Market Power in the Portuguese Non-Financial Corporate Sector: Evidence from Firm-Level Markups

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Abstract

This thesis analyses changes in market power within the Portuguese non-financial corporate sector from 2007 to 2023 using firm-level data. Market power is assessed through production-based markups, defined as the ratio of output prices to marginal costs, estimated using a flexible cost-share approach that infers markups from observed cost information without requiring data on physical output quantities. The analysis outlines how markups change throughout the business cycle, emphasising strong cyclical trends linked to major macroeconomic events. Markups tend to shrink during economic recessions, as shown during the Global Financial Crisis, the sovereign debt crisis, and the COVID-19 pandemic, and then recover in subsequent phases of economic growth. The aftermath of the pandemic period is characterised by a notable increase in markups during 2021–2022, followed by a partial normalisation in 2023. The analysis shows substantial heterogeneity among sectors and firms, with recent overall trends largely influenced by firms in the upper tail of the markup distribution. Overall, the results show that recent movements in market power are mainly driven by cyclical forces rather than a persistent secular trend.

Keywords: Market power, Markups, Competition, Sectoral heterogeneity, Portuguese economy, Elasticity

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Resumo

Esta tese analisa a evolução do poder de mercado no setor empresarial não financeiro português entre 2007 e 2023, utilizando dados ao nível das empresas. O poder de mercado é avaliado através de *markups* baseados na produção e definidos como a relação entre os preços de produção e os custos marginais. Estes são estimados utilizando uma abordagem flexível de rácio de custos que infere os *markups* a partir de custos observados, sem necessitar de dados sobre quantidades físicas produzidas. A análise mostra como os *markups* variam ao longo do ciclo económico, enfatizando padrões cíclicos associados a eventos macroeconómicos importantes. Os *markups* tendem a diminuir durante as recessões económicas, como se verificou durante a crise financeira global, a crise da dívida soberana e a pandemia da COVID-19, e depois recuperam nos períodos subsequentes de crescimento económico. O período pós-pandemia é marcado por um aumento significativo dos *markups* em 2021-2022, seguido de uma normalização parcial em 2023. A análise mostra uma heterogeneidade substancial entre setores e empresas, com as tendências recentes sendo amplamente influenciadas pelas empresas na cauda superior da distribuição dos *markups*. Finalmente, os resultados sugerem que as mudanças recentes do poder de mercado são impulsionadas principalmente por fatores cíclicos, e não por uma tendência secular persistente.

Palavras-chave: Poder de mercado, *Markups*, Concorrência, Heterogeneidade setorial, Economia portuguesa, Elasticidade

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1 Introduction

The level of market power held by firms in an economy has received notable attention over the past few decades, both in academic research and in policy debates. The ability of firms to sustain prices above marginal costs in many developed economies raises concerns regarding the efficiency of resource allocation, the distribution of income between profits and factor payments, and the operation of competitive markets. These issues have become particularly relevant following a series of major macroeconomic disruptions, including the global financial crisis, the sovereign debt crisis, the COVID-19 pandemic, and the post-pandemic recovery.

Market power is frequently assessed using markups, defined as the ratio of a firm's output price to its marginal cost of production. Estimating markups empirically is not straightforward, as both marginal costs and output prices are usually unobserved in standard firm-level datasets. This shortcoming is most noticeable when using economy-wide administrative datasets, as they generally do not include information on output prices and, apart from manufacturing surveys, rarely include data on physical quantities. Therefore, empirical analyses of market power depend on indirect approaches to infer marginal costs from observable data.

Recent research has shown that it is possible to estimate firm-level markups using production and cost data, even without direct price information, provided reasonable assumptions are imposed. A significant contribution is provided by De Loecker and Warzynski (2012, hereafter DLW), who derive a simple expression for markups as the ratio of a variable input's output elasticity to its revenue share. To determine output elasticity, the method requires estimating production functions using proxy methods that address the simultaneity between input choices and unobserved productivity. This methodology has been applied to Portuguese firm-level data by Mesquita et al. (2022) to estimate markups in both manufacturing and services, highlighting its suitability for analysing entire economies.

Most studies that apply the DLW method treat labour as a variable input in the markup estimation. However, this has been challenged in the literature due to hiring and firing frictions and contractual obligations. The alternative is to treat intermediate inputs as variable inputs; however, using proxy methods in a gross-output production function poses challenges. Flynn, Traina and Gandhi (2019) show that the identification conditions for proxy-based Generalised Method of Moments (GMM) estimators fail in this setting, leading to weak or non-identified input elasticities. These limitations motivate the use of alternative approaches that do not rely on proxy methods for estimating production functions.

Raval (2023a) provides such an alternative identification strategy. Instead of estimating elasticities using a parametric production function, Raval uses information contained in firms' cost data, assuming constant returns to scale and cost minimisation, holding in expectation. A fundamental contribution of this approach is to accommodate differences in labour-augmenting productivity across firms while maintaining a common elasticity of substitution. By grouping firms with similar labour-augmenting productivity and estimating elasticities as group-level cost shares, this approach provides flexible elasticity estimates without imposing Hicks-neutral productivity or relying on intermediate input demand as a proxy for productivity. This framework is exceptionally well-suited to the Portuguese accounting data used, as it does not require data on physical output quantities and allows for heterogeneity in technology across firms, which is helpful for analyses that extend beyond the manufacturing sector.

Within this context, this thesis investigates the changes of market power in the Portuguese non-financial corporate sector from 2007 to 2023. By analysing comprehensive financial statement data, we provide estimates of markups at the sector level and across the economy, highlighting cross-sectoral heterogeneity in pricing behaviour and aggregate trends. The Portuguese economy provides a noteworthy example of this type of analysis, given concerns about competitive weakness, the implementation of product-market reforms during the Economic and Financial Assistance Programme, and the series of significant macroeconomic shocks over the last twenty years.

This dissertation contributes to the existing research on firm-level market power, as measured by markups, in several ways. First, it offers updated evidence on the evolution of market power in Portugal, extending the analysis period to 2023 and incorporating the latest economic developments. Second, it applies the flexible-cost-share method proposed by Raval (2023a) to Portuguese firm-level data, offering one of the first economy-wide applications of this approach. Third, the analysis shows substantial variation across sectors, enabling identification of the economic sectors that drive aggregate trends. Finally, the thesis complements the markup study with a descriptive analysis of accounting-based profit margins. This comparison offers further background to comprehend the markup results, without intending to establish causal relationships.

The remainder of this thesis is organised as follows. Chapter 2 reviews the relevant literature on market power and the estimation of production-based markups. Chapter 3 outlines the method used to recover the markups, detailing the data setting and providing some descriptive statistics of the estimation sample. Chapter 4 discusses the main empirical results and their significance, followed by a robustness check in Chapter 5. Lastly, Chapter 6 provides the concluding remarks.

2 Literature Review

In a typical economic model of perfect competition, firms are price takers and set prices equal to marginal costs, where markups summarise deviations from this benchmark and serve as a convenient measure of market power.

Several studies in developed economies have documented substantial levels of market power, and in many cases revealed an upward trend in markups, commonly connected to increased market concentration, consistently high profits and a decreasing share of income going to labour (Hall 2018a; Hall 2018b; Traina 2018; Basu 2019; De Loecker, Eeckhout and Unger 2020; Fernald et al. 2025). Markups are also determinants of aggregate outcomes by shaping how aggregate income is divided between profits and the returns to labour and capital, and by impacting how shocks are transmitted into firms' pricing decisions (De Loecker and Eeckhout 2018; Nekarda and Ramey 2020; Meier and Reinelt 2024).

This chapter reviews alternative measures of market power, the main econometric approaches for estimating markups from production and cost data, and the evidence for Portugal, with emphasis on production-based markup estimators.

A natural starting point is how market power is measured empirically. Several metrics of market power have been proposed in the field of Industrial Organisation, including concentration ratios, the Lerner Index, and the Herfindahl-Hirschman Index. Although these indicators provide valuable insights into market structure, they do not directly reveal how firms set prices. Consequently, a growing body of research focuses on markups as a direct way to quantify how much companies charge above their costs.

The methods used to estimate markups from the production side are grounded in the work of Hall (1988), who estimates industry markups using macroeconomic data by linking observed input shares and growth to marginal costs via a Solow residual identity. Roeger (1995) extends this framework to gross output specification by including intermediate inputs and differencing primal and dual residuals to remove unobserved technological change. Klette (1999) adapts these methods to firm-level data, allowing for the incorporation of firm heterogeneity. This adaptation explains differences in market power within an industry rather than between them, and facilitates the estimation of economies of scale.

