Overhead Costs and Markups Across Technologies

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Abstract

Firms that incur higher overhead costs increase their price markups. Using Dutch administrative data between 2000 and 2021, we show that this relationship is amplified by digital intensity, which we define as the share of overhead costs spent on digital technologies. Digital intensity reshapes the production function: estimating sector-specific elasticities of substitution between capital and labor, we find that inputs are more complementary in more digitally intensive sectors. To rationalize these findings, we develop a two-sector oligopolistic competition model in which sectors differ only in their elasticity of substitution and study the effects of a common increase in overhead costs. Higher overhead costs put downward pressure on wages, with larger effects in high-digital-intensity sector. Because stronger capital–labor complementarity makes production more labor intensive in the high-digital-intensity sector, the resulting wage decline lowers marginal costs more sharply, amplifying markup growth.

Keywords: Markups, Overhead Costs, Inputs' Elasticity of Substitution
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1 Introduction

Over the past forty years, firms' market power has increased across several developed economies, as reflected by trends in price markups, market concentration, and profit margins.[1] A growing literature points to rising overhead costs of production as a major contributing factor.[2] We argue that not only the size but the *nature* of overhead costs matters for markup dynamics: technology-related expenditure that affects the degree of substitutability between inputs amplifies the effect of higher overhead costs on markups.

We develop our empirical argument using a matched firm-employee administrative dataset covering Dutch firms between 2000 and 2021. At the firm level, we document a strong positive relationship between overhead cost growth and markup growth. Since overhead costs encompass a broad range of expenditures with potentially heterogeneous effects on firms' behavior, we investigate whether their composition can help explaining the observed markup dynamics beyond the mechanical effect coming from a pure compensation for non-production expenses.

We distinguish between two broad categories. The first covers selling, general, and administrative expenses, such as marketing and communication costs, which primarily affect demand without altering production technologies. The second category includes technology-related expenditures, namely digital spending, R&D, and patents and licenses; and is more likely to reshape firms' production processes and factor input choices. Among these categories, digital expenditure stands out as the most consistently and robustly associated with markup amplification. The firm-level findings have important sector-level implications. Even among sectors experiencing similar increases in overhead costs, markup growth is systematically higher in sectors with greater *digital intensity*, measured as the share of spending on digital technologies in total costs at the 2-digit sector level.

We then examine how greater digital intensity affects firms' production technologies. Digital investment may increase input substitutability, allowing firms to replace routine and low-skilled labour with intangible capital, consistently with the routinization hypothesis of Autor et al. (2003). Alternatively, intangible capital may be complementary to high-skilled labour, reducing substitutability (Caunedo et al. (2023); Crouzet et al. (2022)).

To distinguish between these scenarios, we first estimate firm-level input elasticity of substitution, contrasting sectors with varying degree of digital intensity. Second, we embed these estimates in a model where sectors differ only in their substitution elasticities and assess whether the implied dynamics can replicate the empirical patterns found in the

[1] For global trends in market power see De Loecker and Eeckhout (2018)

[2] See, for instance, Bloom et al. (2020), Gutiérrez et al. (2021), De Loecker et al. (2020), Hasenzagl and Perez (2026), and De Loecker et al. (2026).

data.

To estimate the elasticity of substitution between capital and labor, we build on León-Ledesma et al. (2010), as well as on recent studies estimating elasticities across sectors (Raval (2019), Oberfield and Raval (2021)) and occupations (Caunedo et al., 2023). We instrument wages by firm-level minimum wage exposure, following Dustmann et al. (2022). Because minimum wages are negotiated through collective bargaining agreements at the 2-digit sector level, sector-specific minimum wage changes provide exogenous variation in firms' wage exposure. We find that in sectors with higher digital intensity, typically services, labor and capital are more complementary than in sectors with lower digital intensity, typically manufacturing. In our baseline estimation, firms in sectors in lowest tercile of digital intensity display an elasticity of substitution of $\sigma = 0.788$ whereas firms in the highest tercile exhibit a substantially lower elasticity, $\sigma = 0.505$.

To assess whether differences in input substitutability can lead to an asymmetric markup response to rising overhead costs, we develop a two-sector general equilibrium model, in the spirit of Atkeson and Burstein (2008). The sectors represent high- (low σ) and low-digital-intensity (high σ) environments and differ only in their elasticity of substitution between capital and labour, as estimated from the data. Each sector consists of a finite and endogenous number of heterogeneous firms. Firms draw productivity upon entry and retain it throughout their lifetime, conditional on survival. They produce differentiated goods using a C.E.S. production technology and compete oligopolistically in an environment with free entry and exit driven by idiosyncratic shocks. In equilibrium, more productive firms are larger, facing lower marginal costs, charge higher markups, and exhibit lower labour shares.

We calibrate the model to the Dutch economy using a combination of parameters estimated from firm-level data between 2000 to 2021 and values taken from the existing literature. Our main experiment assesses the impact of a uniform increase in overhead costs of production across the two sectors. The overhead cost increase is set at 36%, 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. Growing overhead costs put downward pressure on wages, reducing firms' marginal costs. The magnitude of this reduction depends on the elasticity of substitution between capital and labor, which determines the optimal input mix in production. In sectors with greater digital intensity, where capital and labor are more complementary, firms rely more heavily on labor because substituting labor with capital is more difficult. Consequently, a given decline in wages translates into a larger reduction in marginal costs than in low-digital-intensity sectors, where firms can more readily substitute toward capi-

tal. This asymmetric decline in marginal costs generates differential growth in profits and markups across sectors. Firms in high-digital-intensity sectors become disproportionately more profitable, expand their market shares, and raise their markups at the expense of the labor share of income. A single parameter estimated directly from Dutch firm-level data, σ, is sufficient to account for the amplification of markup growth across sectors observed in the data.

Related literature

Our work relates to the growing literature documenting the rise in market concentration and firm markups over recent decades (e.g., Grullon et al. (2019), De Loecker et al. (2020), Autor et al. (2020), and Gutiérrez and Philippon (2019), Markiewicz and Silvestrini (2026)). Rising fixed and overhead costs have been identified as an important driver of these trends. For instance, Bloom et al. (2020), De Loecker et al. (2020), Hasenzagl and Perez (2026), and De Loecker et al. (2026) document substantial increases in overhead costs in the U.S. economy, while Gutiérrez et al. (2021) show that higher entry costs can lead to higher markups. We contribute to this literature by emphasizing that, in addition to the level of overhead costs, their composition also matters for markup dynamics. In particular, we show that technology-related overhead expenditures may amplify the increase in markups associated with higher overhead costs by affecting the degree of substitutability and hence the composition of production inputs.

Assessing this mechanism requires estimating the short-run elasticity of substitution between inputs at the firm level. To estimate this elasticity, we build on León-Ledesma et al. (2010), who derive estimating equations from firms' first-order conditions, as well as on recent studies estimating elasticities across sectors (Raval (2019), Oberfield and Raval (2021)) and occupations (Caunedo et al., 2023). Although we employ a different identification strategy, our estimates are comparable in magnitude to those reported by Oberfield and Raval (2021) and Caunedo et al. (2023).

Our measure of digital intensity is closely related to intangible capital, linking our paper to De Ridder (2024), Crouzet and Eberly (2019), and Covarrubias et al. (2021), who emphasize the role of intangibles in the rise of industry concentration. We identify a novel mechanism through which intangible investments—specifically digital expenditures—may contribute to markup growth by affecting production technology through the degree of substitutability between inputs.

More broadly, the rise of intangible capital has been argued to reshape production technologies (Corrado et al. (2009), Crouzet et al. (2022)). Our paper builds on this view by showing that cross-sector variation in intangible (digital) intensity is associated

with differences in the elasticity of substitution, which partly determines firms' markup behavior.

The remainder of the paper is organized as follows. Section 2 describes the data, with a particular focus on the cost structure of Dutch firms, and presents the estimation of markups. Section 3 examines the relationship between cost structure and markups. Section 4 estimates the elasticity of substitution in production between inputs. Section 5 develops a tractable oligopolistic competition model with a finite number of firms operating in two sectors that differ only in the degree of substitutability between inputs, whose steady state is described in Section 6. Section 7 describes the calibration strategy. Section 8 presents the main quantitative exercise, in which we study the impact of higher overhead costs on markups. Section 9 concludes.

2 Data

We construct a linked firm-worker dataset covering the period 2000–2021 by merging 5 datasets. First, the business registry (ABR) dataset contains basic background statistics such as firm birth date, sector and size. 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 of Dutch firms and we link it to the two administrative datasets described above. The main advantage of this dataset is that it provides detailed information on the costs structure of the Dutch firms including overhead costs and their composition. Finally, we merge the firm-level dataset with worker records included in 2 administrative datasets *Baankenmerkenbus* and *Gbapersoontab*, which cover employment related information such as wages, worked days, tenure at the firm, sector of employment and individual characteristics such as gender, age, or migrant background.

2.1 Cost structure of Dutch firms

The Production Statistics dataset (henceforth PS) provides detailed information on firms' cost structures. We categorize overhead expenditures into two broad types: (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, and automation-related costs.[3]

[3]This last firm expenditure category in PS is called in Dutch *automatiseren kosten* which is somewhat misleading because, as we explain later, it captures broader type of spending than is typically understood by automation.

The automation category recorded in PS captures a much broader set of technologies than the industrial robots typically studied in the literature, e.g., Acemoglu et al. (2015). In fact, this category does not comprise costs of robots and instead is strongly linked to the adoption of digital technologies such as big data analytics, cloud services, and electronic data interchange, as documented by Bessen et al. (2025). These technologies primarily aim at improving coordination and information processing within firms, and tend to complement rather than substitute labor. Given their nature, we henceforth refer to these expenditures as *digital expenditure* to distinguish them from the conventional definition of automation. The remaining two items that we classify as technology related are R&D and patents and licenses.

Table 1: **Descriptive statistics of Dutch firms in our sample.**

	Firm characteristics	
	All Firms	Firms with digital expenditures
Firm size (number of employees)	38.82	38.63
Revenue (1000)	5980.29	6117.88
Overhead cost share (in %)	7.15	7.48
Digital cost share (in %)	0.50	0.70
R&D cost share (in %)	0.08	0.08
Patents & licenses cost share (in %)	0.18	0.18
$\Delta\mu^1$ (yearly, in %)	0.12	0.14
$\Delta\mu^2$ (yearly, in %)	0.11	0.14
Observations	347,038	273,679

Notes: Summary statistics for two samples: left column for all firms; right column for firms with digital expenditure. Overhead cost share fc is the amount of overhead costs divided by total costs, where the latter is the denominator of all variables represented in shares. μ^1 is a markup estimated using the two-step ACF procedure and μ^2 using OLS described in Section 2.2. $\Delta\mu^1$ and $\Delta\mu^2$ are yearly log changes in the respective markup estimates.

Table 1 reports summary statistics for the firms in our sample over the period 2000–2021. The average firm employs 39 workers and generates 5,980K in revenues. Overhead expenses account for approximately 7% of total costs, with digital expenditures representing the largest technology-related component at 0.50% of total costs. Since roughly a quarter of firms in our sample report no digital spending, the second column of Table 1 restricts the sample to firms that incur these costs. The two samples are broadly comparable in terms of size, as measured by employment and revenues. Firms that invest in digital technologies exhibit somewhat higher overhead cost shares, and their digital spending share is around 40% higher compared to the full sample, while R&D and patents and licenses shares remain similar across the two groups. Having described the cost structure of Dutch firms, we next estimate their markups over the same period.

