Overhead Costs and Markups Across Technologies

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Abstract

This paper investigates how rising overhead costs of production affect market outcomes across sectors with different degrees of input complementarity. Using Dutch administrative firm-level data from 2006–2018, we document sectoral heterogeneity in markups' dynamics, which we attribute to variations in ICT investment. We estimate the elasticity of substitution between capital and labor, finding stronger complementarity in sectors that invest more in ICT. A two-sector model with heterogeneous firms and oligopolistic competition shows that higher overhead costs reduce the number of firms able to break even, leading to a contraction in output, lower wages and marginal costs. In sectors with stronger complementarity, lower wages translate into larger marginal cost reductions, boosting profits and markups while reducing the labor share. The model replicates key empirical patterns, including asymmetric markups' growth—explaining 37% of the increase in ICT sectors and 43% in non-ICT.

Keywords: Markups, ICT, Overhead Costs, Inputs' Elasticity of Substitution
JEL: D21, D50, L13.

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1 Introduction

Over the past forty years, firms' market power has changed in several developed economies, as reflected by the trends in price markups, market concentration, and profit margins. Meanwhile, the labor share has fallen.[1] However, the extent of these changes varies substantially between industries. A number of studies suggest the rise in overhead costs of production as a major contributing factor.[2] This paper shows that the impact of higher overhead costs is different depending on the degree of substitutability of inputs of production and can partially explain the observed differences across sectors.

We start by developing several empirical arguments using firm-employee administrative Dutch dataset. We show that, in the aggregate, overhead costs and markups of the Dutch firms have declined over the studied period between 2006 and 2018. At the more disaggregated level, many sectors have seen their markups increase and this increase is positively associated with overhead costs behavior. Nonetheless, sectors with similar increases (decreases) in overhead costs exhibited varying degrees of markup growth (decline). We attribute this variation to differences in technology adoption, particularly ICT investment, across sectors. Since ICT capital is generally more complementary with labor than non-ICT capital, we estimate the elasticity of substitution between inputs of production separately for sectors with above- and below-median growth in ICT investment. To do so, we use administrative firm-level data in the Netherlands between 2006 and 2018. Employing a modified first-order condition (FOC) from firms' cost minimization, we estimate the elasticity of substitution between capital and labor in each group. Similar to Oberfield and Raval (2021), we exploit persistent wage differences across local areas in the Netherlands to identify the micro elasticity of substitution between capital and labor.

Our findings indicate that production inputs are complementary in both cases; however, as expected, the degree of complementarity is stronger in ICT sectors, where the estimated elasticity of substitution is 0.32. In contrast, the elasticity is 0.51 in non-ICT sectors.

To assess the impact of higher overhead costs on markups and labor share, depending on the degree of complementarity between inputs, we build a model economy that aggregates 2 asymmetric sectors, representing ICT and non-ICT sectors. Each of them is populated by a finite and endogenous number of heterogeneous firms, similar to Atkeson and Burstein (2008). The firms are heterogeneous in their productivity, and they compete under oligopoly where entry is free and exit occurs in response to idiosyncratic shocks. Firms produce differentiated goods according to standard C.E.S. technology. The most

[1] For the global trends in market power see De Loecker and Eeckhout (2018), while Autor, Dorn, Katz, Patterson, and Van Reenen (2020) present evidence for the decline in the labor share in the US.

[2] E.g. (Gutierrez Gallardo, Jones, & Philippon, 2019)

productive firms are also the largest, they charge the highest markups and their labor shares are the lowest.

We calibrate the model to the Dutch economy using a combination of parameters estimated from firm-level data between 2006 to 2018 and values taken from the existing literature. Our main experiment assesses the impact of a uniform increase in overhead costs of production across two sectors that differ only in the degree of input complementarity, as previously estimated. The overhead cost increase is set at 12%, consistent with the rise observed in the Dutch data.

In both sectors, higher overhead costs deteriorate competition by reducing the number of firms that are able to break-even in equilibrium, and, as a result, the total output of the economy shrinks. Higher overhead costs put downward pressure on wages that translate into lower marginal costs. We then show that the sensitivity of marginal costs to wage changes is governed by the labor cost share which depends on the degree of complementarity between inputs. Firms in the ICT sector employ more labor than do firms in non-ICT sectors, due to the stronger complementarity between labor and capital, leading to a higher reduction in marginal costs when wages decline.

A larger drop in marginal cost in ICT sector allows firms to be more profitable. We show that profit shares of firms grow faster in ICT than non-ICT sector, allowing them to expand and increase markups at the expense of the labor share of income. Our simple model produces plausible changes in sectoral outcomes. A modest 12% increase in overhead production costs can explain approximately 37% of the observed markup growth in ICT sectors and 43% in non-ICT sectors, based on Dutch data. Importantly, a small difference in production technology—reflected in varying degrees of input complementarity—can generate asymmetric markup dynamics that align closely with empirical patterns. The ratio of markup growth between ICT and non-ICT sectors is 1.4 in the data, which the model replicates closely with a ratio of 1.2.

Related literature

Our paper is related to the growing literature exploring the rise in market concentration and markups in recent decades, e.g. Grullon, Larkin, and Michaely (2019) and De Loecker, Eeckhout, and Unger (2020)). Autor et al. (2020) attribute these developments to the rise of superstar firms, whose advantage in productivity allows them to increase their market shares, without necessarily compromising consumers' welfare and firms' investments. De Loecker et al. (2020) and Gutiérrez and Philippon (2019) argue, instead, that the observed increase in the market concentration and markups reflects an increase in the market power of large firms as well as a reduction in the competition within U.S. industries. In a way, this paper reconciles both hypotheses. Although higher obsolesce rate of innovations is the key trigger of the reallocation of market shares, an increase in fixed entry cost amplifies the increasing trend in markups.

Several studies, including Bessen (2017), Calligaris, Criscuolo, and Marcolin (2018), Bijnens and Konings (2018), Díez, Fan, and Villegas-Sánchez (2021), and Akcigit et al. (2021), have documented the heterogeneous growth of markups and market concentration, conditional on the exposure to the ICT or to digital technologies. To the best of our knowledge, this paper is the first to offer a theoretical framework that can rationalize these findings.

More broadly, we are not the first to link the technological change to the increase in market power. Aghion, Bergeaud, Boppart, Klenow, and Li (2023), De Ridder (2024) and Olmstead-Rumsey (2019) provide theoretical frameworks that can jointly explain the increase in market power and the decline in productivity growth. Our paper is different from these studies in two key dimensions. First, we use a different modelling framework where the key friction arises from oligopolistic competition, when consumers display love for variety. This leads to a product market where multiple firms are active at the same time with non-zero market shares. Second, in contrast to Aghion et al. (2023), De Ridder (2024) and Olmstead-Rumsey (2019) who mainly focus on aggregate dynamics, our paper studies the role of the technology in shaping the magnitude of the growth in markups and market concentration *across* sectors.

2 Facts

An increase in markups does not necessarily indicate growing market power. Higher overhead or entry costs may compel firms to raise their markups in order to remain profitable or simply avoid losses. Bloom, Jones, Van Reenen, and Webb (2020) and De Loecker et al. (2020) document such an increase in overhead costs in the U.S. economy while Gutierrez Gallardo et al. (2019) build a model where higher entry costs lead to increase in markups. Intuitively, in an Atkeson and Burstein (2008) type of framework, higher entry/fixed costs of production can be only sustained by the most productive and the largest firms resulting in higher market concentration and higher markups.

In what follows, we show that consistent with this argument, in aggregate, overhead costs and markups of the Dutch firms have declined over the studied period between 2006 and 2018. At the more disaggregated level, many sectors have seen their markups increase and this increase is positively associated with overhead costs behavior. Nonetheless, firms with similar increases (decreases) in overhead costs exhibited varying degrees of markup growth (decline). We link this heterogeneity to the amount of technology-related spending adopted across sectors.

2.1 Data

We construct a matched employee-firm dataset that includes all non-financial firms that pay corporate tax in the Netherlands, covering the period 2006–2018. For this purpose, we merge 6 datasets. First, the business registry (ABR) dataset contains basic background statistics such as firm birth date, sector and size in terms of employment. Our second, balance sheet dataset (NFO) covers non-financial firms and provides us with information on revenues, profits, and detailed costs of included firms. The third firm-level dataset called "Production Statistics" is a survey database that we link to 3 administrative datasets described above. The main advantage of this dataset is that it provides information on the total overhead costs of the Dutch firms and their composition. Finally, we merge the firm-level dataset with worker records included in two administrative datasets *Baankenmerkenbus* and *Gbapersoontab* that cover employment related information such as wages, worked days, sector of employment and individual characteristics such as gender, age, or migrant background.

2.2 Markups and overhead costs of the Dutch firms

Most of the studies on growing market power focus on the U.S. listed firms. In what follows, we describe trends in markups in the Dutch data that also covers small firms.

We start by estimating firm-level markups defined as follows:

$$\mu_{it} = \theta_t^v (\alpha_{it}^v)^{-1} \tag{1}$$

where θ_t^v is the output elasticity of variable inputs v and α_{it}^v is the share of expenditures on inputs v in total sales ($P_{it}Q_{it}$). θ_t^v is assumed to be the same for all firms within a sector. While the expenditure data on inputs (and therefore α_{it}^v) are available in the data, we do not know θ_t^v and we estimate it using production function approach and Ackerberg, Caves, and Frazer (2015) two-stages technique. We estimate the output elasticity, θ_t^v assuming underlying Cobb-Douglas production function. We observe in balance sheet dataset a variable called: Costs of raw materials and consumables, purchases and other operating expenses and use it as variable input. To control for competition, we include in the first stage of the estimation firms profits, directly reported in the data by the firms. This procedure is implemented for 4-digit SBI sectors and provides us with sector-specific series of θ_t^v. α_{it}^v is directly computed from the data as the firm's ratio of variable inputs to revenues. This gives us the benchmark firm-level markup measure μ^1. μ^2 is the markup constructed with output elasticity θ^v estimated using OLS instead of two-stage ACF technique. Figure 7 in Appendix A plots the distribution of firm-level markups.

The Production Statistics (PS) dataset provides detailed information on firms' cost structures[3]. For each firm in each year, we compute overhead cost share fc as the amount of overhead costs divided by its total costs. We then aggregate the firm-level overhead costs using their cost shares in the entire economy and similarly aggregate firm-level markups μ^1. We plot their behavior between 2006 and 2018 in Figure 1. De Ridder, Grassi, and Morzenti (2021) show that despite two-stage procedure, the levels of markups estimated using revenues in the production are not very informative and, accordingly, we mainly focus on markups changes.

Both series show a declining trend: overhead costs decrease by 11% and markups by 8% over the entire sample period. A decline in the Dutch firms markups of a similar magnitude has been found previously by van Heuvelen, Bettendorf, and Meijerink (2021).