DLW, as mentioned above, make a significant contribution by developing a method to estimate firm- and time-specific markups using only financial statement data. Their approach is based on the firm's cost minimisation problem, along with the first-order condition for a variable input in production, assuming frictionless adjustment within a period. When minimising costs and assuming firms take input prices as given, each firm will choose its inputs so that the marginal product per unit price equals the inverse of its marginal cost. Therefore, for each firm, the markup can be expressed as the ratio of the output elasticity of a variable input to its revenue share. The latter is directly observable in the data, whereas the former requires estimating the firm's production function. As De Loecker, Eeckhout and Unger (2020) point out, this methodology offers greater flexibility, as it avoids the need to assume consumer demand models or market competition. It estimates markups for each firm and year, tracking market diversity.

Notwithstanding its advantages, the DLW approach also imposes challenges. Relying on simple Ordinary Least Squares (OLS) to estimate production functions leads to bias and inconsistent estimates of output elasticities. The bias stems from simultaneity, resulting from the concurrent relationship between input choices and unobserved productivity. Furthermore, selection bias, wherein less productive firms exit the market non-randomly, generates a correlation that renders the capital coefficient inconsistent. To tackle these challenges, control-function methods have been created. These methods use a proxy variable to account for unobserved productivity; hence, they are also known as proxy methods.

Olley and Pakes (1996, hereafter OP) employ investment as a proxy variable and, in a second step, address selection bias by using firm survival probabilities. However, their method requires a strictly positive investment to ensure invertibility for productivity. To circumvent the limitations of the OP model, Levinsohn and Petrin (2003, hereafter LP) employ intermediate inputs as a proxy variable, arguing that for the majority of firms and years, the usage would exceed zero. Ackerberg, Caves and Frazer (2015, hereafter ACF) show that both control functions suffered from identification problems and propose a GMM solution.

Moreover, further critiques have pointed out additional challenges. De Ridder et al. (2022) emphasise that using revenue as the output measure for estimating production functions, rather than physical quantities, leads to an omitted price bias. Furthermore, the ACF correction is most commonly implemented in value-added production functions. Extending it to gross-output settings, where intermediate inputs are treated as variable inputs, raises additional identification constraints. Additionally, Traina (2018) draws attention to the current discussion over which financial account item best represents variable input expenditure. On the one hand, labour may not be entirely flexible due to related hiring and firing costs; on the other hand, by ignoring the Selling, General and Administrative (SGA) expenses, which encompass labour components and marketing costs, the cost of goods sold (COGS) may understate the actual variable costs. When a broader measure of the combined total is considered, the hypothesis of rising market power, as proposed by De Loecker, Eeckhout and Unger (2020), is rejected. Selecting the functional form of the production function can also introduce bias into estimates of output elasticities. The simpler Cobb-Douglas technology assumes a constant elasticity of substitution regardless of input usage, whereas a translog or semi-parametric function accommodates this variation. Flynn, Traina and Gandhi (2019) further argue that conventional proxy methods cannot identify markups without additional assumptions, motivating alternative identification strategies, such as those proposed by Gandhi, Navarro, and Rivers (2020).

In response to these challenges, Raval (2023a) proposes the flexible cost-share approach. This method builds on the foundational cost-share framework established by Foster, Haltiwanger, and Krizan (2001) and subsequently enhanced by Foster, Haltiwanger and Syverson (2008), in which output elasticities are inferred from input cost shares under constant returns to scale. A prominent feature of cost-share-based methods is that they are scale-free, as elasticities are identified from expenditure ratios rather than levels, making the approach independent of firm size and compatible with non-deflated variables. In its original formulation, it is implicitly assumed that all firms within the estimation sample share a common production technology, so that a unique elasticity applies to all firms.

Raval extends this approach by allowing heterogeneity in production technology across firms while maintaining the estimator's scale-free nature. Under constant returns to scale, cost minimisation holding in expectation, input cost shares continue to identify output elasticities in expectation, but these are no longer assumed to be common across all firms. Instead, Raval introduces labour-augmenting productivity as a one-dimensional source of technology heterogeneity and shows that it is proportional to the ratio of labour costs to intermediate-input costs. This observable cost ratio groups firms, and elasticities are estimated in expectation within these technology-homogeneous groups rather than at the firm level. Averaging within groups reduces the impact of firm-level measurement error, particularly in capital, which is often imperfectly observed and economically estimated, and yields more stable elasticity estimates. By not requiring data on physical output quantities, Raval also eliminates the bias associated with estimating output elasticities from revenue production functions.

A potential limitation of this approach arises if relative input prices vary substantially across firms. In that case, differences in labour-to-materials expenditure ratios may reflect variation in wages or input prices rather than differences in labour-augmenting productivity, leading to misclassification of firms across technology groups. This concern highlights the importance of defining sufficiently homogeneous groups and motivates robustness analysis across alternative aggregation levels.

Most of the state-of-the-art on markup estimation focuses on the United States, where evidence shows an increase in average markups since the 1980s, concentrated in the upper tail of the distribution (De Loecker and Eeckhout 2018; De Loecker et al. 2020). These results are associated with declining labour shares and rising profitability.

Few studies focus on European contexts, and even fewer on Portuguese ones. Research using Portuguese firm-level accounting data from *Informação Empresarial Simplificada* (IES), namely Amador and Soares (2012) and Alves and Figueira (2019), provide robust evidence against the hypothesis of perfect competition in the majority of industries, employing the methodology established by Hall (1988). The former identifies an average price-cost margin of 25% to 28% for the overall economy, while demonstrating that enforcing perfect competition in the labour market could lead to an underestimation of product market power. Mesquita et al. (2022) corroborate the earlier findings of the four aforementioned authors that services exhibit broader markups than manufacturing. Nevertheless, this evidence from the 2000s and 2010s contradicts the declining trend in Portuguese markups identified by De Loecker and Eeckhout (2018) for the period between 1980 and 2016, as well as the diverging markups between labour and materials used as variable input, as observed by Raval (2023c).

Taken together, the literature offers limited evidence on changes in firm-level markups in Portugal amid recent macroeconomic instability and has not yet applied the flexible cost-share approach to Portuguese firm-level data, two gaps that this dissertation addresses.

3 Methodology and Data

This chapter outlines the conceptual and empirical frameworks used to estimate firm-level markups and accounting-based profit margins, complemented by information on the data employed in the estimation. The emphasis is placed on identifying production-based markups using the flexible cost-share approach proposed by Raval (2023a).

3.1 Conceptual Framework – Flexible-Cost Share Approach

As demonstrated below, assuming constant returns to scale and average cost minimisation for all inputs, output elasticities can be derived from observable input cost data. This result allows elasticities to be estimated without estimating the production function. However, assuming a constant elasticity for the entire sample or across broad industries implicitly assumes that firms use identical production technologies. This assumption can be unrealistic, even within narrowly defined industries, since companies may differ significantly in their input efficiencies and production processes.

To relax this homogeneity assumption, elasticities are more accurately estimated among firms that use similar technologies. To do so, a unique technology measure that varies across firms, affects elasticities, and can be proxied using observables, independent of production function estimation or unobserved productivity terms, is required. Raval (2023a) proposes that labour-augmenting productivity may be considered a technological measure.

Within this approach, firms can differ in the effectiveness of labour's contribution to output, while differences in substitution elasticities are not considered within each estimation group. Differences in labour-augmenting productivity lead firms to choose different input combinations to minimise costs, despite identical input prices.

To implement this concept, the subsequent step is to link labour-augmenting productivity with measurable firm-level variables. By analysing the firm's cost minimisation problem using a constant elasticity of substitution (CES) production function, it will be shown that productivity is directly proportional to the ratio of labour to intermediate input expenditure, which is observable from cost data. Finally, estimating elasticities in expectation within these groups yields more flexible and informative markup estimates than those derived from pooled or industry-level averages.