2.2 Markups

We begin 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 by Ackerberg et al. (2015) (henceforth ACF) two-stages technique.

We start by estimating firms' revenue productivity, under the assumption that all firms within a sector share the same technology:

$$y_{it} = f(v_{it}, k_{it}; \beta) + x_{it} + \epsilon_{it} \tag{2}$$

where y_{it} is a measure of realized firm's output, v_{it} collects all variable inputs, k_{it} stands for capital, x_{it} for productivity, all of them in logs, and β collects the coefficients. We follow the procedure by De Loecker and Warzynski (2012), which builds on Olley and Pakes (1996): (unobserved) productivity can be expressed as a function of the firm's state variables and observables:

$$x_{it} = h(v_{it}, k_{it})$$

We first obtain estimates of the expected output that removes measurement error and unanticipated shocks by estimating:

$$y_{it} = \phi_t(v_{it}, k_{it}) + \varepsilon_{it} \tag{3}$$

where ϕ_t is a transformation of Cobb-Douglas technology. From the above regression, we obtain expected output $\hat{\phi}_t$ and estimated production function coefficients $\hat{\beta}'$s. Productivity can therefore be computed as the residual:

$$x_{it} = \hat{\phi_{it}} - \hat{\beta}^k k_{it} - \hat{\beta}^v v_{it}, \tag{4}$$

for each firm i in each year t, where β^k is the coefficient associated with capital and β^v with variable input. 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. Capital k_{it} is proxied by firm's capital expenses. We do not observe output so we proxy y_{it} by revenues also obtained from firms' balance sheets.

In the second step, we nonparametrically regress revenue productivity x_{it} from Equation (4) on its lag x_{it-1} to recover the innovation to productivity ξ_{it} and construct the

following moment conditions:

$$E\left(\xi_{it}(\beta)\begin{pmatrix} v_{it-1} \\ k_{it} \end{pmatrix}\right) \tag{5}$$

where the coefficients collected in β are obtained via estimation of Equation 3. This approach identifies the output elasticity of a variable input θ_t^v under the assumption that the variable input v_{it} responds to productivity shocks, but lagged values do not. This procedure is implemented for each sbi 2-digit sector and provides us with sector-specific series of θ_t^v.[4] α_{it}^v is directly computed from the data as the firm's ratio of variable input to sales. This gives us the benchmark markup measure μ^1. μ^2 is the markup constructed with output elasticity θ_t^v estimated using OLS instead of ACF's technique.

Because markup levels estimated using revenues in the production function are generally not very informative, even when applying a two-stage estimation procedure, we focus primarily on changes in markups (De Ridder et al. (2026)). Accordingly, the last 2 rows of Table 1 report markups yearly growth rates across the two firm populations. The average markups across firms grew by between 0.11% per year and in firms with digital expenditure by 0.14% per year, on average.

3 Overhead costs and markups

Bloom et al. (2020) and De Loecker et al. (2020) document a substantial increase in overhead costs in the U.S. economy. However, this well-documented rise masks considerable heterogeneity in the composition of overhead expenditures. Overhead costs encompass a wide range of firm spending with potentially distinct implications for both firm behavior and aggregate dynamics. While SG&A expenses are unlikely to alter firms' production technologies, expenditures on R&D, software, and other digital technologies can directly affect production processes. In particular, investments in digital technologies and other forms of intangible capital may reshape production technologies, thereby influencing the degree of substitutability between inputs and, as a result, the optimal mix of capital and labor used in production.

Detailed information on the cost structure of Dutch firms allows us to investigate this hypothesis. We first confirm the findings that, at the firm level, higher overhead costs are associated with higher markups. The effect is amplified for firms with greater digital technology expenditure. These firm-level facts carry sector-level implications: even among sectors with comparable increases in overhead costs, markup growth is positively correlated with the digital spending share. To conclude, we provide direct evidence on technology

[4]Dutch 2-digit sbi corresponds to U.S. 2-digit NAICS.

differences across sectors by estimating the elasticity of substitution between capital and labor across sectors that vary in their digital technology spending share.

3.1 Firm-level evidence

We start by estimating the following specification at the firm level:

$$\Delta\mu_{itk} = \alpha + \beta\Delta fc_{itk} + \theta X_{itk} + \gamma_t + \phi_k + \eta_{itk} \tag{6}$$

where $\Delta\mu_{itk}$ is a yearly log change in markup of firm i that belongs to sector k in year t and Δfc_{it} is a log change in the share of overhead cost in total firm's costs. ϕ_k and γ_t are sector and year fixed effects and X_{itk} represents a vector of firm-level time-varying controls. Sector is defined as 2-digit sbi (2-digit counterpart to the US NAICS 2-digit).

Table 2 shows results of our panel regressions with Panel A showing results for markups computed using ACF procedure and Panel B using OLS. Table 8 of Appendix B shows results without controls X_{itk}. Each column corresponds to a different specification and columns (cs) and (rs) indicate whether a variable has firm's total costs or revenues in the denominator, respectively. Columns 1 and 2 show a robust positive relationship between overhead costs growth and markup growth. In the case of ACF markups, a 1% increase in the overhead cost share is associated with a 0.006% increase in markup growth when measured as a cost share, and 0.03% when measured as a revenue share. Both estimates are highly significant and stable across markup measures in Panel B, confirming that firms facing rising overhead costs systematically raise their markups.

To assess whether the composition of overhead costs matters for markup dynamics beyond the overall level of overhead spending, we augment the baseline specification with technology-related expenditure shares:

$$\Delta\mu_{itk} = \alpha + \beta^1\Delta fc_{itk} + \beta^2\Delta fc_{itk}\Delta Tech_{itk} + \kappa\Delta Tech_{itk} + \phi_k + X_{itk} + \gamma_t + \eta_{itk} \tag{7}$$

where $\Delta Tech_{itk}$ denotes the log change in the share of one of the technology related firm's expenditure that include (i) digital expenses: Δdig, (ii) patent and licenses expenses: Δpat_lic, and (iii) $\Delta r\&d$ R&D expenses. The coefficient β^2 captures whether technology-related spending amplifies or dampens the relationship between overhead costs and markup growth. The remaining symbols are defined as before in Equation (6).

Columns 3 and 4 of Table 2 add digital expenditures and their interaction with overhead costs. Overhead costs remain positive and highly significant throughout, confirming their robust role in markup dynamics regardless of the technology controls included. Beyond this, the direct effect of digital spending on markup growth is positive and significant, while the interaction term reveals that digital expenditure amplifies the markup response

Table 2: **Technology expenses and markups: firm-level evidence, with controls.**

	(1) baseline	(2) baseline	(3) *dig*	(4) *dig*	(5) *pat_lic*	(6) *pat_lic*	(7) *r&d*	(8) *r&d*
	cs	*rs*	*cs*	*rs*	*cs*	*rs*	*cs*	*rs*
Panel A: $\Delta\mu^1$ (ACF)								
Δfc	0.0064***	0.0331***	0.0049***	0.0363***	0.0026*	0.0397***	0.0031	0.0670***
	(0.0003)	(0.0003)	(0.0006)	(0.0005)	(0.0013)	(0.0011)	(0.0024)	(0.0015)
Δdig			0.0032***	0.0196***				
			(0.0004)	(0.0004)				
$\Delta fc \times \Delta dig$			0.0009*	0.0014***				
			(0.0004)	(0.0002)				
Δpat_lic					0.0016*	0.0099***		
					(0.0008)	(0.0007)		
$\Delta fc \times \Delta pat_lic$					−0.0004	0.0047***		
					(0.0007)	(0.0004)		
$\Delta r\&d$							0.0005	0.0041***
							(0.0010)	(0.0009)
$\Delta fc \times \Delta r\&d$							−0.0033**	−0.0005
							(0.0012)	(0.0004)
Constant	0.0037***	0.0040***	0.0024***	0.0017***	0.0051***	0.0035***	0.0054***	0.0031*
	(0.0003)	(0.0003)	(0.0005)	(0.0004)	(0.0010)	(0.0009)	(0.0015)	(0.0014)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
N	243,548	243,548	125,906	125,906	28,467	28,467	13,835	13,835
Panel B: $\Delta\mu^2$ (OLS)								
Δfc	0.0066***	0.0332***	0.0051***	0.0365***	0.0029*	0.0400***	0.0037	0.0673***
	(0.0003)	(0.0003)	(0.0006)	(0.0005)	(0.0013)	(0.0011)	(0.0024)	(0.0015)
Δdig			0.0032***	0.0195***				
			(0.0004)	(0.0004)				
$\Delta fc \times \Delta dig$			0.0010*	0.0015***				
			(0.0004)	(0.0002)				
Δpat_lic					0.0015	0.0098***		
					(0.0008)	(0.0007)		
$\Delta fc \times \Delta pat_lic$					−0.0005	0.0047***		
					(0.0007)	(0.0004)		
$\Delta r\&d$							0.0004	0.0040***
							(0.0010)	(0.0009)
$\Delta fc \times \Delta r\&d$							−0.0034**	−0.0005
							(0.0012)	(0.0004)
Constant	0.0037***	0.0040***	0.0024***	0.0017***	0.0051***	0.0036***	0.0055***	0.0031*
	(0.0003)	(0.0003)	(0.0005)	(0.0004)	(0.0010)	(0.0009)	(0.0015)	(0.0014)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
N	243,548	243,548	125,906	125,906	28,467	28,467	13,835	13,835

Notes: Firm-level panel regressions of yearly log changes in markups on overhead cost shares and technology-related expenditures and their interactions with the overhead cost share. All specifications control for firm size, measured as the number of workers, and market share, measured as the firm's revenue share within its 2-digit sector. Panel A uses $\Delta\mu^1$ estimated via the ACF two-step procedure; Panel B uses $\Delta\mu^2$ estimated via OLS. *cs*: cost share measure; *rs*: revenue share measure. fc: overhead; *dig*: digital expenditures; *pat_lic*: patents and licenses; *r&d*: R&D. All regressions include sector and year fixed effects. Standard errors in parentheses, clustered at the sector level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

to overhead costs. At the mean digital expenditure revenue share of 0.70%, the total effect of a 1% increase in overhead costs on markup growth is approximately 0.3% larger than for a firm with no digital spending.

Columns 5 and 6 replace digital expenditures with patents and licenses. The direct effect on markup growth is positive and significant but the interaction with overhead costs is significant only for revenue share measure. Columns 7 and 8 show that R&D spending increases markups but its interaction with overhead costs is negative implying that higher R&D spending dampens rather than amplifies the overhead-markup relationship.