At the more disaggregated level, many sectors have seen their overhead costs and markups increase over the same period. Left panel of Figure 2 plots the distribution of the changes in the share of overhead costs, Δfc, in 4-digit SBI sectors. Right panel displays the distribution of cost-weighted markups in those sectors. They both show large dispersion with positive and negative changes, although the the changes in overhead cost shares seem to display tighter distribution. To confirm this observation, we divide the distribution of overhead cost changes into quintiles and compute the mean and dispersion of the changes

[3]Detailed description of the overhead costs can be found in Appendix A

Figure 1: Aggregate overhead costs and markups in the Netherlands between 2006 and 2018

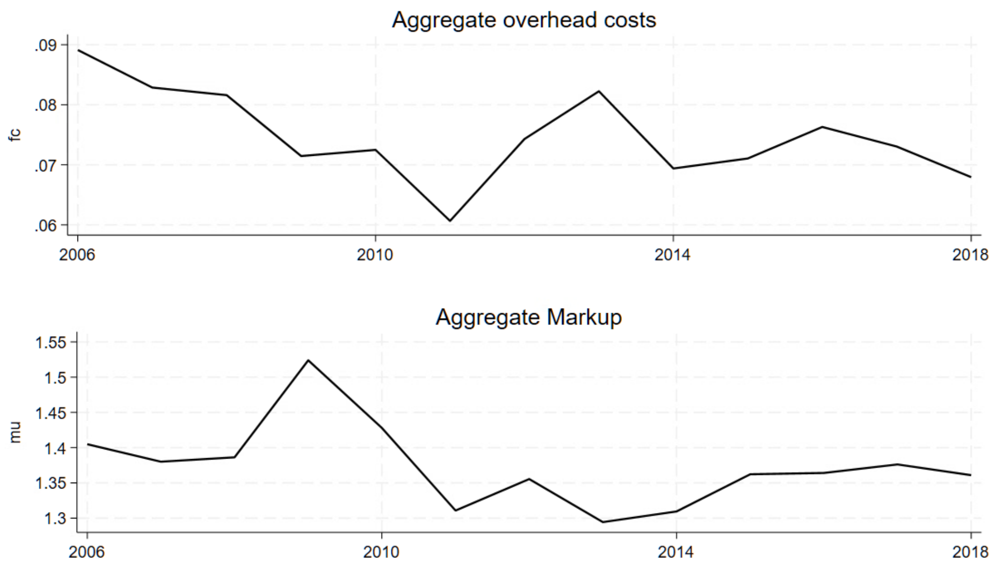
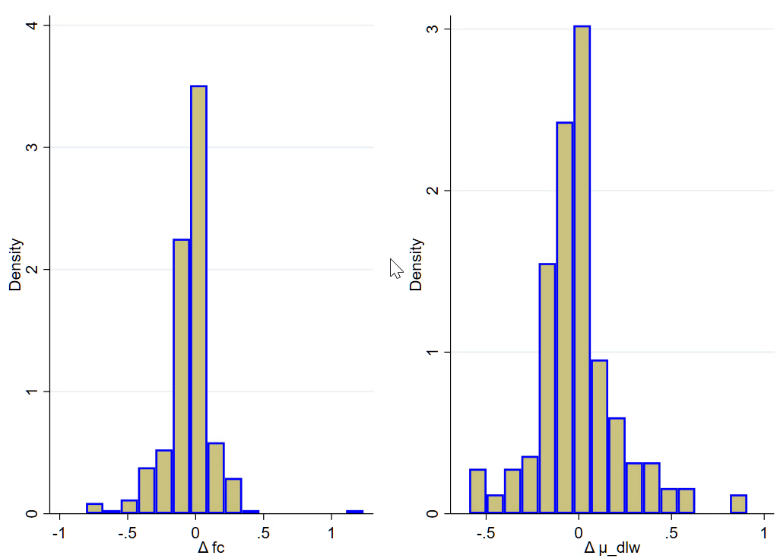


Figure 2: Sector-level changes in markups and overhead costs in the Netherlands between 2006 and 2018.



in overhead costs Δfc and in markups $\Delta\mu^1$. Our aim is to compare the dispersion of changes in markups with the dispersion of overhead costs, in order to assess the extent to which variation in overhead costs can fully account for the observed dispersion in markups.

Table 1: **Changes in the share of overhead costs and markups: quintiles.**

	Q1	Q2	Q3	Q4	Q5
$\Delta\mu^1$	-0.09	-0.29	-0.03	0.05	0.07
Δfc	-0.29	-0.92	-0.03	0.02	0.13
$\sigma_{\Delta\mu^1}$	0.24	0.18	0.14	0.21	0.21
$\sigma_{\Delta fc}$	0.15	0.02	0.01	0.02	0.11
$\frac{\sigma_{\Delta\mu^1}}{\sigma_{\Delta fc}}$	1.6	9	14	10.5	1.9

Notes: Δ denotes the change between the last and the first observation.

The first two rows of Table 1 show the average changes in markups $\Delta\mu^1$ and overhead costs Δfc for each of the quintiles defined over Δfc. The next two rows report the dispersion of $\Delta\mu^1$ and Δfc over those quintiles, computed as standard deviation. The signs in the first two rows are consistent across quintiles, indicating that markups tend to increase in sectors where the share of overhead costs is rising. The next two rows show that, within each quintile, the dispersion of markups changes is substantially greater than that of overhead costs. To facilitate the comparison, the last row of Table 1 displays the ratios of two standard deviations for each quintile. The ratio ranges between 1.6 and 14, suggesting that overhead costs alone cannot fully account for the observed variation in markups.

2.3 Overhead costs, technology and markups.

If overhead production costs alone cannot account for changes in markups, might cross-sectoral differences in technology help explain some of the remaining variation? We explore this hypothesis by investigating the link between technology-related expenses and markups growth.

The Production Statistics (PS) dataset provides detailed information on firms' cost structures, capturing not only total overhead costs but also their components. We categorize them into two broad groups: (i) Selling, General, and Administrative (SG&A) expenses, which include items such as fees and commissions, advertising and communication expenditures, and environmental taxes; and (ii) technology-related expenditures, comprising third-party R&D, patents and licenses expenses and automation-related costs.

While SG&A expenses are generally not expected to influence firms' production technologies, technology-related expenditures are more likely to do so. We therefore focus on their dynamics in relation to markups changes.

Table 2 presents summary statistics for the three categories of technology-related ex-

Table 2: **Technology-related expenses of Dutch firms.**

Moment	Pat.Lic	Aut	R&D
mean	0.5%	2.7%	0.3%
median	0.7%	1.0%	0.0
sd	2.2%	4.5%	1.7%
		correlation	
Pat.Lic	1		
Aut	0.33	1	
R&D	0.18	0.17	1

Notes: Table reports description statistics of the share of each of the expense category in total costs, across all 4-digit sectors. The categories include 1: patents and licences, 2: Automation and 3: R&D. sd stands for standard deviations.

penses. For each category, we calculate its share relative to the firm's total costs, and aggregate these shares to the 4-digit sector level. The top panel of the table reveals that automation accounts for the largest share of total costs among Dutch firms—by a wide margin. On average, sectors spend five times more on automation than on patents and licenses, and nine times more than on R&D.

For each of the technology-related cost component we run a panel regression of the form: $\mu_{it} = \alpha_i + \beta X_{it} + \gamma_t$ where μ_{it} is a markup and X_{it} is a cost share of each of the expenses; α_i and γ_t are sector and year fixed effects, respectively.

Initially, in Figure 1, we calculated overhead costs as the sum of both SGA and technology-related expenses. Since our objective is to identify the sources of markup heterogeneity beyond overhead costs, we include both the overhead cost share and the cost share of technology-related expenditures in our regressions. To ensure that observed changes in overhead costs are not mechanically driven by technology-related spending, we construct an adjusted measure of overhead expenses that excludes such expenditures: fc^{adj}.

Table 3: **Technology expenses and markups.**

fc	Pat.Lic	Aut	R&D	fc^{adj}	Pat.Lic	Aut	R&D
0.33				0.36			
(0.02)				(0.02)			
0.31	0.73			0.33	1.11		
(0.02)	(0.30)			(0.02)	(0.29)		
0.26		0.76		0.27		1.03	
(0.03)		(0.18)		(0.03)		(0.17)	
0.35			−1.44	0.36			−0.92
(0.02)			(0.34)	(0.02)			(0.34)

Notes: This table shows the reuslts of a panel regression of the form: $\mu_{it} = \alpha_i + \beta X_{it} + \gamma_t$ where μ_{it} is a markup computed using ACF procedure and X_{it} is a cost share of each of the expenses relative to total costs. All regressions include sector and year fixed effects.

Table 3 shows results of our panel regressions. The left panel uses the original measure of overhead cost share fc, including both SGA and technology-related expenses while the right panel excludes technology-related expenditure from the cost share measure: fc^{adj}. The first and fifth columns support our initial hypothesis that markups increase more rapidly in sectors where overhead costs have risen as a share of total costs, regardless of the measure of overhead used. The coefficients remain statistically significant after the inclusion of technology related expenditure, and their magnitudes are remarkably stable. Beyond overhead costs, expenditures on patents, licenses, and automation are positively associated with markups, whereas R&D spending exhibits a negative correlation with markup levels.

What impact might increased spending on automation, licenses, and patents have on firms' production technology? To answer this, it is crucial to understand the nature of the investments these expenditures represent. Automation costs, which constitute the largest share of technology-related expenses (Table 2), are closely tied to specific types of investments. They include all expenditures aimed at automating complex production processes and internal operations through the integration of data, software, and hardware technologies. More specifically, Bessen, Goos, Salomons, and van den Berge (2025) highlight that automation spending is strongly linked to technologies that leverage data for automated processing—such as Customer Relationship Management (CRM) systems, Enterprise Resource Planning (ERP) systems, big data analytics, cloud computing, Electronic Data Interchange (EDI) networks, and sales software. These technologies—often referred to as information and communication technologies (ICT)—tend to complement labor more than traditional forms of automation, such as robotics. We verify if this is the case by estimating the elasticity of substitution between capital and labor across sectors, conditional on their investment share in ICT.

2.4 Elasticity of substitution.

We estimate micro elasticity of substitution between capital and labor from the specification proposed by León-Ledesma, McAdam, and Willman (2010):[4]

$$ln\left(\frac{y_{ikt}}{l_{ikt}}\right) = \hat{\beta}_0 + \sigma_k ln\left(W_{ct}\right) + \varepsilon_{ikt}, \tag{2}$$

where y_{ikt} and l_{ikt} measure output and labor of a firm i belonging to sector k in year t and W_{ct} is the local wage. This specification is also consistent with our model and is derived in Appendix B. Similar to Oberfield and Raval (2021), we exploit persistent wage differences

[4]We obtain the same condition they derive in equation (15) if we assume that $A^L_{kt} = A^L_{k0}e^{\gamma_N t}$.

across local areas in the Netherlands to identify the micro elasticity of substitution between capital and labor in sector k. Our measure of local areas is Dutch *Gemente* within which workers should face similar wages. To obtain the local wage, W_{ct}, we first calculate the individual wage for workers with age between 20 and 55 who are employed in the private sector as workers earning more than €1000 per month[5]. Next, we adjust measures of local wages for differences in worker characteristics such as gender, age, tenure, type of contract (temporary vs permanent) and type of occupation. Both, firm's output y_{ikt} proxied by its revenues and the number of employees l_{ikt} are observed in firms' balance sheet data.

We estimate elasticity of substitution in two types of sectors: (i) those with high investment in automation that, given its content, will be labeled ICT and (ii) those with low ICT investment non-ICT. We classify 4-digit sectors in manufacturing and services according to the share they invest in ICT, relative to other expenses. We use two different classifications. First high-ICT sectors are defined as those that have seen the share of ICT investment increase by more than the median and low-ICT below median, across all sectors. Second, because the share of investment in automation is very skewed with many sectors investing very little in ICT, we classify sectors as high-ICT those that have a share of ICT above the 10th percentile and low-ICT below the median. This classification effectively divides sectors into two categories: those that invest significantly in ICT and those that invest little or not at all.

Table 4: σ **in high and low-ICT sectors.**

	High-ICT		Low-ICT	
	Def 1	Def 2	Def 1	Def 2
	0.32**	0.44**	0.44**	0.51**
	(0.17)	(0.17)	(0.12)	(0.18)
	0.33**	0.44**	0.51**	0.51**
	(0.17)	(0.16)	(0.18)	(0.18)
N. obs.	38635	19803	38520	57352

Table 4 reports the results. The first row reports estimates obtained from regressions without controls and the second row with controls such as firm size. In both sector types, elasticity of substitution is below 1 indicating complementarity between capital and labor. Obtained magnitudes are also very similar to micro elasticities estimated by Oberfield and Raval (2021). Regardless of the classification type, estimated σ is lower in high-ICT sectors than in low-ICT sectors implying that capital and labor are more complementary in high-ICT sectors.

To sum up, we have shown that markups and overhead costs of production grow at different speed across sectors. Although, higher overhead costs are systematically associated with faster markups growth, their variation does not entirely account for the observed

[5]This is around 70% of the Dutch minimum wage in the analysis period.

heterogeneity in markups changes. Beyond the dynamics of overhead costs, the share of investment in ICT matters, leading us to estimate the degree of complementarity between capital and labor, conditional on ICT investment share. Unsurprisingly, we find that in sectors with higher ICT investment, labor and capital are more complementary than in sectors that invest less in ICT. In what follows, we build a model of two sectors that differ by capital-labor elasticity of substitution.

3 The Model

Our model is inspired by Atkeson and Burstein (2008). The economy features a finite number $\mathcal{S}$ of sectors, indexed by k, each populated by a finite and endogenous number of heterogeneous firms, indexed by i. At the firm level, the only source of heterogeneity is the idiosyncratic TFP, drawn once upon birth from a known discrete distribution function on a positive support. Capital and labor augmenting technologies are common within sector. Firms compete under oligopoly in an environment where sector-specific entry is free and exit occurs in response to idiosyncratic and uncorrelated shocks.

