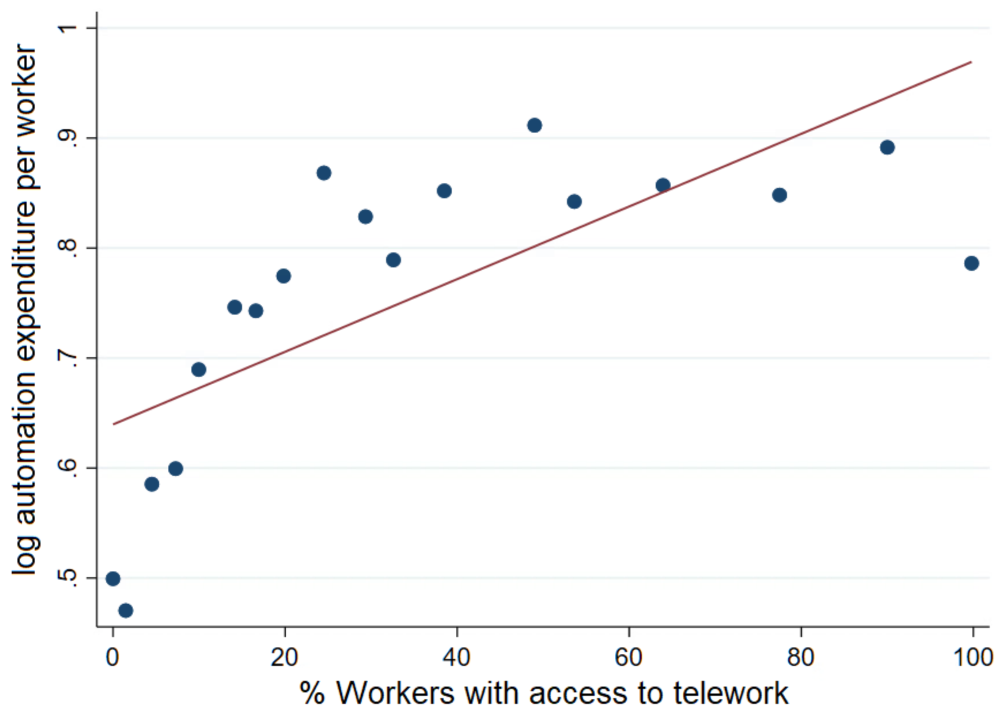


The bar charts present average log automation expenditure per worker (in thousand euros) and 95% confidence intervals in firms that adopt versus do not adopt specific technologies.

Appendix Figure C3: 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 Table C1: 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 C2: 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

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 C3: Firm-level correlations between automation expenditure per worker and type of innovation

	Standardized automation expenditure per worker
Process innovation	0.110***
	(0.026)
Product innovation	0.096***
	(0.026)
Organizational innovation	0.066**
	(0.026)
Number of observations	9,568
Number of firms	4,555

Note: The dependent variable is the standardized automation expenditure per worker. Reported numbers are coefficients from OLS regressions. Industry fixed effects and firm size (measured by the log number of workers) are added as controls. ***/**/* denotes statistical significance at the 1%/5%/10% level.

Appendix Table C4: Partial correlations between labor and product market imperfections and type of innovation at the firm level

	ψ	μ
Process innovation	0.013**	0.006*
	(0.008)	(0.003)
Product innovation	0.013**	0.008***
	(0.006)	(0.003)
Organizational innovation	0.014**	0.006**
	(0.005)	(0.003)
Number of observations	14,718	14,718
Number of firms	7,259	7,259

Note: OLS panel regression of reduced-form firm-level measure of labor market imperfections (ψ) and price-cost markups (μ) on type of innovation (binary indicators) and firm/industry characteristics. Additional controls include firm fixed effects, firm size, firm age, average wage bill and labour productivity. Standard errors are clustered at the firm level and are reported in parentheses. ***/**/* denotes statistical significance at the 1%/5%/10% level.