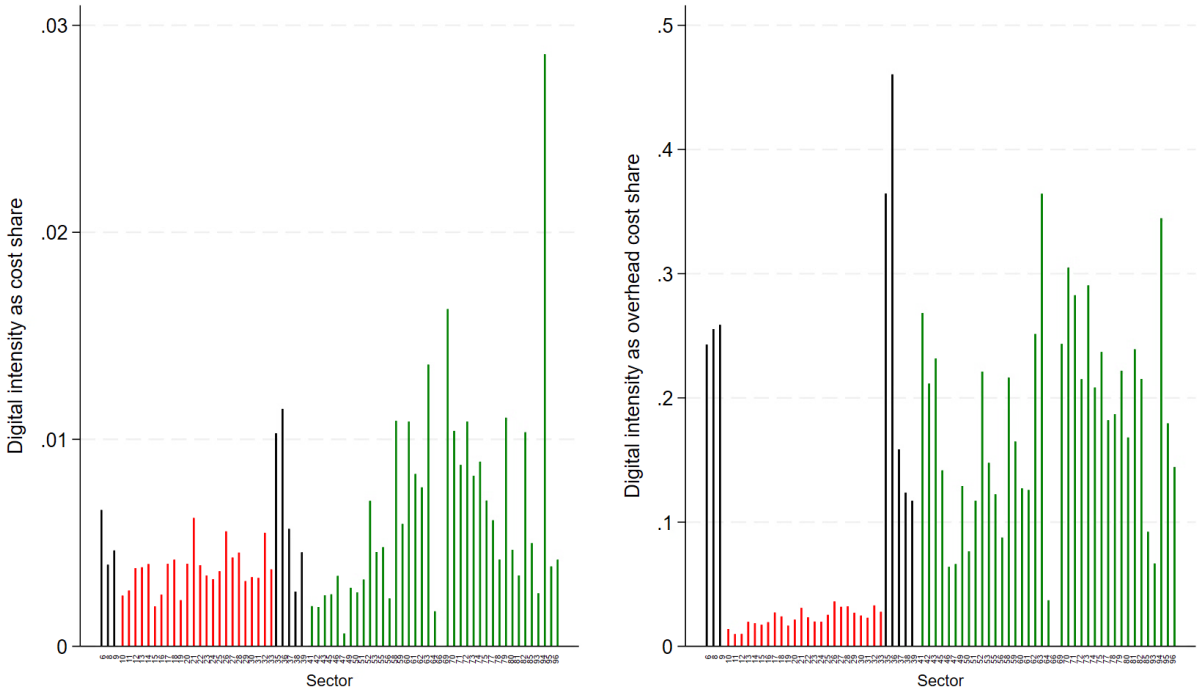
Across all specifications, digital expenditures stand out as the category most consistently and strongly associated with markup amplification, both in terms of the magnitude of the interaction coefficient and its robustness across markup measures and share definitions. Because the regressions reported in Table 2 include sector fixed effects, the estimates reflect within-sector variation. One would expect markup dynamics to differ systematically across sectors, even more than within, as firms within a sector are more similar than firms between sectors. We therefore complement the firm-level findings with a sector-level investigation that assesses whether the patterns documented above also emerge in cross-sector variation.

3.2 Sector-level evidence

Digital intensity We begin by defining digital intensity at the 2-digit sector level using the information on digital spending shares. Specifically, the digital intensity dig_k of a sector k is computed as the ratio of digital expenditure to total costs, averaged across all firms in sector k and over the entire sample period. We additionally consider an alternative measure in which digital expenditure is scaled by overhead costs rather than total costs. The reason is to purge the measure of variation attributable to differences in variable input use across sectors.

Figure 1 reveals substantial heterogeneity in digital intensity across sectors, for both measures. Several patterns stand out. First, a small number of sectors exhibit disproportionately high digital intensity: namely sector 63 ("Information Services"), 69 ("Legal services, accountancy and tax advice and administration") and sector 66 ("Activities auxiliary to financial services"). Second, for both measures, there is a striking sectoral divide: service sectors (green bars) systematically display higher digital intensity than manufacturing sectors (red bars), consistent with the notion that digitalization has penetrated the service economy more deeply (Hsieh and Rossi-Hansberg (2023)). The difference between manufacturing and services is more striking when digital intensity is measured relative to overhead costs.

Figure 1: Digital Intensity by Sector



Notes: Left panel: digital intensity measured as the share of digital expenditures in total costs. Right panel: digital intensity measured as the share of digital expenditures in overhead costs. Values are averages across all firms within each 2-digit sector. Manufacturing (red), Services (green), Other (black).

To examine whether the association between digital intensity and markups growth extends to the sector level, we proceed as follows. Firms are partitioned into 3 or 4 bins based on the average overhead cost growth in a sector, and within each bin we compute the Spearman rank correlation between firm level markup growth and the digital intensity of the firm's sector measured as a share of digital spending in (i) total costs (Column (1) of Table 3), (ii) overhead costs (Column (2)), and (iii) revenues (Column (3)).[5] Table 3 shows that, irrespective of how digital intensity is measured, firms in more digitally intensive sectors experienced systematically stronger markup growth, even in sectors with similar overhead cost growth.

So far, we have shown that higher overhead costs are associated with higher markups at the firm level and that this relationship is stronger for firms with greater digital expenditures. These firm-level results are also reflected in the sectoral data: among sectors experiencing similar increases in overhead costs, those with higher digital intensity exhibit stronger markup growth.

[5]Descriptive statistics of those bins are reported in Table 9 of Appendix B.

Table 3: Spearman Rank Correlations between Markup Growth and Digital Intensity by Bin of Overhead Cost Growth

	Digital intensity measure			
Δfc bin	(1) $\hat{\rho}^{cs}$	(2) $\hat{\rho}^{fc}$	(3) $\hat{\rho}^{rs}$	N
Panel A: Three overhead cost bins (terciles)				
Q1	0.319^{***}	0.180^{***}	0.252^{***}	123,000
Q2	0.143^{***}	0.112^{***}	0.151^{***}	114,000
Q3	0.067^{***}	0.052^{***}	0.100^{***}	110,000
Panel B: Four overhead cost bins (quartiles)				
Q1	0.378^{***}	0.239^{***}	0.361^{***}	91,436
Q2	0.173^{***}	0.127^{***}	0.163^{***}	89,920
Q3	0.135^{***}	0.146^{***}	0.158^{***}	82,915
Q4	0.003	0.060^{***}	0.056^{***}	82,766

Notes: Spearman rank correlations $\hat{\rho}$ between firm-level markup growth $\Delta\mu$ and digital intensity, computed within bins of overhead cost growth Δfc. Digital intensity is measured alternatively as the share of digital expenditure in total costs ($\hat{\rho}^{cs}$), in overhead costs ($\hat{\rho}^{fc}$), and in total revenues ($\hat{\rho}^{rs}$). N is the number of firm–year observations, identical across measures within each bin. Markup estimates follow the ACF two-step estimator. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

The key question is what greater digital intensity implies for firms' production technologies. One possibility is that digital investments increase the substitutability between production inputs, enabling firms to replace routine and low-skilled labour with intangible capital, consistent with the routinization hypothesis of Autor et al. (2003). Alternatively, intangible capital may be complementary to high-skilled labour, thereby reducing rather than increasing substitutability (Caunedo et al. (2023); Crouzet et al. (2022)).

To distinguish between these mechanisms, we proceed in two steps. First, we estimate firm-level elasticities of substitution across sectors with different levels of digital intensity. Second, we incorporate these estimates into a model in which sectors differ only in their elasticity of substitution and assess whether the model-implied dynamics can account for the empirical patterns documented above.

4 Elasticity of substitution

Our baseline specification to estimate micro elasticity of substitution is based on León-Ledesma et al. (2010):[6]

$$\ln\left(\frac{y_{ikt}}{l_{ikt}}\right) = \alpha_0 + \sigma_k \ln\left(W_{ikt}\right) + \beta X_{ikt} + \gamma_k + \delta_t + \varepsilon_{ikt}, \tag{8}$$

where y_{ikt}, l_{ikt}, and W_{ikt} denote output, employment, and wages of firm i belonging to sector k in year t, respectively. The parameter σ_k is the elasticity of substitution between capital and labor. We include sector fixed effects γ_k so that identification comes from within-sector variation, and year fixed effects δ_t to absorb common aggregate shocks. X_{ikt} is a vector of firm-level controls.

Minimum wage exposure as an instrument for wages Since W_{ikt} is endogenous, we instrument it using sector-specific minimum wages in the Netherlands. Beyond the statutory national minimum wage, which is set by the Dutch government, sector-specific wage floors are negotiated through collective bargaining agreements (CAOs) at the 2-digit sector level and apply to all firms within a sector regardless of their individual labor market conditions. These floors are determined through centralized negotiations between employer associations and trade unions, and are thus set independently of the substitution decisions of individual firms, providing plausibly exogenous variation in wages (Dustmann et al. (2022)).

As we observe the characteristics and labor market outcomes of all workers employed at firms in our sample, we can exploit variation in exposure to the minimum wage across firms to construct the instrument. Specifically, we compute for each firm the share of workers earning at most 10% above the sector-level minimum wage in the first year the firm is observed:

$$sh^{mw}_{it_0} = \frac{1}{N_{it_0}} \sum_{j=1}^{N_{it_0}} \mathbf{1}\left[w_{jit_0} \leq 1.1 \times \bar{w}^{mw}_{kt_0}\right], \tag{9}$$

where w_{jit_0} is the wage of worker j employed at firm i in base year t_0, N_{it_0} is the total number of workers at firm i in t_0, and $\bar{w}^{mw}_{st_0}$ is the statutory minimum wage in sector k in the base year. We then interact this predetermined exposure measure with the time-varying sector-level minimum wage to construct the instrument:

$$z_{it} = sh^{mw}_{it_0} \times \bar{w}^{mw}_{kt}, \tag{10}$$

[6] We obtain the same condition derived in their Equation (15) under the assumption that $A^L_{kt} = A^L_{k0} e^{\gamma_N t}$.

where $\bar{w}_{st}^{mw}$ is the minimum wage in sector k at time t. Firms with a higher share of minimum wage workers in the base year experience larger wage increases when the minimum wage rises, providing likely exogenous variation in firm-level wages (Dustmann et al. (2022)).

Since minimum wages in the Netherlands are lower for workers below the age of 21, we restrict our sample to workers aged between 21 and 55 to ensure a uniform minimum wage applies for all workers withing the same sector. Furthermore, because our instrument is based on proximity to the sector minimum wage, we use actual rather than residualized wages in Equation (8), unlike studies that residualize them to construct efficiency units of labor (e.g. Oberfield and Raval (2021), Caunedo et al. (2023)). To account for workforce composition, we instead include as firm-level controls in X_{it}: the average age and tenure of workers and the share of female workers employed at the firm i in year t.

The specification includes two additional controls to address potential sources of bias in the estimation of σ_k. First, we control for firm size, proxied by the number of workers, as larger firms may exhibit increasing returns to scale, which would otherwise confound the elasticity estimate (Oberfield and Raval (2021)). Second, we include the log revenue market share $\ln(ms_{ikt})$ as a proxy for market power of firm i in sector k in year t. The reason is that we do not observe output but revenues and their variation across firms may reflect both output and price differences. $\ln(ms_{ikt})$ that captures markup variation across firms absorbs part of the price variation within sectors.

To check if the elasticity of substitution is different for firms in sectors that spend more on digital technologies, we estimate a following specification:

$$\ln\left(\frac{y_{ikt}}{l_{ikt}}\right) = \alpha_0 + \sigma_k \ln\left(W_{ikt}\right) + \tau \ln\left(W_{ikt}\right) dig_{ik} + \beta X_{ikt} + \gamma_k + \delta_t + \varepsilon_{ikt}, \tag{11}$$

where dig_{ik} is the digital intensity of sector k that firm i belongs to.