In the following, we present the dynamic model: from this environment we derive a steady state in Section 4. This is used in our simulations from Section 6, where we model two representative macro-sectors that differ in the elasticity of substitution across inputs of production, σ_k.

3.1 Competition

Firms produce differentiated goods and compete oligopolistically. Regarding notation, all variables are indexed with the triple subscript $_{ikt}$ when referring to firm i in sector k and period t. Firms' production function is a C.E.S. in labor l_{ikt} and capital k_{ikt}, as in Karabarbounis and Neiman (2014). When we bring our predictions to the data, our notion of capital includes both physical and intangible capital. Firm-level production y_{ikt} is:

$$y_{ikt} = A^Z_{ikt} \left[\alpha^K_k \left(A^K_{kt} k_{ikt} \right)^{\frac{\sigma_k - 1}{\sigma_k}} + (1 - \alpha^K_k) \left(A^L_{kt} l_{ikt} \right)^{\frac{\sigma_k - 1}{\sigma_k}} \right]^{\frac{\sigma_k}{\sigma_k - 1}}, \tag{3}$$

where A^Z_{ikt} is the firm-specific TFP parameter, A^K_{kt} and A^L_{kt} are sector-specific capital and labor augmenting technologies, respectively, σ_k represents the sector-specific elasticity of substitution between the two inputs and α^K_k is a scaling parameters that affects the input shares of income. Note that σ_k determines if the two inputs are gross complements, $\sigma_k < 1$, or substitute, $\sigma_k > 1$.

Firms minimize their total variable costs subject to the technological constraints, i.e.:

$$\min_{l_{ikt},k_{ikt}} W_t l_{ikt} + R_t k_{ikt},$$

subject to equation (3). Using the F.O.C.s for labor and capital, we can show that: $W_t l_{ikt} + R_t k_{ikt} = \lambda_{ikt} y_{ikt}$, where λ_{ikt} is the firm-specific Lagrange multiplier. Thus, idiosyncratic marginal costs MC_{ikt} are represented by the Lagrange multiplier. Solving for λ_{ikt}, we get that the marginal cost is a C.E.S. of (weighted) input prices:

$$MC_{ikt} = \lambda_{ikt} = \frac{1}{A^Z_{ikt}} \left[\left(\frac{R_t}{A^K_{kt} \alpha^K_k} \right)^{1-\sigma_k} \alpha^K_k + \left(\frac{W_t}{A^L_{kt}(1-\alpha^K_k)} \right)^{1-\sigma_k} (1-\alpha^K_k) \right]^{\frac{1}{1-\sigma_k}}.$$

For conciseness, in the following we redefine the part of the marginal cost that is common to firms within the same sector as Ξ_{kt} to write:

$$MC_{ikt} = \frac{\Xi_{kt}}{A^Z_{ikt}}.$$

Firms compete under Cournot oligopolistic competition. Given the optimal conditions from the cost minimization problem, each firm maximizes its nominal profits. Profits d_{ikt} are defined as total revenues, $p_{ikt} y_{ikt}$, net of total variable costs and fixed costs of production f^x_{kt}, measured in terms of final output:

$$\max_{y_{ikt}} p_{ikt} y_{ikt} - W_t l_{ikt} - R_t k_{ikt} - P_t f^x_{kt}$$

subject to equation (3) and to the demand constraint:

$$y_{ikt} = \left(\frac{p_{ikt}}{P_{kt}} \right)^{-\theta_k} Y_{kt} = \left(\frac{p_{ikt}}{P_{kt}} \right)^{-\theta_k} \left(\frac{P_{kt}}{P_t} \right)^{-\gamma} \left(\frac{1}{\chi_k} \right)^{-\gamma} Y_t,$$

where p_{ikt} is the individual price, P_{kt} and Y_{kt} the sectoral prices and quantities, respectively, and P_t and Y_t the aggregate price index and output. θ_k is the elasticity of substitution between goods within sector k, γ the elasticity between sectors, and χ_k a weighting factor.[6] Note that the demand constraint comes from the maximization problem of fictitious sectoral and aggregate bundlers, as discussed in Appendix A. Substituting the demand constraint and the results from the costs minimization problem, we can write:

$$\max_{y_{ikt}} y_{ikt}^{1-\frac{1}{\theta_k}} Y_{kt}^{\frac{1}{\theta_k}-\frac{1}{\gamma}} \chi_k Y_t^{\frac{1}{\gamma}} P_t - \frac{\Xi_{kt}}{A^Z_{ikt}} y_{ikt} - P_t f^x_{kt},$$

[6]When calibrating the model, when simply assume weights χ and $1-\chi$ for the two sectors, targeting their relative shares in the data.

From the F.O.C., we can solve for the optimal price as:

$$p_{ikt} = \left[\frac{\theta_k - 1}{\theta_k} + \left(\frac{1}{\theta_k} - \frac{1}{\gamma} \right) \omega_{ikt} \right]^{-1} \frac{\Xi_{kt}}{A^Z_{ikt}} = \mu_{ikt} \frac{\Xi_{kt}}{A^Z_{ikt}},$$

where μ_{ikt} is the idiosyncratic markup and ω_{ikt} is the market share based on revenues, defined as:

$$\omega_{ikt} \equiv \frac{p_{ikt} y_{ikt}}{P_{kt} Y_{kt}} = \left(\frac{y_{ikt}}{Y_{kt}} \right)^{1 - \frac{1}{\theta_k}},$$

Firms endowed with a higher productivity level have a cost advantage. Due to the lower marginal costs, firms can charge a lower real price, and, thus, gather a large market share, while, at the same time, they are able to extract rents, i.e. they charge high markups.

Finally, we can write nominal profits d_{ikt} as:

$$d_{ikt} = p_{ikt} y_{ikt} - \frac{\Xi_{kt}}{A^Z_{ikt}} y_{ikt} - P_t f^x_{kt} = \left(1 - \frac{1}{\mu_{ikt}} \right) p_{ikt}^{1-\theta_k} P_{kt}^{\theta_k - \gamma} P_t^{\gamma} \left(\frac{1}{\chi_k} \right)^{-\gamma} Y_t - P_t f^x_t.$$

3.2 Entry and Exit

Each period, new firms can freely enter the market endogenously. At the same time, firms might leave the sector for exogenous reasons. Upon birth, entrants draw their productivity level from a discrete distribution function with a positive support, which they keep forever, conditional on surviving. Given the discrete number of available productivity levels, we can refer to a finite set of productivity types, where within each productivity type j, firms are identical. Hence, in the following, we index firms by their type j, with $j \in \{1, 2, ..., S\}$ as the economy presents S distinct types.

Firms can be hit by an exit shock at the end of every period t with a type-specific probability δ_j. Note that the exit shock can hit both incumbents and new entrants. Given that the number of firms is finite, as well as the number of firms of each type, period-$t+1$ incumbents of type j in sector k, i.e. $N^{j,o}_{kt+1}$, are determined by the realization of a binomial stochastic process. This process has success probability $1 - \delta_j$ and $N^j_{kt} = N^{j,o}_{kt} + N^{j,e}_{kt}$ trials, where $N^{j,e}_{kt}$ represents type-j entrants in sector k and $N^{j,o}_{kt}$ type-j incumbents in period t and sector k. In formula:

$$Pr \left[N^{j,o}_{kt+1} = x \right] = \binom{N^j_{kt}}{x} (1 - \delta_j)^x (\delta_j)^{N^j_{kt} - x},$$

with x integer and $x \in [0, N^j_{kt}]$. Note that, if we assume of continuum of firms of mass N^j_{kt}, the formula above converges to $N^{j,o}_{kt+1} = (1 - \delta_j) N^j_{kt}$.

Entry is determined by a sequential and static free entry condition. Firms do not know their realized productivity *ex ante*, and, thus, they enter the market as long as the expected profits are non-negative, i.e. if the expected revenues, net of variable costs, are at least equal to the fixed costs of production.[7] Entry continues to occur until profits possibilities are exhausted and entry is no longer profitable for the *marginal* firm.

New entrants are immediately productive and start competing against incumbents in the period in which entry is realized. Firms are not atomistic, and this is internalized in the entry decision: given the current and observable distribution of types, each potential entrant considers all the possible realizations of the entry choice, i.e. it enters with type 1, or with type 2, and so on. For each state of the world, the potential entrant computes the new distribution of profits in the sector given the new distribution of types.[8] If the expected profits are positive, the potential entrant joins, its productivity is realized, and the next potential entrant decides to enter or not. This sequential process continues until the free entry condition turns negative. In formula, if:

$$\sum_{j=1}^{S} \Omega_j d_{jkt}^{+1} \geq 0,$$

entry occurs, while if:

$$\sum_{j=1}^{S} \Omega_j d_{jkt}^{+1} < 0,$$

the marginal entrants decides against entry and the entry process for period t stops. Regarding the notation, Ω_j represents the *ex ante* probability of drawing type j upon entry, while the superscript $^{+1}$ describes the fact that type-j profits differ from the current ones as they internalizes the so-called *business stealing dynamics*, i.e. the fact that, when entry realizes, the number and type of period-t competitors changes.

3.3 Households

There is a continuum of mass one of identical households who consumes a bundle C_t, works hours L_t and holds capital K_t. The representative household maximizes her utility subject to the budget constraint:

$$\max_{C_t, L_t, K_{t+1}} \mathbf{E}_0 \sum_{t=0}^{\infty} \beta^t \left(logC_t - \nu \frac{L_t^{1+\phi}}{1+\phi} \right),$$

subject to:

$$C_t + I_t = w_t L_t + r_t K_t + \Pi_t,$$

[7] Alternatively, one might assume no fixed costs of production, but the existence of sunk entry costs f_t^e, where entry occurs if expected profits are at least equals to f_t^e. This assumption delivers virtually identical results.

[8] For instance, if the firm enters with type 2, the sector presents N_{kt}^1 type-1 competitors, $N_{kt}^2 + 1$ type-2 competitors, N_{kt}^3 type-3 competitors, and so on.

and

$$I_t = K_{t+1} - (1-\delta) K_t,$$

where I_t represents investment in capital, δ the depreciation rate of capital, and Π_t total real profits received from the ownership of firms. The real wage W_t/P_t and real rental rate R_t/P_t are described by w_t and r_t, respectively.

Since the F.O.C. for consumption is $1/C_t = \lambda_t$, the F.O.C.s for L_t and K_{t+1} are, respectively:

$$\nu C_t L_t^{\phi} = w_t,$$

and

$$1 = \beta \mathbf{E}_t \frac{C_t}{C_{t+1}} \left(r_{t+1} + 1 - \delta \right).$$

3.4 Aggregation

The total output of the economy is either consumed, invested in new capital, or used to cover fixed costs of production:

$$Y_t = C_t + I_t + \sum_k f_{kt}^x N_{kt}.$$

where N_{kt} represents the total number of firms of all types in sector k. Moreover, labor and capital markets need to clear between and within sectors:

$$L_t = \sum_{k=1}^{\mathcal{S}} L_{kt}, \quad \text{where} \quad L_{kt} = \sum_{i=1}^{N_{kt}} l_{ikt},$$

and

$$K_t = \sum_{k=1}^{\mathcal{S}} K_{kt}, \quad \text{where} \quad K_{kt} = \sum_{i=1}^{N_{kt}} k_{ikt},$$

Finally, expressing the price index in real terms:

$$1 = \sum_{k=1}^{\mathcal{S}} \rho_{kt}^{1-\gamma} \chi_k^{\gamma},$$

where $\rho_{kt} \equiv P_{kt}/P_t$ is the real sectoral price, sectoral counterpart of the real idiosyncratic price $\rho_{ikt} \equiv p_{ikt}/P_t$.