3.1.1. Markup Identification from Cost Minimisation

Firm-level markups are defined as the ratio of the output prices to the marginal cost of production:

$$\mu_{it} = \frac{P_{it}}{MC_{it}}. \tag{1}$$

Considering a firm producing output Y_{it} using capital, K_{it}, labour, L_{it}, and materials, M_{it}, the firm minimises costs subject to producing, $\bar{Y}_{it}$, and assuming that input markets are competitive:

$$\min_{\{K_{it}, L_{it}, M_{it}\}} r_{it}K_{it} + w_{it}L_{it} + p_{it}^{M}M_{it} \qquad s.t. \qquad Y_{it}(K_{it}, L_{it}, M_{it}) = \bar{Y}_{it}. \tag{2}$$

The associated Lagrangian is:

$$\mathcal{L}(K_{it}, L_{it}, M_{it}, \lambda_{it}) = r_{it}K_{it} + w_{it}L_{it} + p_{it}^{M}M_{it} + \lambda_{it}\big(\bar{Y}_{it} - Y_{it}(K_{it}, L_{it}, M_{it})\big), \tag{3}$$

where r_{it}, w_{it} and p_{it}^{M} denote the prices of capital, labour (including wages, social security contributions, and other personnel-related costs), and materials, respectively. We can derive the first-order condition for any freely adjustable variable input X_{it} with price p_{it}^{X} as follows:

$$\frac{\partial \mathcal{L}(K_{it}, L_{it}, M_{it}, \lambda_{it})}{\partial X_{it}} = 0 \Rightarrow p_{it}^{X} = \lambda_{it}\frac{\partial Y_{it}(.)}{\partial X_{it}}. \tag{4}$$

Noting that the unobserved marginal cost of production at a given level of output can be written as the Lagrange multiplier associated with the production constraint:

$$\frac{\partial \mathcal{L}\left(K_{it}, L_{it}, X_{it}^{V_j}, \lambda_{it}\right)}{\partial Y_{it}} = \lambda_{it}, \tag{5}$$

we can rewrite (4) by multiplying both sides by $\frac{X_{it}}{Y_{it}}$:

$$p_{it}^{X}\frac{X_{it}}{Y_{it}} = \lambda_{it}\frac{\partial Y_{it}(.)}{\partial X_{it}}\frac{X_{it}}{Y_{it}} \tag{6}$$

$$\Rightarrow \frac{1}{\lambda_{it}}\frac{p_{it}^{X}X_{it}}{Y_{it}} = \frac{\partial Y_{it}(.)}{\partial X_{it}}\frac{X_{it}}{Y_{it}} \tag{7}$$

The right-hand side is the output elasticity of a variable input, X_{it}, denoted as β_{it}^{X}. From this conditional cost function, we can uncover the standard firm's markup identity by rewriting expression (7), recalling the markup identity in (1):

$$\mu_{it} = \frac{\beta_{it}^{X}}{\frac{p_{it}^{X}X_{it}}{P_{it}Y_{it}}}. \tag{8}$$

This expression holds for any variable input within the period. In this thesis, intermediate inputs are treated as variable inputs, labour as quasi-fixed, and capital as fixed over the period. Therefore, markups are identified using the output elasticity and the revenue share of intermediate inputs. The latter is observed in the data, but the output elasticity is not. The remainder of this section focuses on how to identify and estimate the elasticity of intermediate inputs.

3.1.2. Technology and Labour-Augmenting Productivity

In the theoretical derivation that follows, notation is aligned with Raval (2023a) and intermediate inputs are denoted by M_{it} and referred to as materials. However, in the empirical application, intermediate inputs correspond to broader measures that include both cost of goods sold and services purchases (see 3.3).

To characterise firms' production technologies, output is modelled using a constant elasticity of substitution (CES) production function, with labour-augmented productivity.

$$Y_{it} = A_{it}\left[(1-\alpha_l-\alpha_m)K_{it}^{\frac{\sigma-1}{\sigma}} + \alpha_l(B_{it}L_{it})^{\frac{\sigma-1}{\sigma}} + \alpha_m M_{it}^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} = A_{it}S_{it}^{\frac{\sigma}{\sigma-1}} \quad (9)$$

where σ is the elasticity of substitution between inputs, A_{it} is Hicks-neutral productivity, and B_{it} captures labour-augmenting productivity. Differences in B_{it} generate heterogeneity in labour productivity across firms, while assuming a common elasticity of substitution within the estimation group.

3.1.3. Cost Minimisation in Expectation and Identification of Elasticities

The approach proposed by Raval (2023a) provides an alternative identification strategy that avoids the need to estimate firm-level production functions. The key insight is that output elasticities do not need to be identified at the firm level; instead, they can be recovered in expectation under two assumptions.

Assumption 1: On average, the first-order conditions of the cost minimisation problem are satisfied for all production inputs across firms.

$$E[p_{it}^X X_{it}] = \theta_{it}^X E[\lambda_{it} Y_{it}]. \quad (10)$$

Firms might not perfectly minimise costs in every period, but over time, they tend to do so, even when it comes to capital that has adjustment costs and takes time to build. In some periods, firms might over-invest, while at other times they may under-invest; however, the average capital allocation is usually optimised.

Assumption 2: The production function is homogeneous of degree one in inputs, i.e. it has constant returns to scale (CRS).

Under CRS and cost minimisation, the cost function is linear in output, implying that marginal and average costs are equal within the model. This assumption is relevant for using input expenditure data to compute total costs (Raval 2023a):

$$\lambda_{it} Y_{it} = r_{it} K_{it} + w_{it} L_{it} + p_{it}^{M} M_{it}. \tag{11}$$

Taken together, these assumptions imply that the output elasticity of materials can be written as a ratio of expected expenditures:

$$\bar{\beta}^{M} = \frac{E[p_{it}^{M} M_{it}]}{E[r_{it} K_{it} + w_{it} L_{it} + p_{it}^{M} M_{it}]}. \tag{12}$$

Thus, elasticities are identified in expectation, using observable cost data, without estimating a production function.

3.1.4. Mapping Cost Ratios to Labour-Augmenting Productivity

The expression in (12) identifies an average elasticity, but it does not indicate how to form technology-homogeneous groups. The CES structure with labour-augmenting productivity provides a mapping from observable cost ratios to B_{it}, which can be used to construct such groups.

Under the CES technology with labour-augmenting productivity, the elasticities for labour and materials take closed-form expressions as functions of A_{it}, B_{it}, prices and the marginal cost, λ_{it}, which can be derived from the cost minimisation problem and using Shephard's lemma.

Solving the unit cost minimisation problem, hence setting $\bar{Y}_{it} = 1$, associated with the CES technology in equation (9), we have the following Lagrangian function and the first-order conditions:

$$\mathcal{L}\left(K_{it}, L_{it}, X_{it}^{V_j}, \lambda_{it}\right) = r_{it} K_{it} + w_{it} L_{it} + p_{it}^{M} M_{it} + \lambda_{it}\left(1 - Y_{it}(.)\right) \tag{13}$$

$$\begin{cases} \dfrac{\partial \mathcal{L}}{\partial K_{it}} = r_{it} - \lambda_{it} \dfrac{\partial Y_{it}}{\partial K_{it}} = 0 \Rightarrow r_{it} = \lambda_{it} A_{it}\, S_{it}^{\frac{1}{\sigma-1}} (1 - \alpha_l - \alpha_m) K_{it}^{-\frac{1}{\sigma}} \\ \dfrac{\partial \mathcal{L}}{\partial L_{it}} = w_{it} - \lambda_{it} \dfrac{\partial Y_{it}}{\partial L_{it}} = 0 \Rightarrow w_{it} = \lambda_{it} A_{it}\, S_{it}^{\frac{1}{\sigma-1}} \alpha_l B_{it} (B_{it} L_{it})^{-\frac{1}{\sigma}} \\ \dfrac{\partial \mathcal{L}}{\partial M_{it}} = p_{it}^{M} - \lambda_{it} \dfrac{\partial Y_{it}}{\partial M_{it}} = 0 \Rightarrow p_{it}^{M} = \lambda_{it} A_{it}\, S_{it}^{\frac{1}{\sigma-1}} \alpha_m M_{it}^{-\frac{1}{\sigma}} \end{cases} \tag{14}$$