Table 4 reports the estimates of σ across different specifications. Column (1) presents the OLS estimate of $\hat{\sigma} = 0.416$, comparable in magnitude to the micro elasticities reported by Oberfield and Raval (2021). Column (2) instruments firm-level wages with the minimum wage exposure index, z_{it}, yielding a higher estimate $\hat{\sigma} = 0.619$. This upward shift is consistent with attenuation bias corrected by the instrument. Columns (3) to (7) extend the baseline specification by interacting log firm wages with bins of sector digital intensity, using alternative measures and bin definitions. Across all specifications, the interaction coefficients are negative and statistically significant, indicating that in firms in more digitally intensive sectors capital and labor are more complementary. Taking Column (3) as the baseline, firms in the lowest digital intensity tercile exhibit an elasticity of approximately $\hat{\sigma} = 0.79$, while firms in the third tercile face $\hat{\sigma} = 0.51$, about one-third lower.

Table 4: Estimates of the Elasticity of Substitution

	(1) OLS	(2) IV	(3) IV	(4) IV	(5) IV	(6) IV	(7) IV
$\ln(W_{ikt})$	0.416***	0.619***	0.788***	0.882***	1.039***	1.227***	0.880***
	(0.009)	(0.047)	(0.053)	(0.059)	(0.074)	(0.148)	(0.086)
dig.$^{cs} = 2$			−0.185***				
			(0.016)				
dig.$^{cs} = 3$			−0.283***				
			(0.024)				
dig.$^{cs,md} = 2$				−0.295***			
				(0.028)			
dig.$^{cs,md} = 3$				−0.401***			
				(0.037)			
dig.$^{fc} = 2$					−0.586***		
					(0.061)		
dig.$^{fc} = 3$					−0.673***		
					(0.079)		
dig.$^{cs} = 2$						−0.117***	
						(0.019)	
dig.$^{cs} = 3$						−0.906***	
						(0.129)	
dig.$^{cs} = 4$						−0.644	
						(0.707)	
dig.$^{fc} = 2$							−0.157***
							(0.022)
dig.$^{fc} = 3$							−0.476***
							(0.061)
dig.$^{fc} = 4$							−0.238
							(0.269)
Controls	✓	✓	✓	✓	✓	✓	✓
Sector FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓

Notes: The dependent variable is log output per worker $\ln(\frac{y_{ikt}}{l_{ikt}})$. All IV specifications instrument log firm wage with the z_{it} from Equation 10; in columns (3)–(7), the interactions of log firm wage with sector digital intensity bins are instrumented by the corresponding interactions of z_{it} with the same bins. dig.^{cs} denotes sector digital intensity measured as the cost-share-weighted mean across firms; dig.^{cs,md} uses the cost-share median; dig.^{fc} uses the overhead cost-share. Columns (3)–(5) use tercile bins; columns (6)–(7) use quartile bins. The omitted category is bin 1 (lowest digital intensity). Controls include the share of female workers, average workers age at the firm, average tenure, and log market share. Standard errors in parentheses, clustered at the sector level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

This pattern is robust to the choice of digital intensity measure but when digital intensity is measured relative to overhead costs rather than total costs, the gradient across bins steepens. Inputs in firms in the least digitally intensive sectors are gross substitutes, with $\hat{\sigma} > 1$, while the complementarity result is preserved for higher bins.

To summarize, we have established three main findings. First, markup growth and overhead cost growth move in tandem across firms, with higher overhead costs systematically associated with faster markup growth. Second, digital expenditure amplifies this relationship, both at the firm and sector level. Third, the elasticity of substitution between capital and labor varies systematically with digital intensity: sectors with higher digital intensity, typically services, exhibit greater capital-labor complementarity than less digitally intensive sectors, typically manufacturing. In what follows, we develop a model of two sectors that differ by the capital-labor elasticity of substitution and examine the mechanism through which overhead cost changes generate differential markup responses across sectors.

5 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. Firms compete under oligopoly in an environment where sector-specific entry is free and exit occurs in response to idiosyncratic and uncorrelated shocks. More productive firms are larger: they face lower marginal costs, charge higher markups, and exhibit lower labor shares of income. Capital and labor augmenting technologies are common within sector but our calibrations and simulations will assume the elasticity of substitution between inputs to be different across sectors, to reflect empirical findings.

In the following, we present the dynamic model: from this environment we derive a steady state in Section 6. In Section 7, we calibrate the model to the Dutch economy and in Section 8 we simulate it. More specifically, we simulate an economy with 2 representative sectors that differ in the elasticity of substitution across inputs of production, σ_k, as estimated in Section 4.

5.1 Competition

Firms produce differentiated goods and compete oligopolistically. Regarding notation, all variables are indexed with the triple subscript $_{ikt}$ when referring to firm i that belongs to

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:

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

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 parameter 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 (12). 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 captured by the Lagrange multiplier. Solving for λ_{ikt}, we obtain the definition of firms' marginal cost, which 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 marginal cost component that is common to firms within the same sector as Ξ_{kt} to write:[7]

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

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 (overhead) 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 (12) and to the demand constraint:

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

[7] i.e., $\Xi_{kt} = \left[\left(\frac{R_t}{A^K_{kt}\alpha^K_k}\right)^{1-\sigma_k}\alpha^K_k + \left(\frac{W_t}{A^L_{kt}(1-\alpha^K_k)}\right)^{1-\sigma_k}(1-\alpha^K_k)\right]^{\frac{1}{1-\sigma_k}}$

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 sectors' weighting factor. Note that the underlying demand constraint comes from the maximization problem of fictitious sectoral and aggregate bundlers, as discussed in Appendix C. Combining the demand constraint and the results from the costs minimization problem, we can write:

$$\max_{y_{ikt}} y_{ikt}^{1-\frac{1}{\theta_k}} Y_{kt}^{\frac{1}{\theta_k}-\frac{1}{\gamma}} \chi_k Y_t^{\frac{1}{\gamma}} P_t - \frac{\Xi_{kt}}{A_{ikt}^Z} y_{ikt} - P_t f_{kt}^x,$$

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

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

where μ_{ikt} is the idiosyncratic markup and ω_{ikt} is the firm's i revenue market share, 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. Lower marginal costs allow them to charge lower prices, capture larger market shares, and further increase their markups.

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

$$d_{ikt} = p_{ikt} y_{ikt} - \frac{\Xi_{kt}}{A_{ikt}^Z} y_{ikt} - P_t f_{kt}^x = \left(1 - \frac{1}{\mu_{ikt}}\right) p_{ikt}^{1-\theta_k} P_{kt}^{\theta_k - \gamma} P_t^{\gamma} \left(\frac{1}{\chi_k}\right)^{-\gamma} Y_t - P_t f_t^x.$$

Firm's profits increase in markups μ_{ikt} and decrease in marginal and fixed (overhead) costs of production χ_k and $P_t f_t^x$, respectively.

5.2 Entry and Exit

Each period, firms can enter and exit the market. 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 (exogenous) 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:

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

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.[8] 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 reflected in the entry decision. Given the current observable distribution of firm types, each potential entrant considers every possible realization of its own type upon entry. For each such realization, it computes the implied distribution of profits in the sector under the resulting distribution of types.[9] 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. Formally, if:

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

entry occurs, while if:

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

the marginal entrants decides against entry and the entry process for period t stops. In Equation 5.2 Ω_j represents the *ex ante* probability of drawing type j upon entry, while the superscript $^{+1}$ describes the fact that the expected type-j profits differ from the current ones due to smaller market shares of type-j firms, the so-called *business stealing dynamics*.

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

[9] For instance, if the firm enters with type 2, the sector presents N^1_{kt} type-1 competitors, $N^2_{kt}+1$ type-2 competitors, N^3_{kt} type-3 competitors.

5.3 Households

There is a continuum of mass one of identical households who consume a bundle C_t, work hours L_t and hold 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:

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

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

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

5.4 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 $\rho_{ikt} \equiv p_{ikt}/P_t$.

5.5 Income Shares, Markups and Productivity

Let us start by defining income shares at the firm level.[10] By definition, the labor share of income s_{ikt}^L is:

$$s_{ikt}^L \equiv \frac{W_t l_{ikt}}{p_{ikt} y_{ikt}} = \frac{1}{\mu_{ikt}} \left(\frac{\xi_{kt} A_{kt}^L}{w_t} \right)^{\sigma_k - 1} (1 - \alpha_k^K)^{\sigma_k}.$$

Symmetrically, the capital share of income is:

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

Let s_{ikt}^{Π} be the gross profit share (before deducting fixed costs):

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

The *true* (net of fixed costs) profit share is:

$$s_{ikt}^d \equiv \frac{d_{ikt}}{p_{ikt} y_{ikt}} = 1 - \frac{1}{\mu_{ikt}} \left(\frac{tc_{ikt}}{tc_{ikt} - f_{kt}^x} \right),$$

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

$$s_{ikt}^X \equiv \frac{P_t f_{kt}^x}{p_{ikt} y_{ikt}} = \frac{1}{\mu_{ikt}} \left(\frac{f_{kt}^x}{tc_{ikt} - f_{kt}^x} \right),$$

with $s_{ikt}^d + s_{ikt}^X = s_{ikt}^{\Pi}$. This is consistent with the generalized results presented in Hasenzagl and Perez (2026).

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

$$Y_{kt} = A_{kt}^Z \left[\alpha_k^K \left(A_{kt}^K K_{kt} \right)^{\frac{\sigma_k - 1}{\sigma_k}} + (1 - \alpha_k^K) \left(A_{kt}^L L_{kt} \right)^{\frac{\sigma_k - 1}{\sigma_k}} \right]^{\frac{\sigma_k}{\sigma_k - 1}},$$

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

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

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

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 $P_{kt} = \mathcal{M}_{kt}\Xi_{kt}/A_{kt}^{Z}$ or, in real terms:

$$\rho_{kt} = \mathcal{M}_{kt} \frac{\xi_{kt}}{A_{kt}^{Z}}.$$

Using the definition of sectoral productivity:

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

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

From the results above, we can compute the sectoral labor, capital and gross profits shares, respectively s_{kt}^{L}, s_{kt}^{K} and s_{kt}^{Π},

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

By symmetry:

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

and:

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

The sectoral income shares are averages of the idiosyncratic income shares, weighted by the market (revenue) shares ω_{ikt}. 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:

$$s_{kt}^{\Pi} = 1 - \frac{1}{M_{kt}}$$

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

6 Steady State

Given that our economy contains a finite number of firms, idiosyncratic shocks do not follow deterministic laws, even in the aggregate. As a result, 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. $\mathcal{S} = 2$, each populated by six distinct firm types, i.e. $S = 6$, which allows us to calibrate exit rates and productivity levels in Dutch data, as explained in Section 7.

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:

$$\sum_{j=1}^{6} \Omega_j d_{jk} = 0, \tag{13}$$

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:

$$C + \delta K = wL + rK + \Pi, \tag{14}$$

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, real marginal costs in sector k are:

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

Each type maximizes its profits when:

$$\rho_{jk} = \mu_{jk} \frac{\xi_k^Z}{A_{jk}^Z}, \tag{15}$$

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:

$$1 = \sum_{k=1}^{2} \rho_k^{1-\gamma} \chi_k^{\gamma}. \tag{16}$$

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:

$$K = K_1 + K_2. \tag{17}$$

Numbered conditions (13)-(17) define a system of 17 Equations, as (15) 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 $\in [1, 6]$.