3.5 Income Shares, Markups and Productivity

Let us start by defining income shares at the firm level.[9] By definition, the labor share of income s^L_{ikt} is:

$$s^L_{ikt} \equiv \frac{W_t l_{ikt}}{p_{ikt} y_{ikt}} = \frac{1}{\mu_{ikt}} \left(\frac{\xi_{kt} A^L_{kt}}{w_t} \right)^{\sigma_k - 1} (1 - \alpha^K_k)^{\sigma_k}.$$

Symmetrically, the capital share of income is:

$$s^K_{ikt} = \frac{1}{\mu_{ikt}} \left(\frac{\xi_{kt} A^K_{kt}}{r_t} \right)^{\sigma_k - 1} (\alpha^K_k)^{\sigma}.$$

Finally:

$$s^\Pi_{ikt} = 1 - \frac{1}{\mu_{ikt}}.$$

Note that s^Π_{ikt} represents the profit share gross of fixed costs. The *true* profit share is:

$$s^d_{ikt} \equiv \frac{d_{ikt}}{p_{ikt} y_{ikt}} = 1 - \frac{1}{\mu_{ikt}} \left(\frac{tc_{ikt}}{tc_{ikt} - f^x_{kt}} \right),$$

where tc_{it} is the real total cost $w_t l_{ikt} + r_t k_{ikt} + f^x_{kt}$. The share of income *wasted* due to fixed costs is:

$$s^X_{ikt} \equiv \frac{P_t f^x_{kt}}{p_{ikt} y_{ikt}} = \frac{1}{\mu_{ikt}} \left(\frac{f^x_{kt}}{tc_{ikt} - f^x_{kt}} \right),$$

with $s^d_{ikt} + s^X_{ikt} = s^\Pi_{ikt}$. This is consistent with the generalized results presented in Hasenzagl and Perez (2023).

To aggregate the shares, we start by computing a function form for the sectoral productivity and markup. The sectoral productivity A^Z_{kt} is the one that satisfies:

$$Y_{kt} = A^Z_{kt} \left[\alpha^K_k \left(A^K_{kt} K_{kt} \right)^{\frac{\sigma_k - 1}{\sigma_k}} + (1 - \alpha^K_k) \left(A^L_{kt} L_{kt} \right)^{\frac{\sigma_k - 1}{\sigma_k}} \right]^{\frac{\sigma_k}{\sigma_k - 1}},$$

Starting from the F.O.C.s from costs minimization, we can solve for K_{kt} and L_{kt} and then find:

$$A^Z_{kt} = \left(\sum_{i=1}^{N_{kt}} \frac{1}{A^Z_{ikt}} \frac{y_{ikt}}{Y_{kt}} \right)^{-1}$$

where the sectoral productivity is a harmonic average of the idiosyncratic productivities, weighted by the relative output shares. Turning to the sectoral markup $\mathcal{M}_{kt}$, it is the one that satisfies $P_{kt} = \mathcal{M}_{kt} \Xi_{kt} / A^Z_{kt}$ or, in real terms:

$$\rho_{kt} = \mathcal{M}_{kt} \frac{\xi_{kt}}{A^Z_{kt}}.$$

[9] See Appendix A for a detailed derivation of the results described in this section.

Using the definition of sectoral productivity:

$$\mathcal{M}_{kt} = \left(\sum_{i=1}^{N_{kt}} \frac{1}{\mu_{ikt}} \omega_{ikt} \right)^{-1}.$$

Note the sectoral markup is a harmonic average of the idiosyncratic markups, weighted by the market (revenue) shares.

Finally, moving back to the income shares, we can compute the sectoral labor, capital and gross profits shares, respectively s_{kt}^L, s_{kt}^K and s_{kt}^Π, from the results above.

$$s_{kt}^L \equiv \frac{W_t L_{kt}}{P_{kt} Y_{kt}} = \sum_{i=1}^{N_{kt}} s_{ikt}^L \omega_{ikt}.$$

By symmetry:

$$s_{kt}^K = \sum_{i=1}^{N_{kt}} s_{ikt}^K \omega_{ikt}.$$

and:

$$s_{kt}^\Pi = \sum_{i=1}^{N_{kt}} s_{ikt}^\Pi \omega_{ikt}.$$

Note that the sectoral income shares are averages of the idiosyncratic income shares, weighted by the market (revenue) shares. Using the definition of the sectoral markup, we can write the shares in terms of sectoral variables only:

$$s_{kt}^L = \left(\frac{A_{kt}^L \xi_{kt}}{w_t} \right)^{\sigma_k - 1} (1 - \alpha_k^K)^{\sigma_k} \frac{1}{\mathcal{M}_{kt}},$$

and:

$$s_{kt}^K = \left(\frac{A_{kt}^K \xi_{kt}}{r_t} \right)^{\sigma_k - 1} (\alpha_k^K)^{\sigma_k} \frac{1}{\mathcal{M}_{kt}},$$

and:

$$s_{kt}^\Pi = 1 - \frac{1}{\mathcal{M}_{kt}}$$

The sectoral net profit share is:

$$s_{kt}^d \equiv \frac{\Pi_{kt}}{\rho_{kt} Y_{kt}} = 1 - \frac{1}{\mathcal{M}_{kt}} \left(\frac{TC_{kt}}{TC_{kt} - N_{kt} f_{kt}^x} \right),$$

where TC_{kt} is the real sectoral total cost $w_t L_{kt} + r_t K_{kt} + N_{kt} f_{kt}^x$. The share of sectoral income *wasted* due to fixed costs is:

$$s_{kt}^X \equiv \frac{N_{kt} f_{kt}^x}{\rho_{kt} Y_{kt}} = \frac{1}{\mathcal{M}_{kt}} \left(\frac{N_{kt} f_{kt}^x}{TC_{kt} - N_{kt} f_{kt}^x} \right),$$

with $s_{kt}^d + s_{kt}^X = s_{kt}^\Pi$.

4 Steady State

Given that our economy presents a finite number of firms, idiosyncratic shocks do not follow deterministic laws, even in the aggregate. Because of this feature, sectoral dynamics are stochastic.

In order to define a steady state, we proceed as follows: we search for a stationary firm distribution such that it holds in expectations, i.e. given the expected realization of entry and exit shocks, the distribution exactly replicates itself in the following period. Given this distribution, and without imposing that firms' quantities are integers, we make sure that markets clear and solve for the equilibrium. Note that the *stochastic* steady state we define proxies the concept of a stable long-run equilibrium. Indeed, once we set our economy as close as possible to the equilibrium by also imposing that firms' variables are discrete, the sector oscillates over time around the equilibrium provided.

In the following, we calibrate an economy with two macro-sectors, i.e. $\mathcal{S} = 6$, each populated by six distinct firm types, i.e. $S = 6$, which allows us to calibrate exit rates and productivity levels following BDS data, as explained in Section 5. Moreover, note that we augment the baseline model with a common aggregate TFP technology, Z, in the spirit of Clementi and Palazzo (2016). This does not affect our qualitative results, but it is useful for calibration purposes to scale the size of the economy.

To find the stationary firm distribution, note that, given the total mass of entrants N_k^e in sector k, the following holds in expectations:

$$N_k^{j,e} = \Omega_j N_k^e.$$

As entrants must equal exiting firms for each type, we have:

$$N_k^{j,e} = \delta_j (N_k^{j,o} + N_k^{j,e}),$$

or, solving for the equilibrium mass of incumbents of type i:

$$N_k^{j,o} = \frac{1-\delta_j}{\delta_j} N_k^{j,e}.$$

Finally, the total mass of type-j firm in sector k is:

$$N_k^j = N_k^{j,o} + N_k^{j,e} = \frac{1}{\delta_j} N_k^{j,e} = \frac{\Omega_j}{\delta_j} N_k^e,$$

while the total number of firms is:

$$N_k = \sum_{j=1}^{6} N_k^j.$$

Thus, the stationary distribution is pinned down solely by the mass of sectoral entrants N_k^e. To determine entrants, we use the first order conditions of the household, together with market clearing conditions.

Firms enter up to the point where the expected profits are equal to zero:

$$\sum_{j=1}^{6} \Omega_j d_{jk} = 0, \tag{4}$$

where profits d_{jk} are defined below as a function of ρ_{jk}, ρ_k, and Y. Regarding the household, note that, in the steady state, the investment must equal the depreciation of capital, i.e. $I = \delta K$. Hence, the budget constraint is:

$$C + \delta K = wL + rK + \Pi, \tag{5}$$

where $\Pi = \sum_{k=1}^{\mathcal{S}} \Pi_k = \Pi_1 + \Pi_2 = \sum_{j=1}^{6} N_1^j d_{j1}/P + \sum_{j=1}^{6} N_2^j d_{j2}/P$. The F.O.C.s pin down wages (as a function of C and L) and rental rates:

$$w = \nu L^{\phi} C \quad \text{and} \quad r = \frac{1}{\beta} + \delta - 1.$$

Moving to the producers, under the specification with aggregate TFP, Z, real marginal costs in sector k are:

$$mc_{jk} = \frac{1}{Z A_{jk}^Z} \left[\left(\frac{r}{A_k^K \alpha_k^K} \right)^{1-\sigma_k} \alpha_k^K + \left(\frac{w}{A_k^L (1-\alpha_k^K)} \right)^{1-\sigma_k} (1-\alpha_k^K) \right]^{\frac{1}{1-\sigma_k}} = \frac{\xi_k^Z}{A_{jk}^Z}.$$

Each type maximizes its profits when:

$$\rho_{jk} = \mu_{jk} \frac{\xi_k^Z}{A_{jk}^Z}, \tag{6}$$

given the definition of markups μ_{jk} as:

$$\mu_{jk} = \left[\frac{\theta_k - 1}{\theta_k} + \left(\frac{1}{\theta_k} - \frac{1}{\gamma} \right) \omega_{jk} \right]^{-1}.$$

where:

$$\omega_{jk} = \left(\frac{\rho_{jk}}{\rho_k} \right)^{1-\theta_k}.$$

Real profits $\pi_{jk} \equiv d_{jk}/P$ satisfy:

$$\pi_{jk} = \left(1 - \frac{1}{\mu_{jk}} \right) \rho_{jk}^{1-\theta_k} \rho_k^{\theta_k - \gamma} \chi_k^{\gamma} Y - f_k^x.$$

From the definition of the real price we have:

$$\rho_k^{1-\theta_k} = \sum_{j=1}^{6} N_k^j \rho_{jk}^{1-\theta_k},$$

and:

$$1 = \sum_{k=1}^{2} \rho_k^{1-\gamma} \chi_k^{\gamma}. \tag{7}$$

Regarding aggregation, the total output Y can be expressed as:

$$Y = C + f_1^x N_1 + f_2^x N_2 + \delta K.$$

Finally, combining the F.O.C.s from cost minimization, and summing over the number of firms, we have an equation that expresses K_k as a function of prices and L_k:

$$K_k = \left(\frac{w}{r}\right)^{\sigma_k} \left(\frac{1-\alpha_k^K}{\alpha_k^K}\right)^{-\sigma_k} \left(\frac{A_k^L}{A_k^K}\right)^{1-\sigma_k} L_k,$$

where:

$$L = L_1 + L_2.$$

and:

$$K = K_1 + K_2. \tag{8}$$

Numbered conditions (4)-(8) define a system of 17 equations, as (6) groups 12 equations, in 17 variables, i.e. N_1^e, N_2^e, C, K, L, ρ_{j1} for j integer $\in [1,6]$, and ρ_{j2} for j integer $\in [1,6]$.

5 Calibration

We assume 2 sectors in the economy. The parameters are calibrated such that sectors are of equal size and *ex-ante* homogeneous in all dimensions, except for the elasticity of substitution between inputs.

Table 5 reports externally assigned parameters (top panel), internally calibrated aggregate parameters (middle panel) and σ estimated from Dutch micro data (bottom panel). The parameters are calibrated to yearly values where, the discount factor, β, is set to a standard value of 0.96. The inverse of the Frisch labor elasticity, ϕ, is equal to 2, as in Boar and Midrigan (2019), the depreciation rate of capital, δ, is set to a standard year value of 0.06 (Edmond, Midrigan, & Xu, 2019). The elasticity of substitution across sectors, γ, is set to a value of 2, in line with the estimation in Edmond, Midrigan, and Xu (2015a). We assume that sectors are of equal size and set χ to 0.5. A^L and A^K and Z are normalized to 1. We set the elasticity of substitution between goods, θ, to 5.3 to match a median monopolistic markup of 1.23 estimated in Dutch data in Section 2.3. α_K equals 0.34, which, in the limit case of a Cobb-Douglas specification, gives an average value of Dutch capital income share between 2000 and 2019 of 34% (St Louis FRED). ν is set to 4.45 to match the average $\frac{R}{W} = 0.02$ in the Dutch data, from EUROSTAT. The initial overhead cost f_x^0 is calibrated to 0.2, which allows us to generate small sectors with approximately 20 competitors. Importantly, the change in overhead costs Δf_x is also calibrated using CBS data, with the top two quintiles of Δf_x experiencing a 12% rise.