Rearranging the terms and elevating both sides to the power of $(1 - \sigma)$, we can obtain an expression for each term of S_{it}, to then derive an expression for the marginal cost:

$$\begin{cases} (1-\alpha_l-\alpha_m).K_{it}^{\frac{\sigma-1}{\sigma}} = (1-\alpha_l-\alpha_m)^{\sigma}\left[\lambda_{it}A_{it}\,S_{it}^{\frac{1}{\sigma-1}}\right]^{\sigma-1} r_{it}^{1-\sigma} \\ \alpha_l(B_{it}L_{it})^{\frac{\sigma-1}{\sigma}} = \alpha_l^{\sigma}\left[\lambda_{it}A_{it}\,S_{it}^{\frac{1}{\sigma-1}}\right]^{\sigma-1}\left(\frac{w_{it}}{B_{it}}\right)^{1-\sigma} \\ \alpha_m M_{it}^{\frac{\sigma-1}{\sigma}} = \alpha_m^{\sigma}\left[\lambda_{it}A_{it}\,S_{it}^{\frac{1}{\sigma-1}}\right]^{\sigma-1}(p_{it}^{M})^{(1-\sigma)} \end{cases} \tag{15}$$

Using the first-order conditions from (15) and the production function from (9), we can now obtain a simplified expression for the marginal cost, λ_{it}:

$$S_{it} = (1-\alpha_l-\alpha_m)K_{it}^{\frac{\sigma-1}{\sigma}} + \alpha_l(B_{it}L_{it})^{\frac{\sigma-1}{\sigma}} + \alpha_m M_{it}^{\frac{\sigma-1}{\sigma}} \tag{16}$$

$$\Rightarrow S_{it} = \left[(1-\alpha_l-\alpha_m)^{\sigma}r_{it}^{1-\sigma} + \alpha_l^{\sigma}\left(\frac{w_{it}}{B_{it}}\right)^{1-\sigma} + \alpha_m^{\sigma}(p_{it}^{M})^{(1-\sigma)}\right](\lambda_{it}A_{it})^{\sigma-1}S_{it} \tag{17}$$

$$\Rightarrow \lambda_{it}^{1-\sigma} = A_{it}^{\sigma-1}\left[(1-\alpha_l-\alpha_m)^{\sigma}r_{it}^{1-\sigma} + \alpha_l^{\sigma}\left(\frac{w_{it}}{B_{it}}\right)^{1-\sigma} + \alpha_m^{\sigma}(p_{it}^{M})^{(1-\sigma)}\right] \tag{18}$$

$$\Rightarrow \lambda_{it} = \frac{1}{A_{it}}\left[(1-\alpha_l-\alpha_m)^{\sigma}r_{it}^{1-\sigma} + \alpha_l^{\sigma}\left(\frac{w_{it}}{B_{it}}\right)^{1-\sigma} + \alpha_m^{\sigma}(p_{it}^{M})^{(1-\sigma)}\right]^{\frac{1}{1-\sigma}}. \tag{19}$$

Using Shephard's lemma, taking the partial derivative of the cost function with respect to an input's price yields the conditional demand for that input:

$$\begin{cases} \frac{\partial C(.)}{\partial w_{it}} = Y_{it}\frac{\partial \lambda_{it}}{\partial w_{it}} = L^{*}(r_{it}, w_{it}, p_{it}^{M}) \\ \frac{\partial C(.)}{\partial p_{it}^{M}} = Y_{it}\frac{\partial \lambda_{it}}{\partial p_{it}^{M}} = M^{*}(r_{it}, w_{it}, p_{it}^{M}) \end{cases} \tag{20}$$

$$\Rightarrow \begin{cases} \frac{w_{it}}{P_{it}}\frac{\partial \lambda_{it}}{\partial w_{it}} = \frac{w_{it}}{P_{it}}\frac{L^{*}(r_{it}, w_{it}, p_{it}^{M})}{Y_{it}} \\ \frac{p_{it}^{M}}{P_{it}}\frac{\partial \lambda_{it}}{\partial p_{it}^{M}} = \frac{p_{it}^{M}}{P_{it}}\frac{M^{*}(r_{it}, w_{it}, p_{it}^{M})}{Y_{it}} \end{cases}. \tag{21}$$

System of equations (21) is obtained by rearranging equations in (20) and multiplying both sides by the ratio of the respective input prices to output prices. On the right side shows the revenue share of labour and of materials, so rearranging the terms and recalling the markup identity in equation (1), it follows:

$$\begin{cases} \frac{w_{it}L_{it}^{*}(.)}{P_{it}Y_{it}} = \frac{w_{it}}{\mu_{it}\lambda_{it}}\frac{\partial \lambda_{it}}{\partial w_{it}} \\ \frac{p_{it}^{M}M_{it}^{*}(.)}{P_{it}Y_{it}} = \frac{p_{it}^{M}}{\mu_{it}\lambda_{it}}\frac{\partial \lambda_{it}}{\partial p_{it}^{M}} \end{cases} \tag{22}$$

The partial derivatives of λ_{it} with respect to w_{it} and p_{it}^{M} can be obtained using equation (19):

$$\begin{cases} \dfrac{\partial \lambda_{it}}{\partial w_{it}} = \dfrac{1}{A_{it}} \alpha_l^\sigma \left(\dfrac{w_{it}}{B_{it}}\right)^{-\sigma} \dfrac{1}{B_{it}} \left[(1-\alpha_l-\alpha_m)^\sigma r_{it}^{1-\sigma} + \alpha_l^\sigma \left(\dfrac{w_{it}}{B_{it}}\right)^{1-\sigma} + \alpha_m^\sigma (p_{it}^M)^{(1-\sigma)}\right]^{\frac{\sigma}{1-\sigma}} \\ \dfrac{\partial \lambda_{it}}{\partial p_{it}^M} = \dfrac{1}{A_{it}} \alpha_m^\sigma (p_{it}^M)^{-\sigma} \left[(1-\alpha_l-\alpha_m)^\sigma r_{it}^{1-\sigma} + \alpha_l^\sigma \left(\dfrac{w_{it}}{B_{it}}\right)^{1-\sigma} + \alpha_m^\sigma (p_{it}^M)^{(1-\sigma)}\right]^{\frac{\sigma}{1-\sigma}} \end{cases}$$

$$\Rightarrow \begin{cases} \dfrac{\partial \lambda_{it}}{\partial w_{it}} = A_{it}^{\sigma-1} \lambda_{it}^\sigma \alpha_l^\sigma (B_{it})^{\sigma-1} w_{it}^{-\sigma} \\ \dfrac{\partial \lambda_{it}}{\partial p_{it}^M} = A_{it}^{\sigma-1} \lambda_{it}^\sigma \alpha_m^\sigma (p_{it}^M)^{-\sigma} \end{cases}. \tag{23}$$

Plugging together the expressions obtained in the systems of equations (23), the expressions that follow from the Shepard's lemma (22), and once again recalling the markup identity in (8):

$$\begin{cases} \dfrac{w_{it} L_{it}^*(.)}{P_{it} Y_{it}} = \dfrac{w_{it}}{\mu_{it}\lambda_{it}} A_{it}^{\sigma-1} \lambda_{it}^\sigma \alpha_l^\sigma (B_{it})^{\sigma-1} w_{it}^{-\sigma} = \dfrac{1}{\mu_{it}} \left(\dfrac{w_{it}}{A_{it}\lambda_{it}}\right)^{1-\sigma} \alpha_l^\sigma \left(\dfrac{1}{B_{it}}\right)^{1-\sigma} = \dfrac{\beta_{it}^L}{\mu_{it}} \\ \dfrac{p_{it}^M M_{it}^*(.)}{P_{it} Y_{it}} = \dfrac{p_{it}^M}{\mu_{it}\lambda_{it}} A_{it}^{\sigma-1} \lambda_{it}^\sigma \alpha_m^\sigma (p_{it}^M)^{-\sigma} = \dfrac{1}{\mu_{it}} \left(\dfrac{p_{it}^M}{A_{it}\lambda_{it}}\right)^{1-\sigma} \alpha_m^\sigma = \dfrac{\beta_{it}^M}{\mu_{it}} \end{cases} \tag{24}$$

we obtain the expressions for the revenue shares of labour and materials, corresponding to Raval's (2) and (3) equations.