7 Calibration

We assume there are two representative sectors in the economy. To isolate the role of the elasticity of substitution between inputs, sectors are calibrated to be equal in size and *ex-ante* identical across all dimensions, with the elasticity of substitution as the only source of heterogeneity.

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. The discount factor, β, is set to a standard value of 0.96 to target a 4% interest rate. The inverse of the Frisch labor elasticity, ϕ, is equal to 2, as in Boar and Midrigan (2025), while the depreciation rate of capital, δ, is set to a standard yearly value of 0.06 from Boar and Midrigan (2025). The elasticity of substitution across sectors, γ, is set to a value of 2, in line with the estimate of by Edmond et al. (2015). We assume that sectors are of equal size *ex ante* and set χ to 0.5. A^L, A^K, and ν are all normalized to 1. We set the elasticity of substitution between goods, θ, to 6 from Colciago (2016). α_K equals 0.32, which, in the limit case of a Cobb-Douglas specification, gives a labor share of income that targets the average value of the Dutch labor income share between 2000 and 2019 of 68% from Silvestrini and Weder (2026). The initial overhead cost f_x^0 is calibrated to 0.2, which allows us to generate small sectors with approximately 50 competitors. Importantly, the change in overhead costs Δf_x is also calibrated using Dutch firm-level data, with the top quartile of Δf_x experiencing a 36% rise (Table 9 of Appendix B).

Finally, the last two rows of Table 5 report parameter values of σ, 0.788 and 0.505, in the low-digital-intensity sector and high-digital-intensity sector, respectively. These values come from our IV estimation in Table 4, reported in column 3. In section 8.1, we carry out robustness checks using values for σ obtained from alternative specifications.

Table 5: **Calibration**

Parameter	Value	Target/Literature
Assigned parameters		
β	0.96	$\approx 4\%$ interest rate
ϕ	2	Boar and Midrigan (2025)
δ	0.06	Boar and Midrigan (2025)
γ	2	Edmond et al. (2015)
χ	0.5	*ex ante* symmetric sectors
A^L	1	Normalization
A^K	1	Normalization
ν	1	Normalization
θ	6	Colciago (2016)
Internally calibrated aggregate parameters		
α_K	0.32	Labor share under CD = 0.68.
f_x^0	0.2	Number of firms in a sector
Δf_x	36%	Δ in CBS data
Estimated parameters		
σ^L	0.788	σ in low-digital-intensity sectors
σ^H	0.505	σ in high-digital-intensity 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 (i.e. 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.

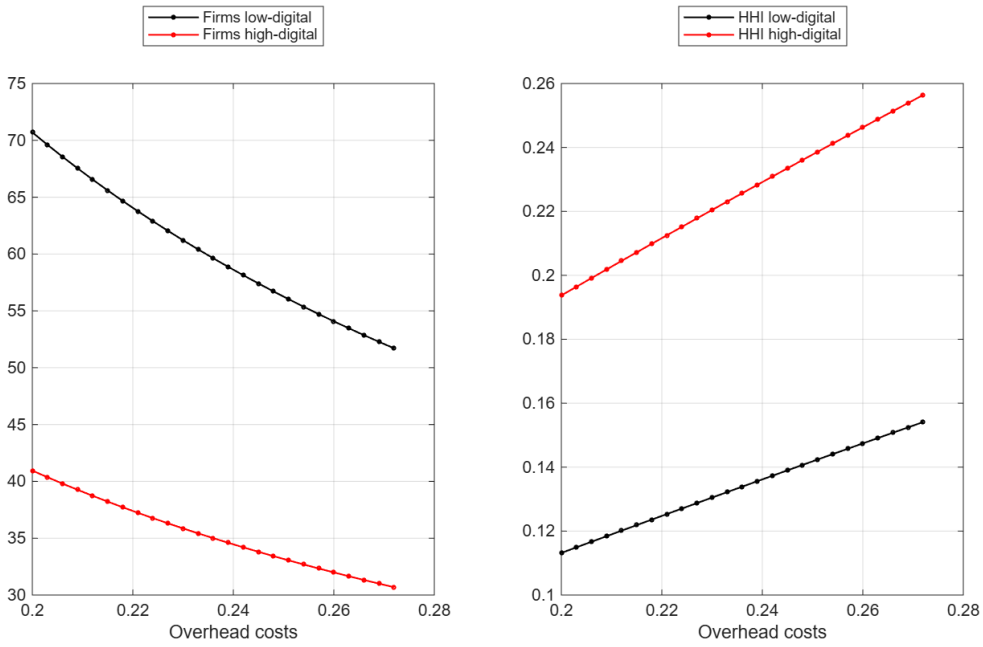
Table 6: **Calibration firm-level parameters**

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	0.044	Dutch firms yearly exit rate, PS
δ_2	0.044	Dutch firms yearly exit rate, PS
δ_3	0.043	Dutch firms yearly exit rate, PS
δ_4	0.042	Dutch firms yearly exit rate, PS
δ_5	0.039	Dutch firms yearly exit rate, PS
δ_6	0.029	Dutch firms yearly exit rate, PS
Ω_1	0.31	Average share type 1 firms, PS
Ω_2	0.17	Average share type 2 firms, PS
Ω_3	0.19	Average share type 3 firms, PS
Ω_4	0.18	Average share type 4 firms, PS
Ω_5	0.07	Average share type 5 firms, PS
Ω_6	0.08	Average share type 6 firms, PS

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 $\delta = 4\%$. The exit rate declines with firms size (and productivity in the model) as indicated by the δ_i in Table 6. 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 2000 and 2021.[11] Bottom rows of Table 6 report the values computed for each Ω_i.

[11] Alternatively, one could infer the Ω_i by assuming an underlying continuous Pareto distribution with minimum 1 and tail parameter 1.05, see Markiewicz and Silvestrini (2026). Then, Ω_i can be computed 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 specification.

Figure 2: Number of firms and HHI as a function of overhead cost.



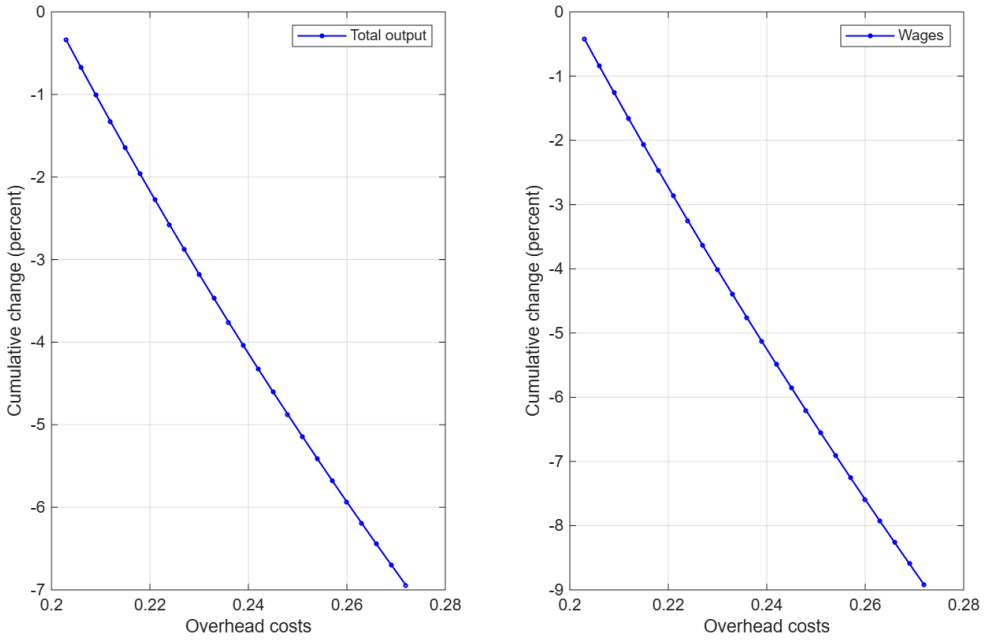
8 Results

Section 3 establishes that firms facing rising overhead costs raise their markups, and that this pass-through is amplified when in sectors with higher digital intensity. Section 4 further shows that firms operating in more digitally intensive sectors tend to exhibit greater complementarity between capital and labor. The quantitative exercise below replicates this environment by introducing an overhead cost shock into a model with two sectors that differ in their elasticity of substitution between capital and labor.

To calibrate the shock, we focus on firms in the top quartile of the overhead cost growth distribution and compute their average cumulative change in both markups and overhead costs over the sample period. Overhead costs grew by 36% on average, and we use this figure as the total magnitude of the shock, introducing it into the model incrementally. All other parameters are held at their baseline values. Concretely, we increase overhead costs by 0.003 per step and solve for the steady state at each increment, so that the figures below trace out a collection of steady states rather than a dynamic transition path — each point corresponds to a distinct equilibrium.

Figure 2 plots the number of firms (left panel) and the HHI (right panel) for each overhead cost value $f_x \in [0.2,\ 0.272]$ across sectors. In every equilibrium, the number of firms is higher in the low-digital-intensity sector than in the high-digital-intensity sector. The mechanism relies on the degree of substitutability between inputs: at given input prices, greater substitutability lowers average costs by allowing firms to shift toward the

Figure 3: Cumulative change in Y and w as a function of overhead cost (in %).



cheaper input, here capital, enabling more firms to break even. Consequently, holding all parameters constant across sectors except σ, market concentration (proxied by HHI) is systematically lower in the low-digital-intensity sector.