Finally, the last 2 rows of Table 5 report parameter values of σ, 0.32 and 0.51 in the ICT sector and non-ICT sector, respectively.

Table 5: **Calibration**

Parameter	Value	Target/Literature
	Assigned parameters	
β	0.96	Edmond et al. (2019)
ϕ	2	Boar and Midrigan (2019).
δ	0.06	Edmond et al. (2019).
γ	2	Edmond, Midrigan, and Xu (2015b)
χ	0.5	*ex ante* symmetric sectors
A^L	1	Normalization.
A^K	1	Normalization.
Z	1	Normalization.
	Internally calibrated aggregate parameters	
θ	5.3	Median markup = 1.23
α_K	0.34	Capital share under CD = 0.34.
ν	4.45	$\frac{R}{W} = 0.02$
f_x^0	0.2	Number of firms in a sector
Δf_x	12%	Δ in CBS data
	Estimated parameters	
σ^H	0.32	σ in high-ICT sectors.
σ^L	0.51	σ in low-ICT sectors.

Table 6 describes firm-type parameter values. We assume that the economy is characterized by 6 distinct productivity types, i.e. $S = 6$. By exploiting the fact that, in our model, there is a 1-to-1 correspondence between productivity and size (in terms of employment in the data), we calibrate type-specific parameters to match empirical targets based on the firm size distribution from Dutch administrative data. In particular, type 1 represents firms with employment between 1 and 4 units, type 2 between 5 and 9, type 3 between 10 and 19, type 4 between 20 and 49, and type 50 and 99 and type 6 above 100 employees. Productivity levels A_i^Z are calibrated accordingly to match these groups. For each type-specific bin, we compute exit probabilities δ_i as the average yearly exit rates in CBS data. On average, the yearly exit rate of the Dutch firms equals $\delta = 5.8\%$, similar to the rate in BDS, documented by Tian (2018). The exit rate declines with firms size (and

Table 6: **Calibration firm-level parameters**

Parameter	Value	Target
S	6	Number of firm types
A_1^Z	1	Productivity firm type 1: $1-4$ employees
A_2^Z	5	Productivity firm type 2: $5-9$ employees
A_3^Z	10	Productivity firm type 3: $10-19$ employees
A_4^Z	20	Productivity firm type 4: $20-49$ employees
A_5^Z	50	Productivity firm type 5: $50-99$ employees
A_6^Z	100	Productivity firm type 6: >100 employees
δ_1	0.060	Dutch firms yearly exit rate, PS
δ_2	0.059	Dutch firms yearly exit rate, PS
δ_3	0.058	Dutch firms yearly exit rate, PS
δ_4	0.055	Dutch firms yearly exit rate, PS
δ_5	0.050	Dutch firms yearly exit rate, PS
δ_6	0.039	Dutch firms yearly exit rate, PS
Ω_1	0.60	Average share type 1 firms, PS
Ω_2	0.11	Average share type 2 firms, PS
Ω_3	0.11	Average share type 3 firms, PS
Ω_4	0.10	Average share type 4 firms, PS
Ω_5	0.04	Average share type 5 firms, PS
Ω_6	0.05	Average share type 6 firms, PS

productivity in the model) as indicated by δ_i's in Table 6. Together with the remainder of the calibration, these exit rates imply a yearly aggregate destruction rate of approximately 10%, in line with Colciago (2016), despite untargeted.

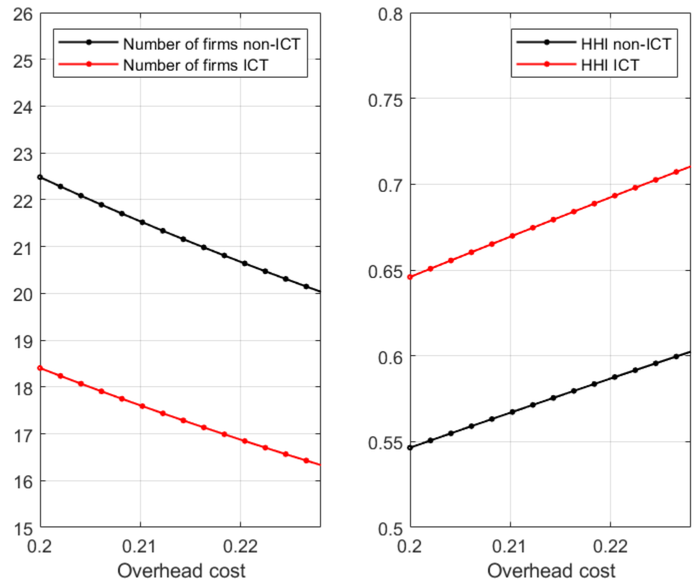
Similar to Hopenhayn (1992), we assume entrants draw their type from the stationary firm distribution, where the *ex ante* probability of drawing type i, Ω_i, is calculated as shares of 6 types of firms in CBS data over the sample between 2006 and 2020.[10] Bottom rows of Table (6) report the values computed for each Ω_i.

6 Results

Table 1 shows that in some sectors, markups increased while in others they declined, with overhead costs moving in the same direction over the sample period. In our model, such changes would lead to markup adjustments of the same sign. However, our aim is to identify the different impact of a uniform change in overhead costs on markups, depending on the technology the sector uses (different σ). Therefore, our main experiment

[10]Alternatively, we also present a different calibration in the replication package where we infer the Ω_i by assuming an underlying continuous Pareto distribution with minimum 1 and tail parameter 1.05. From there, we compute Ω_i as the probability of drawing a level x such that $A_i^Z \leq x \leq A_{i+1}^Z$. Results are similar under this alternative specification.

Figure 3: Number of firms and HHI as a function of overhead cost.



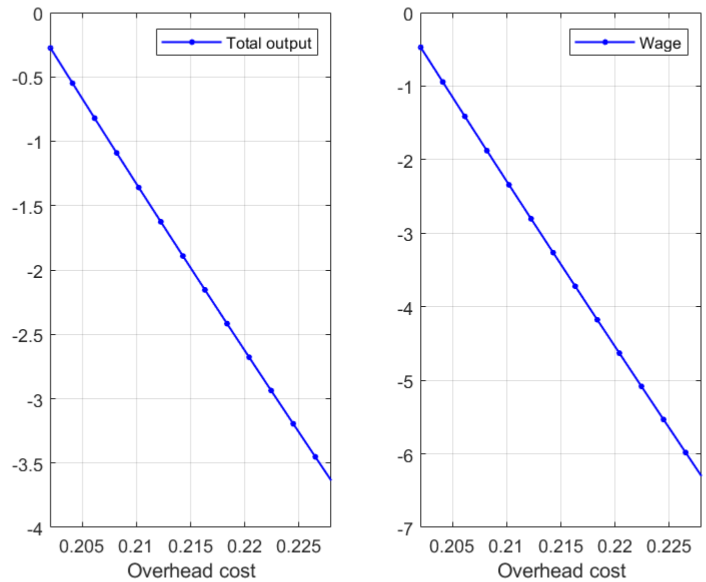
approximates the situation where both sectors experience the shock to overhead costs of the same sign and magnitude. We choose to implement an increase in overhead costs of production although a symmetric case of its reduction could be carried out as well.

We focus of two top quintiles of overhead cost growth distribution computed in Table 1. For these two quintiles, we calculate the average cumulative change of markups and overhead costs. The overhead costs increased over the sample period by 12%, on average, and this is also the shift we introduce into our model in steps. We keep all other parameters unchanged.

In what follows, we present the results of a series of experiments, where we increase the overhead cost by 0.002 in each step and derive the steady state values for each of them. The figures presented below therefore plot the collections of steady states instead of the transition paths of an economy (each dot corresponds to a distinct steady state). Red lines correspond to ICT (low-σ) sector values, black ones to non-ICT (high-σ) outcomes and blue lines depict either ratios or aggregate outcomes.

Figure 3 plots the number of firms (left panel) and HHI index (right panel) for each of the overhead cost value $f_x \in [0.2,\ 0.227]$ and in each sector. In both sectors, growing overhead cost of production reduces the number of firms that can survive. Those that survive are more productive and therefore capture larger market shares, leading to higher market concentration in both sectors shown in the right panel of Figure 3. On aggregate, this leads to a lower output and reduced demand for inputs resulting in lower wages (r is fixed: $r = \frac{1}{\beta} + \delta - 1$). The left panel of Figure 4 shows a decline of total output and the

Figure 4: Cumulative change in Y and w as a function of overhead cost (in %).



right panel a corresponding drop in wage (right panel) as a function of growing overhead costs.

The common decline in wage translates into a reduction in marginal cost of production of different magnitudes, depending on the elasticity of substitution, σ. Although marginal costs fall in both sectors, the decrease is more pronounced in the ICT sector, as shown in the right panel of Figure 5. This figure plots the decline in the ratio of marginal costs between the ICT and non-ICT sectors. The sensitivity of marginal cost to changes in wages is captured by the elasticity $\varepsilon_k^{MC,W}$, which is equal to the labor (variable) cost share, $s_k^{L,c}$:

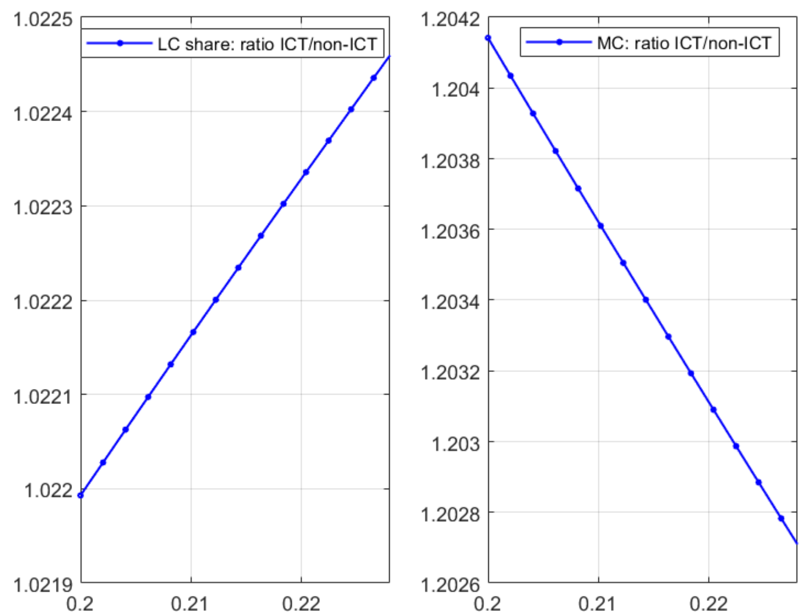
$$\varepsilon_k^{MC,W} = \frac{\partial log MC_k}{\partial log W} = \frac{\frac{\partial MC_k}{MC_k}}{\frac{\partial W}{W}} = \left(\frac{\Xi_k}{W}\right)^{\sigma_k - 1} (1-\alpha^K)^{\sigma_k} = s_k^{L,c}. \tag{9}$$

Consequently, the higher the labor cost share, the more responsive marginal cost is to changes in wages. Intuitively, sectors that rely more heavily on labor are more sensitive to wage fluctuations. Despite the lower cost of capital, firms in the ICT sector employ more labor due to the stronger complementarity between labor and capital (low σ). In contrast, firms in non-ICT sectors can more readily substitute labor with cheaper capital (higher σ), leading to lower labor usage and a smaller reduction in marginal costs when wages decline.

In line with this intuition, the left panel of Figure 5 shows the ratio of labour cost shares in ICT and non-ICT sectors is always higher than 1.

A larger drop in marginal cost in ICT sector allows firms to be more profitable. Figure

Figure 5: Ratio of labour cost share in ICT and non-ICT sectors and MC ratio between ICT and non-ICT as a function of overhead cost.