Taking the ratio of both expressions of (24), the markup, μ_{it}, the marginal cost, λ_{it}, and the Hicks-neutral productivity term A_{it} are eliminated, obtaining a relationship linking labour-augmenting productivity, B_{it}, to observable expenditure ratios:

$$\frac{w_{it} L_{it}}{p_{it}^M M_{it}} = \left(\frac{\alpha_l}{\alpha_m}\right)^\sigma \left(\frac{w_{it}}{p_{it}^M}\right)^{1-\sigma} (B_{it})^{\sigma-1} \Rightarrow B_{it} = \left(\frac{w_{it} L_{it}}{p_{it}^M M_{it}}\right)^{\frac{1}{\sigma-1}} \left(\frac{\alpha_l}{\alpha_m}\right)^{\frac{-\sigma}{\sigma-1}} \frac{w_{it}}{p_{it}^M}. \tag{25}$$

It follows that labour-augmenting productivity, B_{it}, is directly proportional to the labour-to-materials cost ratio: $\frac{w_{it} L_{it}}{p_{it}^M M_{it}}$. Hence, firms with similar labour-to-materials cost ratios are expected to have similar values of B_{it}, and therefore similar elasticities. This result provides a basis for grouping firms according to observable cost data and for estimating elasticities in expectation within quintiles of the labour-to-materials cost ratio. Specifically, under CRS and cost minimisation holding in expectation, the elasticity of materials for firms in group g at year t can be estimated as:

$$\beta_{g,t}^M = \frac{E[p_{it}^M M_{it} | G = g, t]}{E[r_{it} K_{it} + w_{it} L_{it} + p_{it}^M M_{it} | G = g, t]}. \tag{26}$$

Firm-level markups are then recovered by combining the group-level elasticity with each firm's observed materials revenue share:

$$\mu_{it} = \frac{\beta_{g,t}^{M}}{\frac{p_{it}^{M} M_{it}}{P_{it} Y_{it}}} \tag{27}$$

Profit Margins – Accounting Side

Formally, profit margins can be defined generically as the ratio between profits, Π_{it}, and revenues, R_{it}:

$$PM_{it} = \frac{\Pi_{it}}{R_{it}}. \tag{28}$$

In the theoretical framework, where revenue equals $P_{it}Y_{it}$, profit margins can be expressed in relation to average costs, AC_{it}, as:

$$PM_{it} = \frac{P_{it}Y_{it} - TC_{it}}{P_{it}Y_{it}} = 1 - \frac{AC_{it}}{P_{it}}, \tag{29}$$

where TC_{it} represents total costs and $AC_{it} = TC_{it}/Y_{it}$ indicates the average cost per unit of output.

Unlike markups, which relate prices to marginal costs, profit margins show the relationship between average costs and prices. Markups might increase if firms raise prices in relation to marginal costs, even when average costs remain high due to fixed or financing costs. In contrast, profit margins might grow due to lower overhead or improved operational efficiency, even if pricing power remains unchanged. Therefore, comparing these two measures provides a more complete understanding of firms' pricing practices and cost frameworks.

3.2 Data

3.2.1 Data Sources

The analysis relies on two primary data sources: one managed by Banco de Portugal (Banco de Portugal Microdata Research Laboratory (BPLIM) 2025) and the other provided by Gouveia and Pereira (2022).

The Central Balance Sheet Harmonised Panel (CBHP) (BPLIM 2025) compiles fiscal, accounting, and statistical information that Portuguese firms are legally required to report to the Portuguese Tax Authority through the *Informação Empresarial Simplificada* (IES)[1]. The dataset variables are adjusted to reflect changes in Portuguese accounting standards, from the Plano Oficial de Contabilidade (POC, Official Chart of Accounts) used before 2010 to the Sistema de Normalização Contabilística (SNC, Accounting Standards System) introduced after 2010. The panel dataset covers all Portuguese non-financial corporations operating between 2006 and 2023, with all monetary variables reported in euros.

Following Raval (2023b), to estimate markups using the flexible cost-share estimator, we need data on sales, labour costs, materials, and capital costs. Sales are measured as the total production value, combining turnover (revenue from the sale of products, goods, and services), capitalised production, and variation in production. Labour costs encompass all employee-related expenses, including salaries, social security contributions, and other personnel-related costs. As stated above, in the theoretical framework, intermediate inputs are referred to as materials, but in practice, they encompass the sum of the costs of goods sold and materials consumed, as well as expenditures on supplies and external services. Raval estimates markups only for the manufacturing sector, and the available data differs from that in the financial statements. Hence, we follow Traina (2018) in proxying the intermediate input expenditure. To obtain the capital costs, we also used the other dataset.

The other dataset provides estimates of the economic real tangible capital stock from 2006 to 2023, constructed by Gouveia and Pereira (2022) using a modified Perpetual Inventory Method (PIM)[2]. In generic terms, the PIM is described by the following accumulation equation:

$$K_{s,t} = (1 - \delta_s) * K_{s,t-1} + I_{s,t}. \tag{30}$$

where $K_{s,t}$ represents the tangible capital stock for sector *s,* at year t, $I_{s,t}$ denotes the net investment made by sector *s,* during year *t,* and δ_s is the depreciation rate for capital, particular to sector s.

The authors estimated capital stock series for each asset type a independently, hence the aggregate of all these series provides a unique measure of tangible capital stock:

[1] Specifically the information considered about turnover, variation in production, capitalised production, costs of goods sold and material consumed, and expenditures on supplies and external services appears on Tables 03 and 0544 (*Nota 44 ao Anexo ao Balanço e Demonstração de Resultados*) for the years up to 2009 and Table 03-A for 2010 onwards, due to the change in the national accounting standards from *Plano Oficial de Contabilidade* (POC) to *Sistema de Normalização Contabilística* (SNC).

[2] For further details on the estimation of the measure of tangible capital used in this study, please refer to Gouveia and Pereira (2022).

$$K_{s,t}^{PIM\,(real)} = \sum_a K_{a,s,t}^{PIM(real)}, \quad (31)$$

where a includes land, buildings and structures, machinery, transport equipment, other equipment, other assets (including cultivated assets), and work in progress. This data is a crucial input for estimating markup to build a measure of capital stock, instead of relying on firms' reported book values, which can mix accounting conventions. The authors' strategy factors in the switchover from POC to SNC, which is important for accurately estimating the initial tangible capital stock. The real series are expressed in 2020 prices. To convert the series into nominal terms, we use sector-specific capital stock price indices constructed from chain-linked price series from the Instituto Nacional de Estatística (INE, Statistics Portugal). Following Amador and Soares (2012), intangible capital stock is also included in the total capital stock, given its relevance in the services sectors. The book value of the intangible capital stock is therefore added to the nominal tangible PIM capital stock[3].

The user cost of capital ($r_{i,t}$), commonly referred to as the rental price of capital, used in the construction of the capital costs variable, follows Hall and Jorgenson (1967), as applied in Amador and Soares (2012):

$$r_{i,t} = \left(i_{i,t} - \widehat{P_t^{GFCF}} + \delta_{i,t}\right) * P_t^{GFCF}, \quad (32)$$

where $i_{i,t}$ represents the firm-specific financial cost of capital, $\hat{P}_t$ and P_t are the growth rate, and the level of investment goods prices, respectively, and $\delta_{i,t}$ the depreciation rate. The financial cost of capital is determined by the ratio of interest expenses to financial debt; the depreciation rate is calculated as the ratio of reported depreciation and amortisation charges to the lagged gross capital stock. Additionally, the investment-goods price indices are obtained from Eurostat's deflators for gross fixed capital formation. By multiplying the user cost of capital by the capital stock, we obtain a measure of capital costs, as Raval does.

The classification of sectors follows the economic activities classification, CAE Rev. 3 (*Classificação da Atividade Económica*, Portuguese implementation of NACE Rev. 2 classification), as established by INE. Five-digit CAE codes (revisions 2.1 and 3) set by INE are recorded for each firm-year. From 2006 to 2008, firms reported their main activity using revision 2.1 of the CAE (CAE Rev. 2.1). However, starting in 2008, reporting has followed

[3] For simplicity, it is assumed semi-equivalence between fiscal and economic amortisation rates, hence we assume equality between the book value of the intangible capital stock and the economic intangible capital stock.

CAE Rev 3. CAE Rev. 3 codes were manually added for firms that reported the code solely under CAE Rev. 2.1, to uphold consistency.

The construction of the sector was based on the grouping of the first two digits of CAE Rev. 3 codes, as specified in INE (2007). Firms in sectors A (agriculture, forestry, and fishing), K (financial services), L (real estate), and O to U (covering public administration, education, and health services) are not included in the analysis. The removal of sector A stems from significant government intervention in the market's functioning, while the exclusion of the other supra-mentioned sectors is consistent with the decision made in Gouveia and Pereira (2022). The final dataset focuses on eleven sectors of the Portuguese economy.