In both sectors, growing overhead costs of production reduce the number of firms that can survive. Those that survive are more productive and therefore capture larger market shares, leading to higher market concentration. On aggregate, this leads to a lower output (left panel of Figure 3) and reduced demand for inputs resulting in lower wages (right panel of Figure 3).[12]

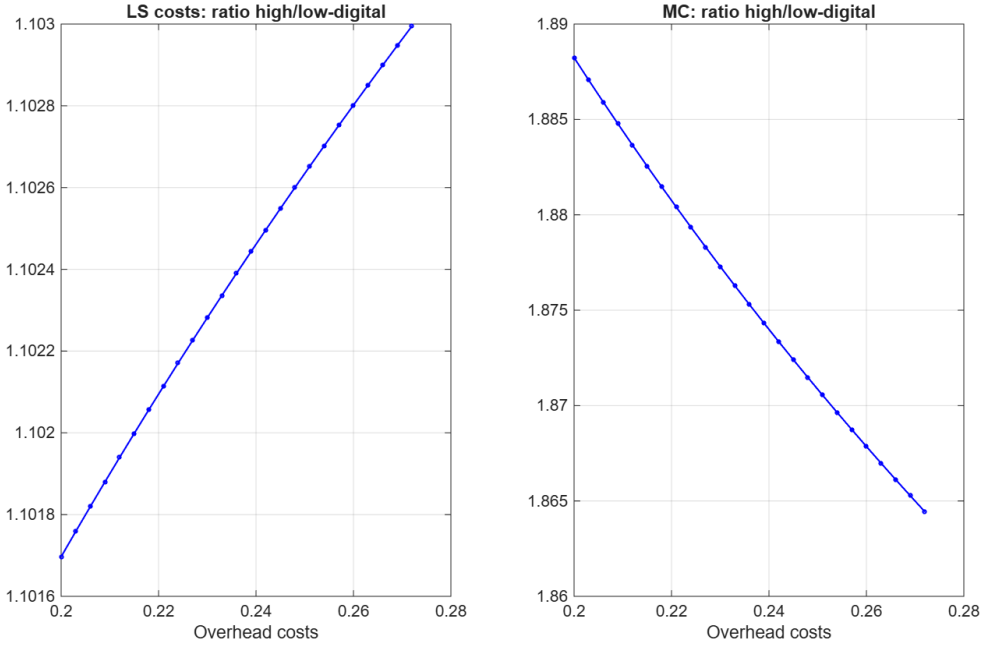
The common decline in wage translates into a reduction in marginal cost of production of different magnitudes, depending on the elasticity of substitution between inputs, σ_k. To determine the impact of the wage change on marginal cost, we compute the following elasticity $\varepsilon_k^{MC,W}$:

$$\varepsilon_k^{MC,W} = \frac{\partial log MC_k}{\partial log W} = \frac{\frac{\partial MC_k}{MC_k}}{\frac{\partial W}{W}} = \left(\frac{\Xi_k}{W}\right)^{\sigma_k - 1} (1-\alpha^K)^{\sigma_k} = s_k^{L,c}. \tag{18}$$

This elasticity is equal to the labor cost share, $s_k^{L,c}$, and is closely linked to the degree of substitutability between labor and capital inputs. A lower elasticity of substitution implies a higher labor cost share and, therefore, greater sensitivity of marginal costs to wage fluctuations. The intuition is straightforward. When the relative cost of capital is lower than that of labor, firms substitute capital for labor to the extent permitted by the

[12] r is fixed: $r = \frac{1}{\beta} + \delta - 1$

Figure 4: Ratio of labour cost share in high-digital and low-digital sectors and MC ratio between high-digital and low-digital as a function of overhead cost.



production technology. In high-digital-intensity sectors, where σ_k is relatively low, labor and capital are more complementary, constraining firms' ability to replace labor with capital. Consequently, labor constitutes a larger share of production costs than in low-digital-intensity sectors, implying that a given decline in wages produces a larger reduction in marginal costs.

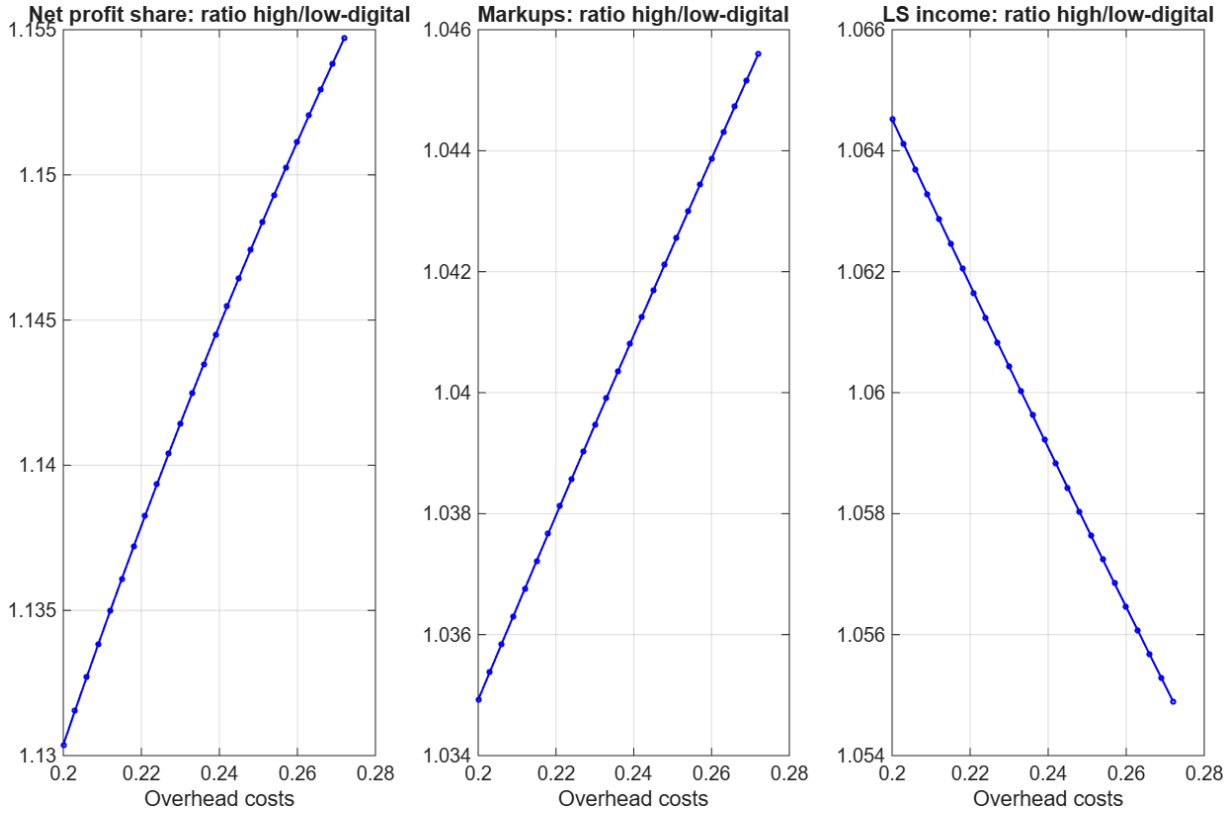
Consistent with this mechanism, the left panel of Figure 4 shows that the ratio of labor cost shares in high- to low-digital-intensity sectors remains above one throughout the simulation. Correspondingly, the right panel demonstrates that marginal costs decline more sharply in high-digital-intensity sectors.

The larger reduction in marginal costs increases firm profitability in high-digital-intensity sectors by more that it does in low-digital-intensity sectors. As shown in Figure 5, profit shares rise more rapidly in these sectors than in low-digital-intensity sectors (left panel), enabling firms to expand and increase their markups (middle panel). These gains occur alongside a decline in the labor share of income (right panel), reflecting the redistribution of income from labor to profits.

Markups rise by 2.79% in the high-digital-intensity sector, compared to 1.74% in the low-digital-intensity sector. The corresponding empirical averages, computed by classifying sectors according to their digital intensity, are 5.37% and 1.70%, respectively.[13] A

[13]To classify sectors into high- and low-digital-intensity, we split them into 2 groups according to 3 digital intensity measures. Summary statistics of markups changes by digital intensity are reported in

Figure 5: Profit shares, markups and labor share: ratios between high and low digital



realistic increase in overhead production costs can therefore account for the entire observed markup growth in the low-digital-intensity sector, and roughly 50% of it in the high-digital-intensity sector. Crucially, a small difference in the production function, captured by the degree of capital-labor complementarity σ, is sufficient to generate an important asymmetry in markup growth.

8.1 Alternative simulations

The baseline calibration relies on a specific pair of elasticity-of-substitution parameters, σ_k, for high- and low-digital-intensity sectors. Section 4, however, provides a broader set of empirical estimates. Although all specifications consistently indicate a lower σ_k in high-digital-intensity sectors, the estimated elasticities exhibit substantial variation in magnitude, with Columns 5 and 6 of Table 4 suggesting that capital and labor may be gross substitutes in sectors with lowest digital intensity. To examine the sensitivity of our results to these alternative estimates, we re-calibrate the model using the σ_k pairs reported in Table 4 and evaluate the implied changes in markups.

Table 7 confirms that the baseline finding is robust across alternative calibrations: a

Table **??** of Appendix B.

Table 7: **Alternative values for σ**

	σ_1	σ_2	$\Delta\mu_1$	$\Delta\mu_2$	ratio $\Delta\mu$
IV(3)	0.788	0.505	1.74%	2.79%	1.60
IV(4)	0.882	0.481	1.25%	2.79%	2.24
IV(5)	1.039	0.366	0.22%	2.50%	11.22
IV(6)	1.227	0.321	0.13%	2.40%	18.94
IV(7)	0.880	0.404	1.26%	3.00%	2.38

Notes: The Table shows the response of the economy to a 36% increase in overhead costs f_x for different pairs of the elasticity of substitution between inputs in the two sectors. The first column includes the number of the specification estimated in Table 4. Column σ_1 reports the value for the elasticity of substitution in the low-digital-intensity sector and column σ_2 for high-digital-intensity sector. Columns $\Delta\mu_1$ and $\Delta\mu_2$ describe, respectively, the change in markups in the two sectors in response to the aggregate overhead cost shock, while their ratio $\Delta\mu_2/\Delta\mu_1$ is presented in the last column.

36% increase in overhead costs consistently generates a larger markup response in the high-digital-intensity sector than in the low-digital-intensity sector. The ratio $\Delta\mu_2/\Delta\mu_1$ rises sharply as σ_1 approaches or exceeds unity. In the baseline specification and IV(4) and (7), where both sectors exhibit gross complementarity, the ratio is moderate at around 1.6–2.4. Once σ_1 crosses one, Columns IV(5) and IV(6), capital and labor become gross substitutes in the low-digital-intensity sector and the differential widens dramatically, with the high-digital-intensity sector experiencing markups growth ten to nineteen times larger. This pattern is intuitive: when firms in the low-digital-intensity sector can readily substitute toward cheaper inputs, the cost-amplifying effect of digital overhead is largely absent, making the contrast with the high-digital-intensity sector more pronounced. The implied ratios are also largely consistent with the empirical evidence reported in Table **??**.

9 Conclusions

This paper studies how the degree of substitutability between inputs of production can magnify the effects of an increase in overhead costs on markups. Using Dutch administrative firm-level data, covering the period from 2000 to 2021, we first document a strong positive relationship between overhead costs growth and markup growth, confirming existing results in the empirical literature. We then show that this correlation depends crucially on overhead costs' composition: digital expenditure is the category of overhead spending that explains the increase in markups the most. The relationship emerges both at the firm and sector levels: firms that invest more heavily in digital technologies experience the stronger increase in markups following an increase in overhead costs, as well as sectors with higher digital intensity exhibit systematically stronger markup growth for a given increase in overhead spending.

What is the driver behind this amplification? Since digital expenditure transforms production, modifying how capital and technology are combined with labor, a potential candidate is the elasticity of substitution between inputs in production. Thus, we estimate the elasticity of substitution between capital and labor across sectors, finding that firms in more digitally intensive sectors exhibit substantially lower elasticities of substitution. These estimates suggest that digital technologies transform production in a way that makes labor and capital more complementary.

To test whether the sectoral heterogeneity in the elasticity of substitution is sufficient to explain the magnification in markup growth we observe, we present a general equilibrium two-sector model with heterogeneous firms, endogenous entry and exit, and oligopolistic competition. In the model, we characterize two *ex ante* identical sectors, which differ solely in the elasticity of substitution between capital and labor in production: the high-digital-intensity sector displays a lower elasticity, meaning the capital and labor are more complement relatively to the low-digital-intensity sector.