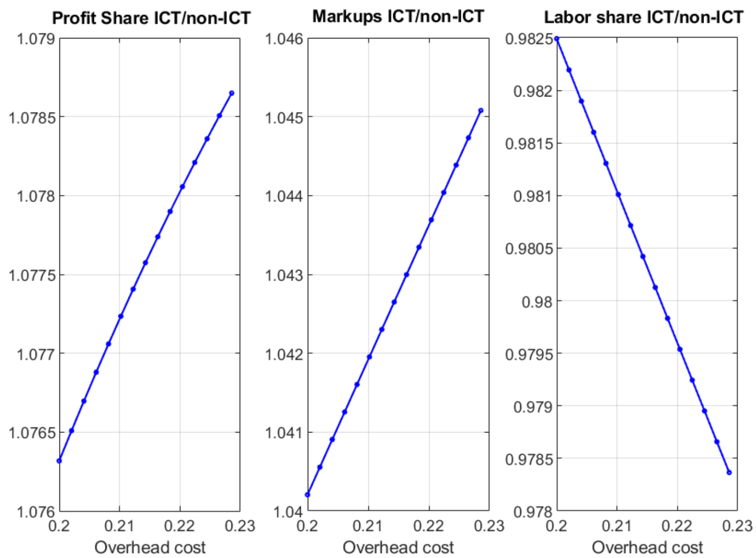


6 shows that profit shares of firms grow faster in ICT than non-ICT sector (left panel), allowing them to expand and increase markups (middle panel) at the expense of the labor share of income (right panel).

Markups in the ICT sector increase by 2.78%, compared to 2.31% in the non-ICT sector. In the data, the corresponding average increases are 7.60% and 5.38%, respectively, based on a classification of sectors by their investment in automation.[11] Thus, a modest rise in overhead production costs can account for approximately 37% of the markup increase in ICT sectors and 43% in non-ICT sectors. Importantly, a small variation in the production function—captured by different degree of complementarity between inputs σ—can generate asymmetry in markup growth of a magnitude comparable to that observed in the data. The ratio of markup growth between ICT and non-ICT sectors is 1.4 in the data, closely mirrored by a ratio of 1.2 in the model.

[11]ICT sectors are defined as those with ICT investment growth above the median, while non-ICT sectors fall below the median.

Figure 6: Profit shares, markups and labor share of income: ratios between ICT and non-ICT



7 Conclusion

This paper investigates how rising overhead production costs interact with sector-specific production technologies to shape the dynamics of markups and labor income shares. Using rich administrative data from Dutch firms between 2006 and 2018, we document that while aggregate overhead costs and markups declined, many sectors experienced rising markups, alongside growing overhead costs. However, the magnitude of markup growth varied even among sectors with similar changes in overhead costs. We trace this heterogeneity to differences in input substitutability, driven in part by differential adoption of ICT capital across sectors.

By estimating sector-specific elasticities of substitution between labor and capital, we show that production inputs are more complementary in ICT-intensive sectors. Embedding these empirical estimates into a general equilibrium model with heterogeneous firms, we demonstrate that a modest increase in overhead costs disproportionately boosts markups and reduces labor shares in sectors with stronger input complementarity. Our calibrated model accounts for a substantial share of the observed markup growth and captures the relative differences between ICT and non-ICT sectors.

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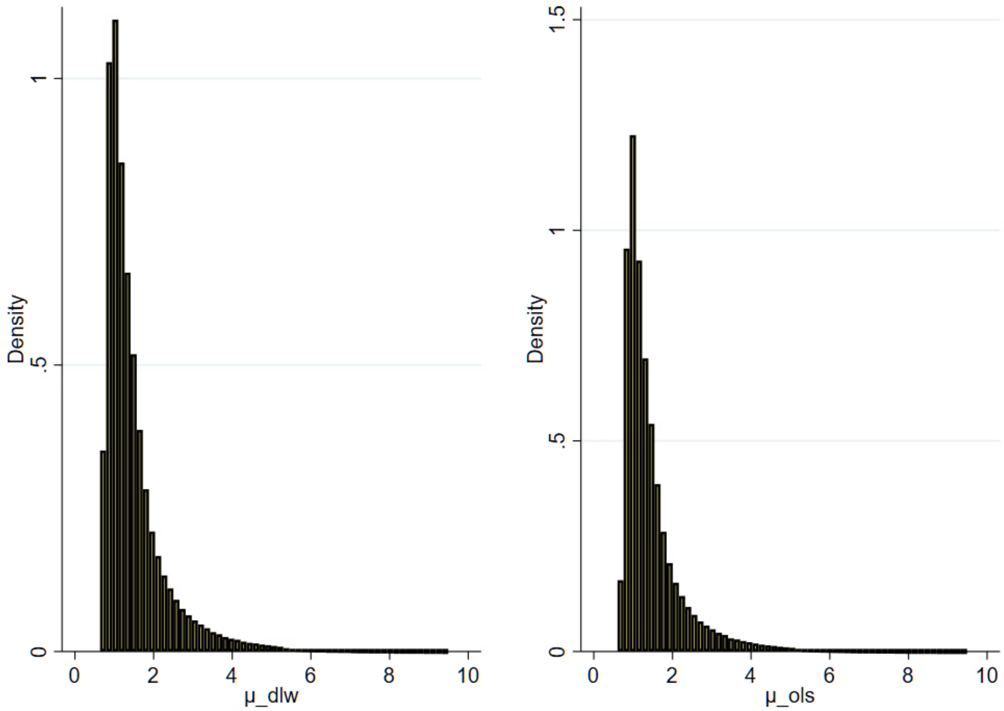
Figure 7: Firm-level markups in the Netherlands between 2006 and 2018.



Appendix A

Appendix B

Bundlers

Aggregate output Y_t is a C.E.S. aggregate of sectoral production Y_{kt}:

$$Y_t = \left(\sum_{k=1}^{\mathcal{S}} \chi_k Y_{kt}^{\frac{\gamma-1}{\gamma}} \right)^{\frac{\gamma}{\gamma-1}}. \tag{10}$$

The aggregate bundler combines sectoral quantities under a zero profit condition:

$$\max_{Y_{kt}} P_t Y_t - \sum_{k=1}^{\mathcal{S}} P_{kt} Y_{kt}$$

subject to equation (10). The F.O.C. is:

$$P_{kt} = \Lambda_t \chi_k \left(\frac{Y_{kt}}{Y_t} \right)^{-\frac{1}{\gamma}},$$

where it can be shown that the Lagrange multiplier Λ_t equals P_t, using that $\sum P_{kt} Y_{kt} = P_t Y_t$, and since $P_t \equiv \left(\sum_{k=1}^{\mathcal{S}} \chi_k^{\gamma} P_{kt}^{1-\gamma} \right)^{\frac{1}{1-\gamma}}$.

The same structure exists within each sector, where each sectoral output Y_{kt} is a C.E.S. aggregate of individual production y_{ikt}:

$$Y_{kt} = \left(\sum_{i=1}^{N_{kt}} y_{ikt}^{\frac{\theta_k-1}{\theta_k}} \right)^{\frac{\theta_k}{\theta_k-1}}. \tag{11}$$

Each sectoral bundler maximizes profits:

$$\max_{y_{ikt}} P_{kt} Y_{kt} - \sum_{i=1}^{N_{kt}} p_{ikt} y_{ikt}$$

subject to equation (11). The F.O.C. is:

$$p_{ikt} = \Lambda_{kt} \left(\frac{y_{ikt}}{Y_{kt}} \right)^{-\frac{1}{\theta_k}},$$

where it can be shown that the Lagrange multiplier Λ_{kt} equals P_{kt}. This gives a sectoral price:

$$P_{kt} = \left[\sum_{i=1}^{N_{kt}} p_{ikt}^{1-\theta_k} \right]^{\frac{1}{1-\theta_k}}.$$

Competition

The production function is a C.E.S. in labor l_{ikt} and in capital k_{ikt}. Firm-level production y_{ikt} is:

$$y_{ikt} = A^Z_{ikt}\left[\alpha^K_k\left(A^K_{kt}k_{ikt}\right)^{\frac{\sigma_k-1}{\sigma_k}} + (1-\alpha^K_k)\left(A^L_{kt}l_{ikt}\right)^{\frac{\sigma_k-1}{\sigma_k}}\right]^{\frac{\sigma_k}{\sigma_k-1}}, \tag{12}$$

Firms minimize their total variable costs subject to the technological constraints, i.e.:

$$\min_{l_{ikt},k_{ikt}} W_t l_{ikt} + R_t k_{ikt}$$

subject to equation (12). The F.O.C.s for labor and capital are, respectively:

$$W_t = \lambda_{ikt}\left(A^Z_{ikt}\right)^{\frac{\sigma_k-1}{\sigma_k}} y_{ikt}^{\frac{1}{\sigma_k}}(1-\alpha^K_k)\left(A^L_{kt}\right)^{\frac{\sigma_k-1}{\sigma_k}} l_{ikt}^{-\frac{1}{\sigma_k}}$$

and

$$R_t = \lambda_{ikt}\left(A^Z_{ikt}\right)^{\frac{\sigma_k-1}{\sigma_k}} y_{ikt}^{\frac{1}{\sigma_k}}\alpha^K_k\left(A^K_{kt}\right)^{\frac{\sigma_k-1}{\sigma_k}} k_{ikt}^{-\frac{1}{\sigma_k}},$$

where λ_{ikt} is the firm-specific Lagrange multiplier.

We can use these expression to rewrite total variable costs as:

$$\begin{aligned} W_t l_{ikt} + R_t k_{ikt} &= \\ = \lambda_{ikt}\left(A^Z_{ikt}\right)^{\frac{\sigma_k-1}{\sigma_k}} y_{ikt}^{\frac{1}{\sigma_k}}(1-\alpha^K_k)\left(A^L_{kt}\right)^{\frac{\sigma_k-1}{\sigma_k}} l_{ikt}^{1-\frac{1}{\sigma_k}} &+ \lambda_{ikt}\left(A^Z_{ikt}\right)^{\frac{\sigma_k-1}{\sigma_k}} y_{ikt}^{\frac{1}{\sigma_k}}\alpha^K_k\left(A^K_{kt}\right)^{\frac{\sigma_k-1}{\sigma_k}} k_{it}^{1-\frac{1}{\sigma_k}} = \\ = \lambda_{ikt} y_{ikt}^{\frac{1}{\sigma_k}}\left(A^Z_{ikt}\right)^{\frac{\sigma_k-1}{\sigma_k}}\left[(1-\alpha^K_k)\left(A^L_{kt}l_{ikt}\right)^{\frac{\sigma_k-1}{\sigma_k}} + \alpha^K_k\left(A^K_{kt}k_{ikt}\right)^{\frac{\sigma_k-1}{\sigma_k}}\right] &= \lambda_{ikt}y_{ikt}. \end{aligned}$$

Thus, individual marginal costs MC_{it} are represented by the Lagrange multiplier. To solve for λ_{ikt}, we take the ratio of the two first order conditions:

$$\frac{W_t}{R_t} = \frac{1-\alpha^K_k}{\alpha^K_k}\left(\frac{A^L_{kt}}{A^K_{kt}}\right)^{\frac{\sigma_k-1}{\sigma_k}}\left(\frac{l_{ikt}}{k_{ikt}}\right)^{-\frac{1}{\sigma_k}},$$

which gives capital as a function of labor:

$$k_{ikt}^{\frac{\sigma_k-1}{\sigma_k}} = \left(\frac{W_t}{R_t}\right)^{\sigma_k-1}\left(\frac{1-\alpha^K_k}{\alpha^K_k}\right)^{1-\sigma_k}\left(\frac{A^K_{kt}}{A^L_{kt}}\right)^{\frac{(\sigma_k-1)^2}{\sigma_k}}\left(l_{ikt}\right)^{\frac{\sigma_k-1}{\sigma_k}}.$$

From the first F.O.C.:

$$\lambda_{ikt} = W_t\left(A^Z_{ikt}\right)^{-\frac{\sigma_k-1}{\sigma_k}}\left(\frac{l_{ikt}}{y_{ikt}}\right)^{\frac{1}{\sigma_k}}(1-\alpha^K_k)^{-1}\left(A^L_{kt}\right)^{-\frac{\sigma_k-1}{\sigma_k}}.$$