3.2.2 Sample Selection

The initial sample covers the complete universe from 2006 to 2023 and is then refined through a series of steps.

Initially, firms lacking a valid CAE code required for sector aggregation were removed, along with those belonging to the supra-mentioned excluded sectors (A, K, L and O-U). To match Gouveia and Pereira (2022), firms operating in Madeira and holding companies were also excluded.

Following standard practice in studies using firm-level accounting data (Greenstreet 2006; Amador and Soares 2012; Traina 2018; Raval 2022), we inspect data consistency. Observations reporting non-positive values for output, labour costs, intermediate inputs, or capital stock are excluded to address issues related to inactive firms or potential reporting and coding errors. Implausible figures for interest expenses, financial debt and depreciation are removed. Observations where the share of labour costs and intermediate inputs in total sales, or where depreciation rates were outside the [0,1] range, are eliminated. Due to the absence of lagged gross capital data for 2006, the analysis period begins in 2007.

To preserve the panel structure required by the estimation routine, firms with fewer than two consecutive years of data are excluded from the analysis. Economic outliers were removed by trimming observations that fell outside the interval defined by the 1st and 99th percentiles of the growth-rate distributions for key variables. Finally, groups, classes, and subclasses (identified at the 3-, 4-, and 5-digit CAE code levels, respectively) with fewer than five observations per year were discarded to ensure that the elasticities estimated using cost shares do not reflect unique firm behaviour.

The resulting dataset serves as the basis for all subsequent calculations. The unbalanced panel consists of approximately 2.64 million firm-year observations, averaging about 155,500 unique firms each year.

3.2.3 Descriptive Statistics

Table 1 summarises the sector-level coverage for the estimation sample. The sample is dominated by manufacturing, wholesale and retail trade, construction, and services.

Table 1: Sector-level breakdown.

Sector	Observations	Firms	Share of micro and small firms (%)
B - Extractive industries (mining & quarrying)	7,393	854	94.38
C - Manufacturing industries	436,488	51,984	94.12
D - Electricity, gas, steam, hot and cold water, cold air	2,661	381	86.88
E - Water collection, treatment, and distribution; sewerage, waste management, and remediation	9,178	1,141	86.50
F - Construction	335,777	55,370	97.81
G - Wholesale and retail trade; repair of motor vehicles and motorcycles	904,031	118,670	98.68
H - Transport and storage	193,320	26,256	98.46
I - Accommodation, catering and similar	298,288	46,435	98.71
J - Information and communication activities	68,327	12,177	97.34
M - Consultancy, scientific and technical activities	290,649	43,349	99.22
N - Administrative and support services activities	96,326	16,305	95.02

The overall structure confirms the well-known dominance of micro- and small-sized enterprises in the Portuguese economy. Despite being few in number, medium- and large-sized companies account for the majority of total economic activity, as indicated by output measured as total production value (*Figure 1*).

Figure 1: Composition of the Portuguese economy by firm dimension.

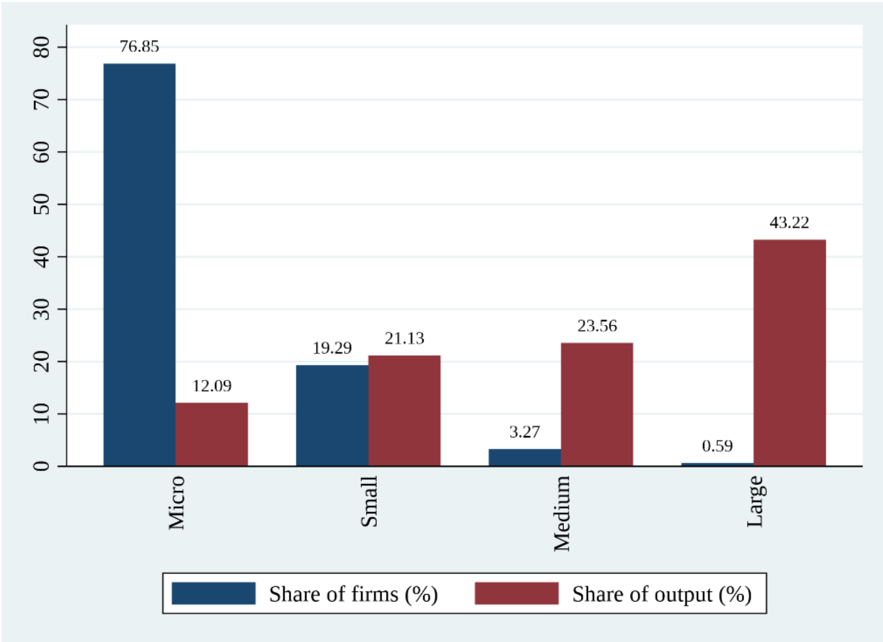


Table 2 reports summary statistics for the main firm-level variables during the average year in the sample. It reflects the significant asymmetries in the Portuguese corporate sector, as *Figure 1* had already anticipated. The average total production reaches approximately 1.8 million euros, while the median firm pulls in only about 0.2 million euros, a strong indicator of the prevalence of micro and small enterprises. Both labour and intermediate input costs exhibit a similar pattern: high means driven by a small percentage of large firms and much lower medians for most of the sample. The significant variances further emphasise the heterogeneity in firm size and cost structures throughout the economy. The distributions of production and input expenditures in levels are highly right-skewed; however, their logarithmic transformations exhibit smooth, unimodal distributions, though capital shows greater asymmetry due to a minority of firms being capital-intensive, consistent with standard firm-size and input-use distributions in the existing literature.

Table 2: Summary Statistics.

	Mean	Median	Variance	Skewness
Total Production	1,781,501	208,554	8.85E+14	138.9
Labour Costs	260,251	50,541	7.76E+12	96.5
Intermediate Input Costs	1,363,004	128,840	6.82E+14	162.9
Capital Costs	80,224	4,547	8.86E+12	194.4

3.3 Empirical Framework

Markups

Empirically, implementing Raval's methodology requires firms to be grouped by similar labour-augmenting productivities, so that output elasticities can be estimated in expectation within each group. Following the theoretical derivation above, labour-augmenting productivity is proxied by the labour-to-intermediates cost ratio, which provides a monotonic mapping to productivity under CES cost minimisation.

We consider two dimensions of variation to determine the grouping strategy. The first dimension is the degree of technological aggregation, which in the Portuguese data is defined using the CAE classification system. Elasticities can be assessed at the 3-digit (Group), 4-digit (Class) or 5-digit (Subclass) CAE levels, which serve a similar purpose to the industry classification referenced in Raval (2023a). This means that every firm within a particular Group-year, Class-year, or Subclass-year has the same estimate of the elasticity of intermediate inputs. The second dimension is the degree of within-group heterogeneity. Even within specific technological units, firms may differ in labour-augmenting productivity. To account for this, firms within each CAE unit and year can be further divided into quintiles based on the labour-to-intermediates cost ratio. This results in Group-Quintile, Class-Quintile, and Subclass-Quintile specifications. These specifications, similar to Raval's industry-quintile approach, allow for flexible changes in elasticities across different productivity types within the same technological category.

In this dissertation, the baseline specification corresponds to the Class-Quintile grouping, which provides a compromise between technological homogeneity and sufficient sample size within each group, ensuring stable elasticity estimates while allowing for meaningful within-class heterogeneity. Simpler specifications that vary only by CAE unit and year, without quintile partitioning, are treated as benchmarks and used to assess the sensitivity of the results to alternative grouping assumptions. The results are presented in Chapter 5 and in Appendix B.

In the following discussions, the Class-Quintile specification will be used for all baseline results reported in Chapter 4. Within each Class-Quintile unit, the elasticity of intermediate inputs is calculated as follows:

$$\theta_{G,Q,t}^{M} = \frac{E[p_{it}^{M} M_{it} | G = Class, Q, t]}{E[r_{it} K_{it} + w_{it} L_{it} + p_{it}^{M} M_{it} | G = Class, Q, t]}, \tag{33}$$

where G is the Class of firm i, Q its corresponding quintile and t the year. Firm-level markups are estimated by combining these elasticities with each firm's specific intermediate input revenue shares, as shown in (27).