We use the model to quantify the effects of an aggregate increase in overhead spending: higher overhead costs reduce the number of firms able to survive, leading to lower competition, lower aggregate output, and downward pressure on wages. The resulting decline in labor costs reduces firms' marginal costs, but its pass-through depends on the elasticity of substitution. Because firms in digitally intensive sectors rely more heavily on labor, they benefit disproportionately more from falling wages, experience larger reductions in marginal costs, and, thus, increase markups and profits more strongly. The model successfully reproduces the asymmetric markup dynamics observed in the data, simply relying on sectoral heterogeneity in the elasticity of substitution.

References

Acemoglu, Daron, Ufuk Akcigit, and William Kerr, "Networks and the Macroeconomy: An Empirical Exploration," *NBER Macroeconomics Annual*, 2015.

Ackerberg, D., K. Caves, and G. Frazer, "Identification properties of recent production function estimators," *Econometrica*, 2015, *83*, 2411–2451.

Atkeson, Andrew and Ariel Burstein, "Pricing-to-market, trade costs, and international relative prices," *American Economic Review*, 2008, *98* (5), 1998–2031.

Autor, David, David Dorn, Lawrence F Katz, Christina Patterson, and John Van Reenen, "The fall of the labor share and the rise of superstar firms," *The Quarterly Journal of Economics*, 2020, *135* (2), 645–709.

Autor, David H., Frank Levy, and Richard J. Murnane, "The Skill Content of Recent Technological Change: An Empirical Exploration," *The Quarterly Journal of Economics*, 2003, *118* (4), 1279–1333.

Bessen, James, Maarten Goos, Anna Salomons, and Wiljan van den Berge, "What Happens to Workers at Firms that Automate?," *The Review of Economics and Statistics*, 2025, *107* (1), 125–141.

Bloom, Nicholas, Charles I Jones, John Van Reenen, and Michael Webb, "Are ideas getting harder to find?," *American Economic Review*, 2020, *110* (4), 1104–44.

Boar, Corina and Virgiliu Midrigan, "Markups and inequality," *Review of Economic Studies*, 2025, *92* (5), 2828–2860.

Caunedo, Julieta, David Jaume, and Elisa Keller, "Occupational Exposure to Capital-Embodied Technical Change," *American Economic Review*, 2023, *113* (6), 1642–1685.

Colciago, Andrea, "Endogenous market structures and optimal taxation," *Economic Journal*, 2016, *126* (594), 1441–1483.

Corrado, Carol A., Charles R. Hulten, and Daniel E. Sichel, "Intangible Capital and U.S. Economic Growth," *Review of Income and Wealth*, 2009, *55* (3), 661–685.

Covarrubias, Matias, Germán Gutiérrez, and Thomas Philippon, "From Good to Bad Concentration? U.S. Industries over the past 30 Years," *NBER Macroeconomics Annual*, 2021, *35*.

Crouzet, Nicolas and Janice C Eberly, "Understanding weak capital investment: The role of market concentration and intangibles," *NBER Working Paper Series 25869*, 2019.

_ , Janice C. Eberly, Andrea L. Eisfeldt, and Dimitris Papanikolaou, "The Economics of Intangible Capital," *Journal of Economic Perspectives*, 2022, *36* (3), 29–54.

Dustmann, Christian, Attila Lindner, Uta Schönberg, Matthias Umkehrer, and Philipp vom Berge, "Reallocation Effects of the Minimum Wage," *The Quarterly Journal of Economics*, 2022, *137* (1), 267–328.

Edmond, Chris, Virgiliu Midrigan, and Daniel Yi Xu, "Competition, markups, and the gains from international trade," *American Economic Review*, 2015, *105*, 3183–3221.

Grullon, Gustavo, Yelena Larkin, and Roni Michaely, "Are US industries becoming more concentrated?," *Review of Finance*, 2019, *23* (4), 697–743.

Gutiérrez, Germán and Thomas Philippon, "The failure of free entry," *NBER Working Paper Series 26001*, 2019.

_ , Callum Jones, and Thomas Philippon, "Entry costs and aggregate dynamics," *Journal of Monetary Economics*, 2021, *124*, S77–S91.

Hasenzagl, Thomas and Luis Perez, "The Micro-Aggregated Profit Share," *Working Paper*, 2026.

Hopenhayn, Hugo A, "Entry, exit, and firm dynamics in long run equilibrium," *Econometrica*, 1992, *60* (5), 1127–1150.

Hsieh, Chang-Tai and Esteban Rossi-Hansberg, "The Industrial Revolution in Services," *Journal of Political Economy Macroeconomics*, 2023, *1* (1), 3–42.

Karabarbounis, Loukas and Brent Neiman, "The global decline of the labor share," *The Quarterly journal of economics*, 2014, *129* (1), 61–103.

León-Ledesma, Miguel A, Peter McAdam, and Alpo Willman, "Identifying the elasticity of substitution with biased technical change," *American Economic Review*, 2010, *100* (4), 1330–57.

Loecker, Jan De and Frederic Warzynski, "Markups and firm-level export status," *American Economic Review*, 2012, *102* (6), 2437–71.

_ **and Jan Eeckhout**, "Global market power," *NBER Working Paper Series 24768*, 2018.

_ **, Catherine Fuss, and Nathan Quiller-Doust**, "The anatomy of costs and firm performance: Evidence from Belgium," *International Journal of Industrial Organization*, 2026, *105.*

_ **, Jan Eeckhout, and Gabriel Unger**, "The rise of market power and the macroeconomic implications," *The Quarterly Journal of Economics*, 2020, *135* (2), 561–644.

Markiewicz, Agnieszka and Riccardo Silvestrini, "The Increase in Turbulence and Market Power," *The Economic Journal*, 2026, *136* (674), 507–559.

Oberfield, Ezra and Devesh Raval, "Micro Data and Macro Technology," *Econometrica*, 2021, *89* (2), 703–732.

Olley, Steven and Ariel Pakes, "The dynamics of productivity in the telecommunications equipment industry," *Econometrica*, 1996, *64* (6), 1263–1297.

Raval, Devesh, "The Micro Elasticity of Substitution and Non-Neutral Technology," *RAND Journal of Economics*, 2019, *50* (1), 147–167.

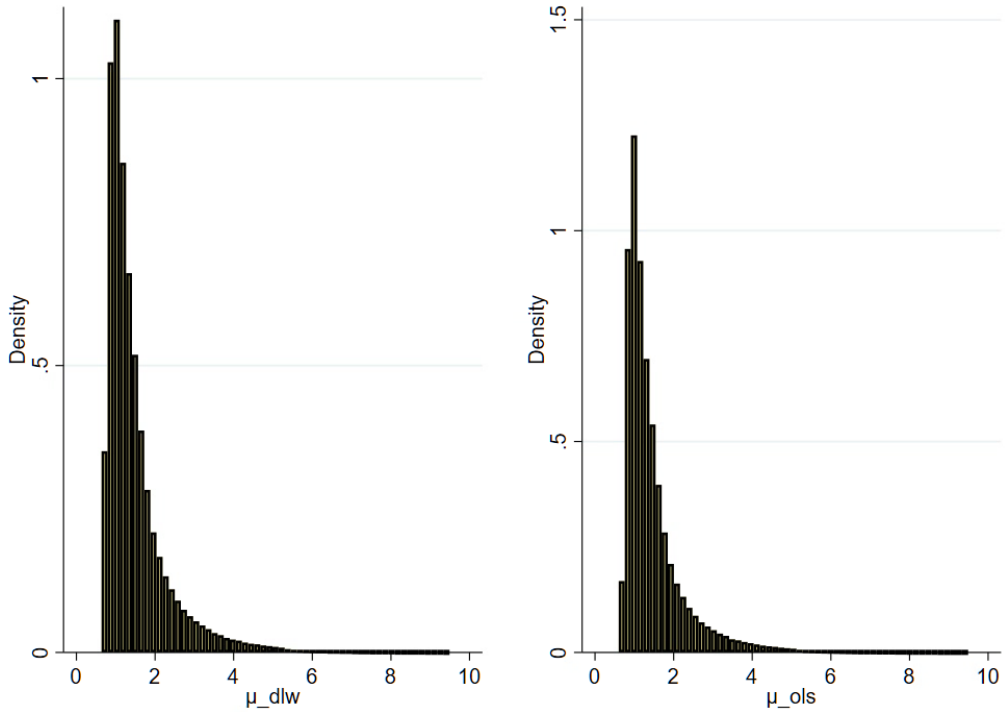
Ridder, Maarten De, "Market power and innovation in the intangible economy," *American Economic Review*, 2024, *114* (1), 199–251.

_ **, Basile Grassi, and Giovanni Morzenti**, "The Hitchhiker's Guide to Markup Estimation," *Econometrica*, 2026, *94*, 137–168.

Silvestrini, Riccardo and Elliott Weder, "Don't Touch My Deductions: The Macroeconomic Effects of Balanced Corporate Tax Reforms," *Working Paper*, 2026.

Appendix A: Data

Figure 6: Firm-level markups in the Netherlands between 2000 and 2018.



Appendix B: Additional empirical results

Table 8: **Technology expenses and markups: firm-level evidence (without controls X_{itk}).**

	(1) baseline	(2) baseline	(3) *dig*	(4) *dig*	(5) *pat_lic*	(6) *pat_lic*	(7) *r&d*	(8) *r&d*
	cs	*rs*	*cs*	*rs*	*cs*	*rs*	*cs*	*rs*
Panel A: $\Delta\mu^1$ (ACF)								
Δfc	0.0065***	0.0331***	0.0049***	0.0364***	0.0026*	0.0398***	0.0031	0.0673***
	(0.0003)	(0.0003)	(0.0006)	(0.0005)	(0.0013)	(0.0011)	(0.0024)	(0.0015)
Δdig			0.0032***	0.0196***				
			(0.0004)	(0.0004)				
$\Delta fc \times \Delta dig$			0.0010*	0.0015***				
			(0.0004)	(0.0002)				
Δpat_lic					0.0016*	0.0100***		
					(0.0008)	(0.0007)		
$\Delta fc \times \Delta pat_lic$					−0.0003	0.0047***		
					(0.0007)	(0.0004)		
$\Delta r\&d$							0.0007	0.0042***
							(0.0010)	(0.0009)
$\Delta fc \times \Delta r\&d$							−0.0032**	−0.0004
							(0.0012)	(0.0004)
Sector FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
N	243,553	243,553	125,906	125,906	28,467	28,467	13,835	13,835
Panel B: $\Delta\mu^2$ (OLS)								
Δfc	0.0066***	0.0332***	0.0051***	0.0366***	0.0029*	0.0400***	0.0037	0.0676***
	(0.0003)	(0.0003)	(0.0006)	(0.0005)	(0.0013)	(0.0011)	(0.0024)	(0.0015)
Δdig			0.0032***	0.0195***				
			(0.0004)	(0.0004)				
$\Delta fc \times \Delta dig$			0.0010*	0.0015***				
			(0.0004)	(0.0002)				
Δpat_lic					0.0016*	0.0099***		
					(0.0008)	(0.0007)		
$\Delta fc \times \Delta pat_lic$					−0.0004	0.0047***		
					(0.0007)	(0.0004)		
$\Delta r\&d$							0.0006	0.0041***
							(0.0010)	(0.0009)
$\Delta fc \times \Delta r\&d$							−0.0033**	−0.0004
							(0.0012)	(0.0004)
Sector FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
N	243,553	243,553	125,906	125,906	28,467	28,467	13,835	13,835