Plugging in the definition of y_{ikt}, we can write:

$$\lambda_{ikt} = \frac{W_t}{A^Z_{ikt}}(1-\alpha^K_k)^{-1}\left(A^L_{kt}\right)^{-\frac{\sigma_k-1}{\sigma_k}}\left(l_{ikt}\right)^{\frac{1}{\sigma_k}}\left[\alpha^K_k\left(A^K_{kt}k_{ikt}\right)^{\frac{\sigma_k-1}{\sigma_k}} + (1-\alpha^K_k)\left(A^L_{kt}l_{ikt}\right)^{\frac{\sigma_k-1}{\sigma_k}}\right]^{\frac{1}{1-\sigma_k}},$$

and, using the definition of k_{ikt} as a function of l_{ikt}:

$$\lambda_{ikt} = \frac{W_t}{A^Z_{ikt}}(1-\alpha^K_k)^{-1}\left(A^L_{kt}\right)^{-\frac{\sigma_k-1}{\sigma_k}}\left(l_{ikt}\right)^{\frac{1}{\sigma_k}}\cdot$$

$$\left[\alpha^K_k\left(A^K_{kt}\right)^{\frac{\sigma_k-1}{\sigma_k}}\left(\frac{W_t}{R_t}\right)^{\sigma_k-1}\left(\frac{1-\alpha^K_k}{\alpha^K_k}\right)^{1-\sigma_k}\left(\frac{A^K_{kt}}{A^L_{kt}}\right)^{\frac{(\sigma_k-1)^2}{\sigma_k}}\left(l_{ikt}\right)^{\frac{\sigma_k-1}{\sigma_k}}+(1-\alpha^K_k)\left(A^L_{kt}l_{ikt}\right)^{\frac{\sigma_k-1}{\sigma_k}}\right]^{\frac{1}{1-\sigma_k}},$$

or:

$$\lambda_{ikt} = \frac{W_t}{A^Z_{ikt}}(1-\alpha^K_k)^{-1}\left(A^L_{kt}\right)^{-\frac{\sigma_k-1}{\sigma_k}}\cdot$$

$$\left[(\alpha^K_k)^{\sigma_k}\left(A^K_{kt}\right)^{\sigma_k-1}\left(\frac{W_t}{R_t}\right)^{\sigma_k-1}(1-\alpha^K_k)^{1-\sigma_k}\left(\frac{1}{A^L_{kt}}\right)^{\frac{(\sigma_k-1)^2}{\sigma_k}}+(1-\alpha^K_k)\left(A^L_{kt}\right)^{\frac{\sigma_k-1}{\sigma_k}}\right]^{\frac{1}{1-\sigma_k}}.$$

Finally:

$$\lambda_{ikt} = \frac{1}{A^Z_{ikt}}\left[R_t^{1-\sigma_k}(\alpha^K_k)^{\sigma_k}\left(A^K_{kt}\right)^{\sigma_k-1}+W_t^{1-\sigma_k}(1-\alpha^K_k)^{\sigma_k}\left(A^L_{kt}\right)^{\sigma_k-1}\right]^{\frac{1}{1-\sigma_k}}.$$

Following the standard result for a Cobb-Douglas production function, we rewrite the nominal marginal cost as:

$$MC_{ikt} = \lambda_{ikt} = \frac{1}{A^Z_{ikt}}\left[\left(\frac{R_t}{A^K_{kt}\alpha^K_k}\right)^{1-\sigma_k}\alpha^K_k+\left(\frac{W_t}{A^L_{kt}(1-\alpha^K_k)}\right)^{1-\sigma_k}(1-\alpha^K_k)\right]^{\frac{1}{1-\sigma_k}}.$$

For conciseness, we redefine the sector-specific part of the marginal cost as Ξ_{kt} to write:

$$MC_{ikt} = \frac{\Xi_{kt}}{A^Z_{ikt}}.$$

Firms compete under Cournot oligopolistic competition. Given the optimal conditions from the cost minimization problem, each firm maximizes its nominal profits given the demand constraint:

$$\max_{y_{ikt}} p_{ikt}y_{ikt} - W_t l_{ikt} - R_t k_{ikt} - P_t f^x_{kt},$$

subject to condition (12) and to:

$$y_{ikt} = \left(\frac{p_{ikt}}{P_{kt}}\right)^{-\theta_k}\left(\frac{P_{kt}}{P_t}\right)^{-\gamma}\left(\frac{1}{\chi_k}\right)^{-\gamma}Y_t.$$

Substituting the constraint and the results from the costs minimization problem, we can write:

$$\max_{y_{ikt}} y_{ikt}^{1-\frac{1}{\theta_k}}Y_{kt}^{\frac{1}{\theta_k}-\frac{1}{\gamma}}Y_t^{\frac{1}{\gamma}}\chi_k P_t - \frac{\Xi_{kt}}{A^Z_{ikt}}y_{ikt} - P_t f^x_{kt}.$$

The F.O.C. is:

$$\left(\frac{\theta_k-1}{\theta_k}\right)y_{ikt}^{-\frac{1}{\theta_k}}Y_{kt}^{\frac{1}{\theta_k}-\frac{1}{\gamma}}Y_t^{\frac{1}{\gamma}}\chi_kP_t+\left(\frac{1}{\theta_k}-\frac{1}{\gamma}\right)y_{ikt}^{1-\frac{1}{\theta_k}}Y_{kt}^{\frac{1}{\theta_k}-\frac{1}{\gamma}-1}Y_t^{\frac{1}{\gamma}}\chi_kP_t\left(\frac{y_{ikt}}{Y_{kt}}\right)^{-\frac{1}{\theta_k}}=\frac{\Xi_{kt}}{A_{ikt}^Z}.$$

Rewriting:

$$p_{ikt}\left[\left(\frac{\theta_k-1}{\theta_k}\right)+\left(\frac{1}{\theta_k}-\frac{1}{\gamma}\right)\left(\frac{y_{ikt}}{Y_{kt}}\right)^{1-\frac{1}{\theta_k}}\right]=\frac{\Xi_{kt}}{A_{ikt}^Z}.$$

Note that the market share ω_{ikt} is defined as:

$$\omega_{ikt}=\frac{p_{ikt}y_{ikt}}{P_{kt}Y_{kt}}=\left(\frac{y_{ikt}}{Y_{kt}}\right)^{1-\frac{1}{\theta_k}}.$$

Thus, in real terms:

$$\rho_{ikt}=\left[\left(\frac{\theta_k-1}{\theta_k}\right)+\left(\frac{1}{\theta_k}-\frac{1}{\gamma}\right)\omega_{ikt}\right]^{-1}\frac{\xi_{kt}}{A_{ikt}^Z}=\mu_{ikt}\frac{\xi_{kt}}{A_{ikt}^Z},$$

where ξ_{kt} is the real counterpart of Ξ_{kt}.

Income Shares, Markups and Productivity

We can define income shares at the firm level. By definition, the labor share of income s_{ikt}^L is:

$$s_{ikt}^L=\frac{W_tl_{ikt}}{p_{ikt}y_{ikt}}=\frac{w_tl_{ikt}}{\rho_{ikt}y_{ikt}}=\frac{w_tl_{ikt}}{\rho_{ikt}(mc_{ikt})^{-1}(w_tl_{ikt}+r_tk_{ikt})}=\frac{w_tl_{ikt}}{\mu_{ikt}(w_tl_{ikt}+r_tk_{ikt})},$$

where the real marginal cost $mc_{ikt}=\xi_{kt}/A_{ikt}^Z$. Thus, using symmetry:

$$s_{ikt}^K=\frac{1}{\mu_{ikt}}\frac{r_tk_{ikt}}{w_tl_{ikt}+r_tk_{ikt}},$$

while, since $1=s_{ikt}^L+s_{ikt}^K+s_{ikt}^\Pi$:

$$s_{ikt}^\Pi=1-\frac{1}{\mu_{ikt}}.$$

Using the C.E.S. functional form, we can rewrite further by solving for l_{ikt}/y_{ikt} and k_{ikt}/y_{ikt} from the two F.O.C.s from the costs minimization problem.

$$s_{ikt}^L=\frac{w_tA_{ikt}^Z}{\mu_{ikt}\xi_{kt}}w_t^{-\sigma_k}\xi_{kt}^{\sigma_k}\left(A_{ikt}^Z\right)^{-1}\left(A_{kt}^L\right)^{\sigma_k-1}(1-\alpha_k^K)^{\sigma_k}=\frac{1}{\mu_{ikt}}\left(\frac{\xi_{kt}A_{kt}^L}{w_t}\right)^{\sigma_k-1}(1-\alpha_k^K)^{\sigma_k}.$$

Symmetrically, the capital share of income is:

$$s_{ikt}^K=\frac{1}{\mu_{ikt}}\left(\frac{\xi_{kt}A_{kt}^K}{r_t}\right)^{\sigma_k-1}(\alpha_k^K)^{\sigma}.$$

Finally:

$$s^{\Pi}_{ikt} = 1 - \frac{1}{\mu_{ikt}}.$$

To aggregate the shares, we start by computing a function form, respectively, for the sectoral productivity and the sectoral markup. The sectoral productivity A^Z_{kt} is the one that satisfies:

$$Y_{kt} = A^Z_{kt}\left[\alpha^K_k\left(A^K_{kt}K_{kt}\right)^{\frac{\sigma_k-1}{\sigma_k}} + (1-\alpha^K_k)\left(A^L_{kt}L_{kt}\right)^{\frac{\sigma_k-1}{\sigma_k}}\right]^{\frac{\sigma_k}{\sigma_k-1}},$$

Starting again from the F.O.C.s from costs minimization:

$$L_{kt} = \sum_{i=1}^{N_{kt}} l_{ikt} = \sum_{i=1}^{N_{kt}} w_t^{-\sigma_k}\xi_{kt}^{\sigma_k}\left(A^Z_{ikt}\right)^{-1}\frac{y_{ikt}}{Y_{kt}}Y_{kt}(1-\alpha^K_k)^{\sigma_k}\left(A^L_{kt}\right)^{\sigma_k-1},$$

and,

$$K_{kt} = \sum_{i=1}^{N_{kt}} k_{ikt} = \sum_{i=1}^{N_{kt}} r_t^{-\sigma_k}\xi_{kt}^{\sigma_k}\left(A^Z_{ikt}\right)^{-1}\frac{y_{ikt}}{Y_{kt}}Y_{kt}(\alpha^K_k)^{\sigma_k}\left(A^K_{kt}\right)^{\sigma_k-1}.$$

Plugging in the definition of sectoral output:

$$Y_{kt} = A^Z_{kt}\Bigg[(\alpha^K_k)^{\sigma_k}\left(A^K_{kt}\right)^{\sigma_k-1}Y_{kt}^{\frac{\sigma_k-1}{\sigma_k}}r_t^{1-\sigma_k}\xi_{kt}^{\sigma_k-1}\left(\sum_{i=1}^{N_{kt}}\frac{1}{A^Z_{ikt}}\frac{y_{ikt}}{Y_{kt}}\right)^{\frac{\sigma_k-1}{\sigma_k}} +$$

$$+(1-\alpha^K_k)^{\sigma_k}\left(A^L_{kt}\right)^{\sigma_k-1}Y_{kt}^{\frac{\sigma_k-1}{\sigma_k}}w_t^{1-\sigma_k}\xi_{kt}^{\sigma_k-1}\left(\sum_{i=1}^{N_{kt}}\frac{1}{A^Z_{ikt}}\frac{y_{ikt}}{Y_{kt}}\right)^{\frac{\sigma_k-1}{\sigma_k}}\Bigg]^{\frac{\sigma_k}{\sigma_k-1}},$$

or:

$$1 = A^Z_{kt}\xi^{\sigma_k}_{kt}\left[\left(\frac{r_t}{A^K_{kt}\alpha^K_k}\right)^{1-\sigma_k}\alpha^K_k + \left(\frac{w_t}{A^L_{kt}(1-\alpha^K_k)}\right)^{1-\sigma_k}(1-\alpha^K_k)\right]^{-\frac{\sigma_k}{1-\sigma_k}}\left(\sum_{i=1}^{N_{kt}}\frac{1}{A^Z_{ikt}}\frac{y_{ikt}}{Y_{kt}}\right).$$

Thus:

$$A^Z_{kt} = \left(\sum_{i=1}^{N_{kt}}\frac{1}{A^Z_{ikt}}\frac{y_{ikt}}{Y_{kt}}\right)^{-1}$$

Turning to the sectoral markup $\mathcal{M}_{kt}$, it is the one that satisfies $P_{kt} = \mathcal{M}_{kt}\Xi_{kt}/A^Z_{kt}$ or, in real terms:

$$\rho_{kt} = \mathcal{M}_{kt}\frac{\xi_{kt}}{A^Z_{kt}}.$$

Using the definition of sectoral productivity:

$$\frac{1}{\mathcal{M}_{kt}} = \frac{1}{\rho_{kt}}\xi_{kt}\sum_{i=1}^{N_{kt}}\frac{1}{A^Z_{ikt}}\frac{y_{ikt}}{Y_{kt}} = \frac{1}{\rho_{kt}}\xi_{kt}\sum_{i=1}^{N_{kt}}\frac{\rho_{ikt}}{\mu_{ikt}\xi_{kt}}\frac{y_{ikt}}{Y_{kt}} = \sum_{i=1}^{N_{kt}}\frac{\rho_{ikt}}{\mu_{ikt}\rho_{kt}}\frac{y_{ikt}}{Y_{kt}}.$$