Before aggregation, firm-level markup estimates are trimmed at the 1st and 99th percentiles each year to reduce the impact of extreme observations. Aggregate markups at both the sector and economy-wide levels are computed as production value-weighted averages of firm-level markups. For a specific sector S in year t:

$$\mu_{S,t} = \sum_{i \in S} \mu_{it} * \frac{P_{it} \cdot Q_{it}}{\sum_{j \in S} P_{jt} \cdot Q_{jt}}, \tag{34}$$

moreover, the economy-wide markup is defined analogously:

$$\mu_{t} = \sum_{i} \mu_{it} * \frac{P_{it} \cdot Q_{it}}{\sum_{j} P_{jt} \cdot Q_{jt}}, \tag{35}$$

This guarantees that small firms contribute less to the overall markup than larger firms, representing their economic relevance in a specific sector or the national economy.

We compute standard errors using a nonparametric cluster bootstrap at the firm level to quantify sampling uncertainty for sector- and economy-wide markup levels. In each bootstrap replication, we sample firms with replacement, retaining the complete time-series data for each selected firm. This method preserved the panel structure of the data. Using the new sample, we recompute the output-weighted markups for the eleven sectors and the economy, following the same baseline specification. The standard error for each markup estimate is calculated as the standard deviation of the bootstrap estimates across replications.

Profit Margins

Two measures of profit margins are presented. The EBITDA margin is defined as earnings before interest, taxes, depreciation, and amortisation divided by operating revenues (turnover). It captures operational profitability before financing and depreciation, making it helpful in understanding how costs are transferred into prices. The EBT margin is calculated as earnings before taxes divided by operating revenues. It assesses a firm's overall profitability before any fiscal redistribution. As it takes financing conditions into account, it is more susceptible to movements in interest rates.

4 Results

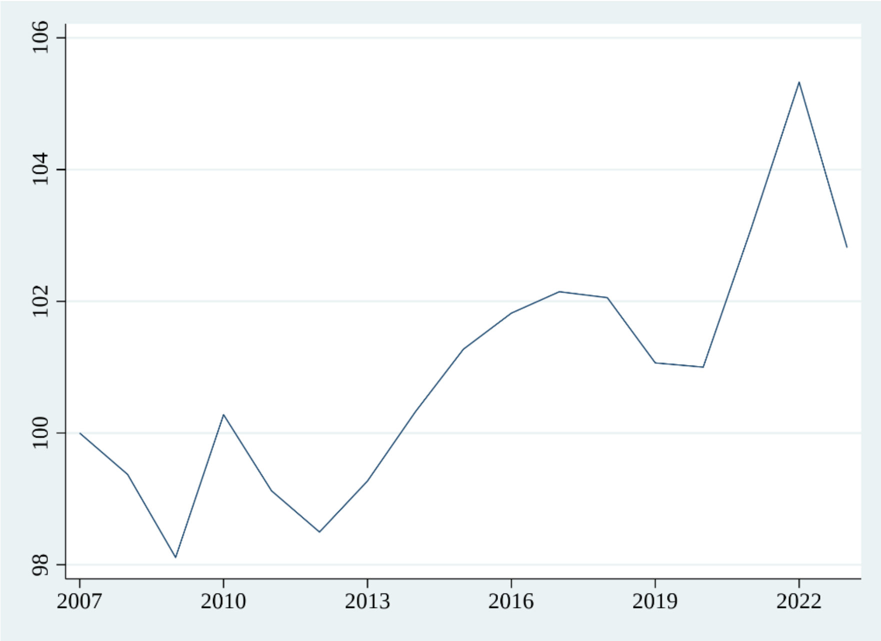
This chapter presents empirical results on the evolution of markups within the Portuguese non-financial corporate sector from 2007 to 2023, using the flexible cost-share method proposed by Raval (2023a), as discussed in Chapter 3.13. The analysis unfolds in four distinct steps. Initially, we describe how economy-wide markups have changed under the baseline specification. Next, we examine differences across sectors and estimate the extent to which each contributes to overall dynamics. Third, we study the distribution of firm-level markups to determine how changes are allocated across firms. Finally, we support the markup analysis by including evidence related to accounting-based profit margins.

The results presented in this chapter are markup indices rather than levels, emphasising changes over time rather than static levels. Appendix B.1 presents the absolute markup levels, along with bootstrap standard errors under different specifications. The levels presented may be affected by the assumptions made during measurement and the chosen model; hence, we refrain from discussing them in this chapter.

4.1 Economy-wide Markup Dynamics

Figure 2 illustrates how the economy-wide markup index evolved, using the baseline Class-Quintile specification, normalised to 100 in 2007. The markup exhibits a series of cyclical movements closely linked to major macroeconomic events affecting the Portuguese economy.

Figure 2: Economy-wide markup index (Class-Quintile baseline, 2007=100).



The economy-wide markup declines significantly from 2007 to 2009. This period corresponds to the Global Financial Crisis, which caused a marked economic downturn in Portugal. The crisis featured a sharp decline in domestic demand and heightened uncertainty for businesses (Banco de Portugal 2008). Under these circumstances, competitive pressures increase, and firms' capacity to set prices above marginal cost diminishes, as certain costs remain rigid, resulting in a decline in markups. By 2010, the markup had bounced back to levels seen before the crisis. After the 2009 trough, a brief recovery in demand occurred, possibly due to changes in the types of businesses that survived the crisis, as only the stronger enterprises remained (Eichenbaum, Rebelo and de Resende 2017). A worsening of the sovereign debt crisis followed this. There was a second decline in markups, a trend that coincided with the Portuguese sovereign debt crisis and the subsequent Economic and Financial Assistance Programme. This period was distinguished by austerity measures, tight credit conditions for firms, government budget cuts, and weak domestic demand, all of which restricted firms' pricing power and further compressed markups (Pereira and Wemans 2015; Banco de Portugal 2010, November).

By the end of 2012, the markup across the economy had started to rise steadily, coinciding with the recovery phase of the Portuguese economy following a prolonged recession. This recovery was supported by enhanced financing conditions, a resurgence in exports and tourism, and accommodative monetary policy within the euro area (European Commission 2015; Banco de

Portugal 2015, May). While the rise is modest, it indicates a gradual recovery of firms' pricing power as demand conditions improved.

In 2020, the markup index fell again, a clear indication of the extraordinary disruption caused by the COVID-19 pandemic. The implementation of quarantine measures, mobility restrictions, and supply-chain constraints had a severe impact on firms' operations, especially within contact-intensive services (Banco de Portugal 2020, December), resulting in a temporary reduction of markups at the aggregate level.

The most pronounced increase in the markup index takes place between 2020 and 2022. Following the easing of lockdown restrictions, demand surged, overlapping with severe supply constraints and steep increases in input costs, primarily in energy and intermediate goods (Banco de Portugal 2022, November). The considerable uptick in markups suggests that, on average, firms were more effective at passing through cost pressures into prices than in earlier years.

In 2023, the markup index decreased from its 2022 peak, denoting a partial normalisation as supply constraints eased, demand growth slowed, and financial conditions tightened (Banco de Portugal 2023, May). Nonetheless, markups continue to exceed pre-pandemic levels, suggesting that companies' pricing practices may have fundamentally shifted. In brief, the evidence across the economy indicates that markup dynamics in Portugal are highly cyclical and closely linked to macroeconomic conditions, unlike the steady, long-term trends documented in other developed economies (De Loecker and Eeckhout 2018; De Loecker et al. 2020).