Notes: Firm-level panel regressions of yearly log changes in markups on overhead cost shares and technology-related expenditures. Panel A uses μ^1 estimated via the ACF procedure; Panel B uses μ^2 estimated via OLS. *cs*: cost share measure; *rs*: revenue share measure. *fc*: overhead; *dig*: digital expenditures; *pat_lic*: patents and licenses; *r&d*: R&D. All regressions include sector and year fixed effects. Standard errors in parentheses, clustered at the sector level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 9: Markup Growth by Digital Intensity Group

Digital intensity group		$\Delta\mu_1^{mn}$	$\Delta\mu_1^{med}$
Panel A: Split at mean digital intensity ($dig.^{fc}$)			
Low	mn	0.003	0.017
	sd	0.136	0.131
High	mn	0.057	0.053
	sd	0.220	0.221
H/L	mn	20.52	3.18
	sd	1.61	1.69
Panel B: Split at median digital intensity ($dig.^{fc}$)			
Low	mn	0.007	0.021
	sd	0.132	0.125
High	mn	0.053	0.049
	sd	0.223	0.225
H/L	mn	7.66	2.36
	sd	1.69	1.80
Panel C: Split at median digital intensity ($dig.^{cs}$)			
Low	mn	0.009	0.013
	sd	0.127	0.113
High	mn	0.051	0.057
	sd	0.227	0.231
H/L	mn	5.95	4.47
	sd	1.79	2.03

Notes: Means (mn) and standard deviations (sd) computed within groups of sector-level digital intensity. Panel A splits sectors at the mean of digital expenditure as a share of overhead costs (dig^{fc}); Panel B splits at the median of dig^{fc}; Panel C splits at the median of digital expenditure as a share of total costs (dig^{cs}). H/L reports the ratio of the High-group value to the Low-group value for each statistic (mean and sd). $\Delta\mu_1^{mn}$: change in sector-level mean markup growth (ACF); $\Delta\mu_1^{med}$: change in sector-level median markup growth (alternative measure).

Appendix C

Bundlers

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

$$Y_t = \left(\sum_{k=1}^{\mathcal{S}} \chi_k Y_{kt}^{\frac{\gamma-1}{\gamma}} \right)^{\frac{\gamma}{\gamma-1}}. \tag{19}$$

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 (19). 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}:

$$Y_{kt} = \left(\sum_{i=1}^{N_{kt}} y_{ikt}^{\frac{\theta_k-1}{\theta_k}} \right)^{\frac{\theta_k}{\theta_k-1}}. \tag{20}$$

Each sectoral bundler maximizes profits:

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

subject to Equation (20). 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:

$$y_{ikt} = A_{ikt}^{Z}\left[\alpha_k^K \left(A_{kt}^K k_{ikt}\right)^{\frac{\sigma_k-1}{\sigma_k}} + (1-\alpha_k^K)\left(A_{kt}^L l_{ikt}\right)^{\frac{\sigma_k-1}{\sigma_k}}\right]^{\frac{\sigma_k}{\sigma_k-1}}, \tag{21}$$

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 (21). The F.O.C.s for labor and capital are, respectively:

$$W_t = \lambda_{ikt}\left(A_{ikt}^Z\right)^{\frac{\sigma_k-1}{\sigma_k}} y_{ikt}^{\frac{1}{\sigma_k}}(1-\alpha_k^K)\left(A_{kt}^L\right)^{\frac{\sigma_k-1}{\sigma_k}} l_{ikt}^{-\frac{1}{\sigma_k}}$$

and

$$R_t = \lambda_{ikt}\left(A_{ikt}^Z\right)^{\frac{\sigma_k-1}{\sigma_k}} y_{ikt}^{\frac{1}{\sigma_k}}\alpha_k^K\left(A_{kt}^K\right)^{\frac{\sigma_k-1}{\sigma_k}} k_{ikt}^{-\frac{1}{\sigma_k}},$$

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

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

$$W_t l_{ikt} + R_t k_{ikt} =$$

$$= \lambda_{ikt}\left(A_{ikt}^Z\right)^{\frac{\sigma_k-1}{\sigma_k}} y_{ikt}^{\frac{1}{\sigma_k}}(1-\alpha_k^K)\left(A_{kt}^L\right)^{\frac{\sigma_k-1}{\sigma_k}} l_{ikt}^{1-\frac{1}{\sigma_k}} + \lambda_{ikt}\left(A_{ikt}^Z\right)^{\frac{\sigma_k-1}{\sigma_k}} y_{ikt}^{\frac{1}{\sigma_k}}\alpha_k^K\left(A_{kt}^K\right)^{\frac{\sigma_k-1}{\sigma_k}} k_{it}^{1-\frac{1}{\sigma_k}} =$$

$$= \lambda_{ikt} y_{ikt}^{\frac{1}{\sigma_k}}\left(A_{ikt}^Z\right)^{\frac{\sigma_k-1}{\sigma_k}}\left[(1-\alpha_k^K)\left(A_{kt}^L l_{ikt}\right)^{\frac{\sigma_k-1}{\sigma_k}} + \alpha_k^K\left(A_{kt}^K k_{ikt}\right)^{\frac{\sigma_k-1}{\sigma_k}}\right] = \lambda_{ikt} y_{ikt}.$$

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:

$$\frac{W_t}{R_t} = \frac{1-\alpha_k^K}{\alpha_k^K}\left(\frac{A_{kt}^L}{A_{kt}^K}\right)^{\frac{\sigma_k-1}{\sigma_k}}\left(\frac{l_{ikt}}{k_{ikt}}\right)^{-\frac{1}{\sigma_k}},$$

which gives capital as a function of labor:

$$k_{ikt}^{\frac{\sigma_k-1}{\sigma_k}} = \left(\frac{W_t}{R_t}\right)^{\sigma_k-1}\left(\frac{1-\alpha_k^K}{\alpha_k^K}\right)^{1-\sigma_k}\left(\frac{A_{kt}^K}{A_{kt}^L}\right)^{\frac{(\sigma_k-1)^2}{\sigma_k}}(l_{ikt})^{\frac{\sigma_k-1}{\sigma_k}}.$$

From the first F.O.C.:

$$\lambda_{ikt} = W_t\left(A_{ikt}^Z\right)^{-\frac{\sigma_k-1}{\sigma_k}}\left(\frac{l_{ikt}}{y_{ikt}}\right)^{\frac{1}{\sigma_k}}(1-\alpha_k^K)^{-1}\left(A_{kt}^L\right)^{-\frac{\sigma_k-1}{\sigma_k}}.$$

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

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

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:

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

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

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 (21) 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:

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

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:

$$s_{ikt}^L = \frac{W_t l_{ikt}}{p_{ikt}y_{ikt}} = \frac{w_t l_{ikt}}{\rho_{ikt}y_{ikt}} = \frac{w_t l_{ikt}}{\rho_{ikt}(mc_{ikt})^{-1}(w_t l_{ikt} + r_t k_{ikt})} = \frac{w_t l_{ikt}}{\mu_{ikt}(w_t l_{ikt} + r_t k_{ikt})},$$

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

$$s_{ikt}^K = \frac{1}{\mu_{ikt}}\frac{r_t k_{ikt}}{w_t l_{ikt} + r_t k_{ikt}},$$

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.

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

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:

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

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

$$Y_{kt} = A_{kt}^{Z}\left[\alpha_k^K \left(A_{kt}^K K_{kt}\right)^{\frac{\sigma_k-1}{\sigma_k}} + (1-\alpha_k^K)\left(A_{kt}^L L_{kt}\right)^{\frac{\sigma_k-1}{\sigma_k}}\right]^{\frac{\sigma_k}{\sigma_k-1}},$$

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

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

and,

$$K_{kt} = \sum_{i=1}^{N_{kt}} k_{ikt} = \sum_{i=1}^{N_{kt}} r_t^{-\sigma_k}\xi_{kt}^{\sigma_k}\left(A_{ikt}^{Z}\right)^{-1}\frac{y_{ikt}}{Y_{kt}}Y_{kt}(\alpha_k^K)^{\sigma_k}\left(A_{kt}^K\right)^{\sigma_k-1}.$$

Plugging in the definition of sectoral output:

$$Y_{kt} = A_{kt}^{Z}\Bigg[(\alpha_k^K)^{\sigma_k}\left(A_{kt}^K\right)^{\sigma_k-1}Y_{kt}^{\frac{\sigma_k-1}{\sigma_k}}r_t^{1-\sigma_k}\xi_{kt}^{\sigma_k-1}\left(\sum_{i=1}^{N_{kt}}\frac{1}{A_{ikt}^{Z}}\frac{y_{ikt}}{Y_{kt}}\right)^{\frac{\sigma_k-1}{\sigma_k}} +$$

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

or:

$$1 = A_{kt}^{Z}\xi_{kt}^{\sigma_k}\left[\left(\frac{r_t}{A_{kt}^K\alpha_k^K}\right)^{1-\sigma_k}\alpha_k^K + \left(\frac{w_t}{A_{kt}^L(1-\alpha_k^K)}\right)^{1-\sigma_k}(1-\alpha_k^K)\right]^{-\frac{\sigma_k}{1-\sigma_k}}\left(\sum_{i=1}^{N_{kt}}\frac{1}{A_{ikt}^{Z}}\frac{y_{ikt}}{Y_{kt}}\right).$$

Thus:

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

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

$$\rho_{kt} = \mathcal{M}_{kt}\frac{\xi_{kt}}{A_{kt}^{Z}}.$$

Using the definition of sectoral productivity:

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

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^L_{kt}, s^K_{kt} and s^Π_{kt}, from the results above. Note that the ratio L_{kt}/Y_{kt} can be written as:

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

Thus:

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

By symmetry:

$$s^K_{kt} = \sum_{i=1}^{N_{kt}} s^K_{ikt}\omega_{ikt}.$$

Given that $1 = s^L_{kt} + s^K_{kt} + s^\Pi_{kt}$:

$$s^\Pi_{kt} = 1 - s^L_{kt} + s^K_{kt} = 1 - \sum_{i=1}^{N_{kt}} s^L_{ikt}\omega_{ikt} - \sum_{i=1}^{N_{kt}} s^K_{ikt}\omega_{ikt},$$

and since $s^L_{ikt} + s^K_{ikt} = 1 - s^\Pi_{ikt}$

$$s^\Pi_{kt} = 1 - \sum_{i=1}^{N_{kt}} \left(s^L_{ikt} + s^K_{ikt}\right) \omega_{ikt} = 1 - \sum_{i=1}^{N_{kt}} \left(1 - s^\Pi_{ikt}\right) \omega_{ikt} = \sum_{i=1}^{N_{kt}} s^\Pi_{ikt}\omega_{ikt}.$$

Decomposing:

$$s^\Pi_{kt} = \sum_{i=1}^{N_{kt}} s^\Pi_{ikt}\omega_{ikt} = \sum_{i=1}^{N} \left(s^d_{ikt} + s^X_{ikt}\right) \omega_{ikt} = \sum_{i=1}^{N_{kt}} s^d_{ikt}\omega_{ikt} + \sum_{i=1}^{N_{kt}} s^X_{ikt}\omega_{ikt} = s^d_{kt} + s^X_{kt}.$$

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:

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

and:

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

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