Hence:

$$\mathcal{M}_{kt} = \left(\sum_{i=1}^{N_{kt}} \frac{1}{\mu_{ikt}} \omega_{ikt} \right)^{-1}.$$

Finally, moving back to the income shares, we can compute the sectoral labor, capital and gross profits shares, respectively s_{kt}^{L}, s_{kt}^{K} and s_{kt}^{Π}, from the results above. Note that the ratio L_{kt}/Y_{kt} can be written as:

$$\frac{L_{kt}}{Y_{kt}} = \sum_{i=1}^{N_{kt}} w_t^{-\sigma_k} \xi_{kt}^{\sigma_k} \frac{\rho_{ikt}}{\mu_{ikt}\xi_{kt}} \frac{y_{ikt}}{Y_{kt}} (1-\alpha_k^K)^{\sigma_k} \left(A_{kt}^L\right)^{\sigma_k - 1},$$

Thus:

$$s_{kt}^L = \frac{W_t L_{kt}}{P_{kt} Y_{kt}} = w_t \frac{L_{kt}}{Y_{kt}\rho_{kt}} = \sum_{i=1}^{N_{kt}} w_t^{1-\sigma_k} \xi_{kt}^{\sigma_k - 1} \frac{1}{\mu_{ikt}} \omega_{ikt} (1-\alpha_k^K)^{\sigma_k} \left(A_{kt}^L\right)^{\sigma_k - 1} = \sum_{i=1}^{N_{kt}} s_{ikt}^L \omega_{ikt}.$$

By symmetry:

$$s_{kt}^K = \sum_{i=1}^{N_{kt}} s_{ikt}^K \omega_{ikt}.$$

Given that $1 = s_{kt}^L + s_{kt}^K + s_{kt}^{\Pi}$:

$$s_{kt}^{\Pi} = 1 - s_{kt}^L + s_{kt}^K = 1 - \sum_{i=1}^{N_{kt}} s_{ikt}^L \omega_{ikt} - \sum_{i=1}^{N_{kt}} s_{ikt}^K \omega_{ikt},$$

and since $s_{ikt}^L + s_{ikt}^K = 1 - s_{ikt}^{\Pi}$

$$s_{kt}^{\Pi} = 1 - \sum_{i=1}^{N_{kt}} \left(s_{ikt}^L + s_{ikt}^K\right) \omega_{ikt} = 1 - \sum_{i=1}^{N_{kt}} \left(1 - s_{ikt}^{\Pi}\right) \omega_{ikt} = \sum_{i=1}^{N_{kt}} s_{ikt}^{\Pi} \omega_{ikt}.$$

Decomposing:

$$s_{kt}^{\Pi} = \sum_{i=1}^{N_{kt}} s_{ikt}^{\Pi} \omega_{ikt} = \sum_{i=1}^{N} \left(s_{ikt}^d + s_{ikt}^X\right) \omega_{ikt} = \sum_{i=1}^{N_{kt}} s_{ikt}^d \omega_{ikt} + \sum_{i=1}^{N_{kt}} s_{ikt}^X \omega_{ikt} = s_{kt}^d + s_{kt}^X.$$

Note that the sectoral income shares are averages of the idiosyncratic income shares, weighted by the market (revenue) shares. Using the definition of the sectoral markup, we can write the shares in terms of sectoral variables only:

$$s_{kt}^L = \left(\frac{A_{kt}^L \xi_{kt}}{w_t}\right)^{\sigma_k - 1} (1-\alpha_k^K)^{\sigma_k} \sum_{i=1}^{N_{kt}} \frac{1}{\mu_{ikt}} \omega_{ikt} = \left(\frac{A_{kt}^L \xi_{kt}}{w_t}\right)^{\sigma_k - 1} (1-\alpha_k^K)^{\sigma_k} \frac{1}{\mathcal{M}_{kt}},$$

and:

$$s_{kt}^K = \left(\frac{A_{kt}^K \xi_{kt}}{r_t}\right)^{\sigma_k - 1} (\alpha_k^K)^{\sigma_k} \frac{1}{\mathcal{M}_{kt}},$$

and:

$$s_{kt}^{\Pi} = 1 - \frac{1}{\mathcal{M}_{kt}}$$

The sectoral net profit share is:

$$s_{kt}^{d} \equiv \frac{\Pi_{kt}}{\rho_{kt} Y_{kt}} = 1 - \frac{1}{\mathcal{M}_{kt}} \left(\frac{TC_{kt}}{TC_{kt} - N_{kt} f_{kt}^{x}} \right),$$

where TC_{kt} is the real sectoral total cost $w_t L_{kt} + r_t K_{kt} + N_{kt} f_{kt}^{x}$. The share of sectoral income *wasted* due to fixed costs is:

$$s_{kt}^{X} \equiv \frac{N_{kt} f_{kt}^{x}}{\rho_{kt} Y_{kt}} = \frac{1}{\mathcal{M}_{kt}} \left(\frac{N_{kt} f_{kt}^{x}}{TC_{kt} - N_{kt} f_{kt}^{x}} \right),$$

with $s_{kt}^{d} + s_{kt}^{X} = s_{kt}^{\Pi}$.

Appendix B: elasticity of substitution empirical specification

Firms minimize their total variable costs subject to the technological constraints, i.e.:

$$\min_{l_{ikt}, k_{ikt}} W_{ikt} l_{ikt} + R_{ikt} k_{ikt}$$

subject to equation (**??**). Here we still assume firms are price-takers regarding their input prices, e.g. due to firm-specific unions. The F.O.C.s for labor and capital are, respectively:

$$W_{ikt} = \lambda_{ikt} \left(A_{ikt}^{Z}\right)^{\frac{\sigma_{kt}-1}{\sigma_{kt}}} y_{ikt}^{\frac{1}{\sigma_{kt}}} (1 - \alpha_{kt}^{K}) \left(A_{kt}^{L}\right)^{\frac{\sigma_{kt}-1}{\sigma_{kt}}} l_{ikt}^{-\frac{1}{\sigma_{kt}}}$$

and

$$R_{ikt} = \lambda_{ikt} \left(A_{ikt}^{Z}\right)^{\frac{\sigma_{kt}-1}{\sigma_{kt}}} y_{ikt}^{\frac{1}{\sigma_{kt}}} \alpha_{kt}^{K} \left(A_{kt}^{K}\right)^{\frac{\sigma_{kt}-1}{\sigma_{kt}}} k_{ikt}^{-\frac{1}{\sigma_{kt}}},$$

where λ_{ikt} is the firm-specific Lagrange multiplier.

To solve for λ_{ikt}, we take the ratio of the two first order conditions to write:

$$k_{ikt}^{\frac{\sigma_{kt}-1}{\sigma_{kt}}} = \left(\frac{W_{ikt}}{R_{ikt}}\right)^{\sigma_{kt}-1} \left(\frac{1-\alpha_{kt}^{K}}{\alpha_{kt}^{K}}\right)^{1-\sigma_{kt}} \left(\frac{A_{kt}^{K}}{A_{kt}^{L}}\right)^{\frac{(\sigma_{kt}-1)^2}{\sigma_{kt}}} (l_{ikt})^{\frac{\sigma_{kt}-1}{\sigma_{kt}}}.$$

From the first F.O.C., and by plugging in the definition of y_{it}, we can write:

$$\lambda_{ikt} = \frac{W_{ikt}}{A_{ikt}^{Z}} \frac{\left(A_{kt}^{L}\right)^{-\frac{\sigma_{kt}-1}{\sigma_{kt}}}}{(1-\alpha_{kt}^{K})} (l_{ikt})^{\frac{1}{\sigma_{kt}}} \left[\alpha_{kt}^{K} \left(A_{kt}^{K} k_{ikt}\right)^{\frac{\sigma_{kt}-1}{\sigma_{kt}}} + (1-\alpha_{kt}^{K}) \left(A_{kt}^{L} l_{ikt}\right)^{\frac{\sigma_{kt}-1}{\sigma_{kt}}}\right]^{\frac{1}{1-\sigma_{kt}}},$$

and, using the definition of k_{ikt} as a function of l_{ikt} above:

$$\lambda_{ikt} = \frac{1}{A_{ikt}^{Z}} \left[R_{ikt}^{1-\sigma_{kt}} \left(\alpha_{kt}^{K}\right)^{\sigma_{kt}} \left(A_{kt}^{K}\right)^{\sigma_{kt}-1} + W_{ikt}^{1-\sigma_{kt}} (1-\alpha_{kt}^{K})^{\sigma_{kt}} \left(A_{kt}^{L}\right)^{\sigma_{kt}-1}\right]^{\frac{1}{1-\sigma_{kt}}}.$$

This gives:

$$\lambda_{ikt} = \frac{1}{A^Z_{ikt}} \left[\left(\frac{R_{ikt}}{A^K_{kt}\alpha^K_{kt}} \right)^{1-\sigma_{kt}} \alpha^K_{kt} + \left(\frac{W_{ikt}}{A^L_{kt}(1-\alpha^K_{kt})} \right)^{1-\sigma_{kt}} (1-\alpha^K_{kt}) \right]^{\frac{1}{1-\sigma_{kt}}} = \frac{\Xi_{ikt}}{A^Z_{ikt}}.$$

If we assume profits maximization under Cournot competition, the optimal price p_{ikt} chosen by the firm satisfies:

$$p_{ikt} = \mu_{ikt} \frac{\Xi_{ikt}}{A^Z_{ikt}},$$

where $\mu_{ikt} = \left(\frac{\theta_{kt}}{\theta_{kt}-1}\right)\left(\frac{1}{1-\omega_{ikt}}\right)$ is the firm-level markup (and ω_{ikt} the firm-level market share). Plugging it back in the F.O.C. for labor:

$$W_{ikt} = \frac{p_{ikt}}{\mu_{ikt}} \left(A^Z_{ikt}\right)^{\frac{\sigma_{kt}-1}{\sigma_{kt}}} y_{ikt}^{\frac{1}{\sigma_{kt}}} (1-\alpha^K_{kt}) \left(A^L_{kt}\right)^{\frac{\sigma_{kt}-1}{\sigma_{kt}}} l_{ikt}^{-\frac{1}{\sigma_{kt}}}$$

Taking the log:

$$ln\left(\frac{y_{ikt}}{l_{ikt}}\right) = \sigma_{kt} ln\left(W_{ikt}\right) - \sigma_{kt} ln\left(p_{ikt}\right) + \sigma_{kt} ln\left(\mu_{ikt}\right) - \left(\sigma_{kt}-1\right) ln\left(A^Z_{ikt}\right) + \hat{\alpha_0},$$

where $\hat{\alpha_0} = -\sigma_{kt} ln\left(1-\alpha^K_{kt}\right) - \left(\sigma_{kt}-1\right) ln\left(A^L_{kt}\right)$. Since we do not observe firm-level output y_{ikt}, we re-write the condition in terms of revenues $s_{ikt} \equiv p_{ikt}y_{ikt}$. Using the definition of the market share $\omega_{ikt} \equiv \frac{p_{ikt}y_{ikt}}{P_{kt}Y_{kt}} = \left(\frac{p_{ikt}}{P_{kt}}\right)^{1-\theta_{kt}}$ we can write:

$$ln\left(\frac{s_{ikt}}{l_{ikt}}\right) = \alpha_0 + \sigma_{kt} ln\left(W_{ikt}\mu_{ikt}\right) + \alpha_1 ln\left(\omega_{ikt}\right) + \epsilon_{ikt}, \tag{13}$$

where $\alpha_0 = -\sigma_{kt} ln\left(1-\alpha^K_{kt}\right) - \left(\sigma_{kt}-1\right) ln\left(A^L_{kt}\right) + \left(1-\sigma_{kt}\right) ln\left(P_{kt}\right)$, $\alpha_1 = \frac{1-\sigma_{kt}}{1-\theta_{kt}}$ and $\epsilon_{ikt} = -\left(\sigma_{kt}-1\right) ln\left(A^Z_{ikt}\right)$.