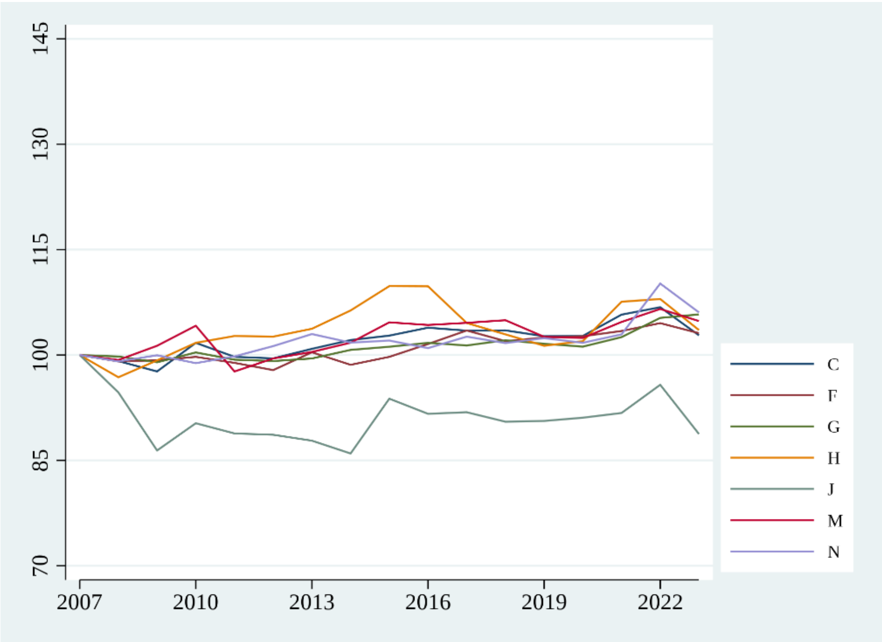
While this chapter primarily examines markup dynamics rather than levels, it is beneficial to briefly contextualise the estimated economy-wide markups against current evidence from Portugal. Studies based on the Hall and Roeger (HR) framework, such as those by Amador and Soares (2012) and Alves and Figueira (2019), report substantially higher price-cost margins for Portugal. Mesquita et al. (2022) show that markups estimated using the HR methodology tend to be consistently higher than those derived from the DLW approach, even when using the same firm-level data.

The lower markup levels shown in Appendix B.1 highlight differences in both methodology and aggregation. The flexible cost-share approach identifies markups under constant returns to scale and cost minimisation holding in expectation, resulting in a more stringent assessment of pricing power than industry-level methods. Moreover, economy-wide markups are calculated using production-weighted averages, thus diminishing the impact of high-markup observations. While levels may not be directly comparable across the different studies, the evidence consistently indicates significant market power and notable cyclical fluctuations in markups throughout the business cycle.

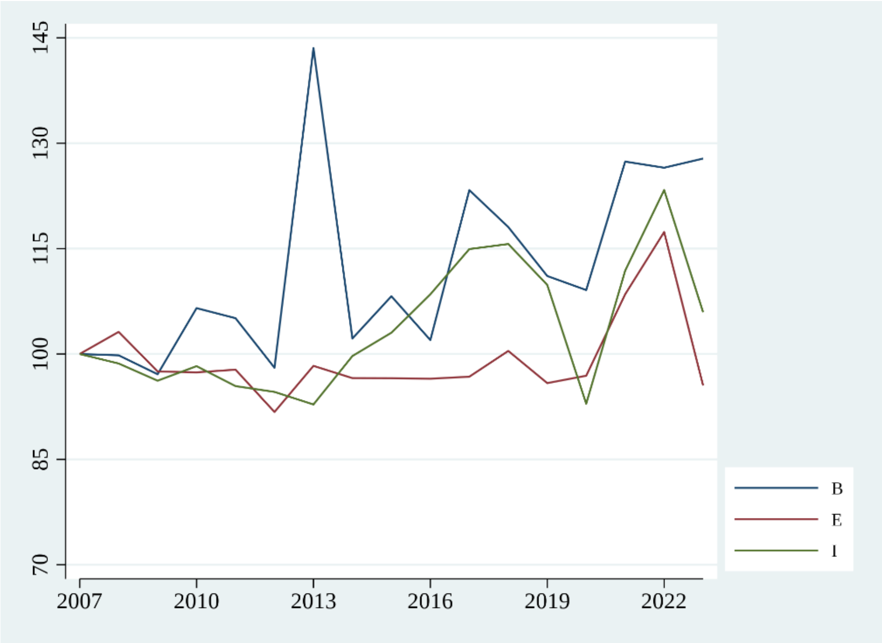
4.2 Sector Heterogeneity and Contribution to Aggregate Trends

While aggregate markups offer insight into macro developments, a closer look at sector-level analysis reveals a deeper narrative: the extent to which specific industries diverge from the aggregate trend or play a substantial role in shaping it. *Figure 3* illustrates the changes in sector-level markup indices, normalised to 100 in 2007, under the baseline specification, while Appendix B.1 contains the corresponding markup levels. Sectors are split into three categories according to their long-run trends compared to 2007: stable, rising, and declining markups.

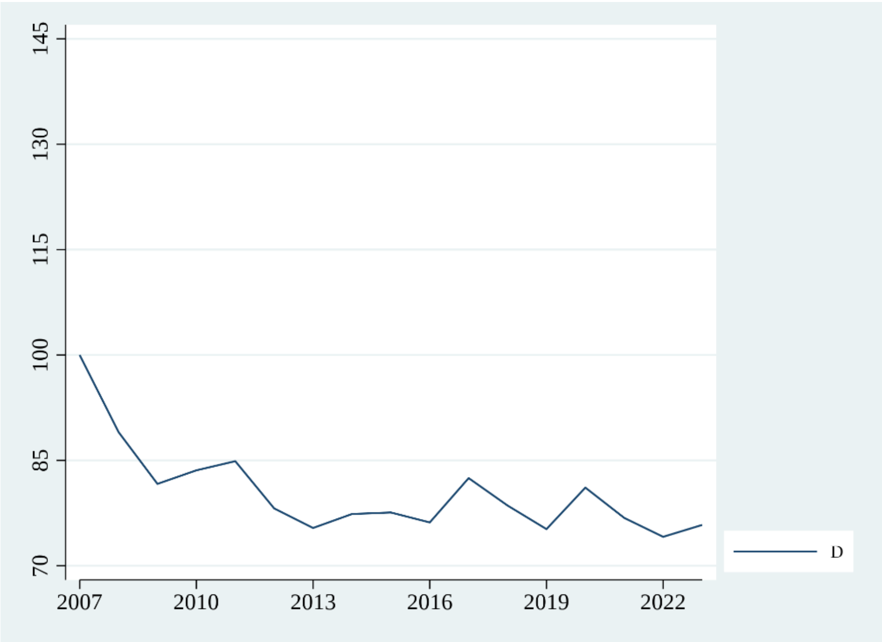
Figure 3: Sector-level markup indices, grouped by long-run trend (Class-Quintile baseline, 2007=100).



i)



ii)



iii)

Panel i) presents sectors C (manufacturing industries), F (construction), G (wholesale and retail trade; repair of motor vehicles and motorcycles), H (transport and storage), M (consultancy, scientific and technical activities) and N (administrative and support services activities). These sectors collectively account for around 90 per cent of total output. Their markup indices showed a largely stable pattern throughout the sample period, with very slight cyclical changes.

In the manufacturing (C) and trade (G) sectors, markups slightly decreased during the crisis periods (2008-2009 and 2011-2013), followed by gradual recoveries. Following the pandemic, markups in these sectors increased only moderately. This pattern reflects firms' impact from global supply-chain disruptions, heightened geopolitical risks, and sudden increases in production costs, combined with strong competitive pressures that constrain price-setting (Banco de Portugal 2022, June). As a result, firms were able to pass through costs into prices, but not to the extent that would generate a significant or persistent increase in markups.

The construction (F) sector essentially mimics the pattern of the above-mentioned sections. It also saw its markups reduced during periods of weak investment and tight credit conditions, a trend especially evident during the sovereign debt crisis (European Commission 2015). Similarly, service-based business sectors (J, M and N) display stable dynamics, reflecting their reliance on domestic demand and contractual pricing arrangements.

The relative stability of these large sectors, when considered together, explains the small changes in the economy-wide markup until 2020.

Panel ii) encompasses sectors B (extractive industries), E (water collection, treatment, and distribution; sewerage, waste management, and remediation), and I (accommodation, catering and similar), which show moderate upward trends, but are influenced by distinct sources in each case.

The accommodation and food services (I) sector has the most distinct shock-driven pattern. In 2020, its markups dipped amid the near-total shutdown of tourism and hospitality activities amid lockdowns. Following the downturn, a strong rebound occurred between 2021 and 2022, in line with the economy's reopening and the rapid recovery of tourism demand (Banco de Portugal 2022, June). The post-COVID increase in markups in this sector is therefore closely related to the recovery of demand rather than a steady structural change.

Sector E shows a relatively stable trend, but it also peaks strongly in 2022. This pattern is consistent with the energy-related cost increases observed during this period, which affected utilities and waste management services. As these services usually operate within regulated or semi-regulated pricing frameworks, this pattern does not necessarily suggest a rise in market power. Instead, it could indicate the influence of tariff adjustment protocols, delayed cost pass-through or regulatory compensation systems. These factors might cause transitory deviations between observed prices and marginal costs during periods of significant input price fluctuations.

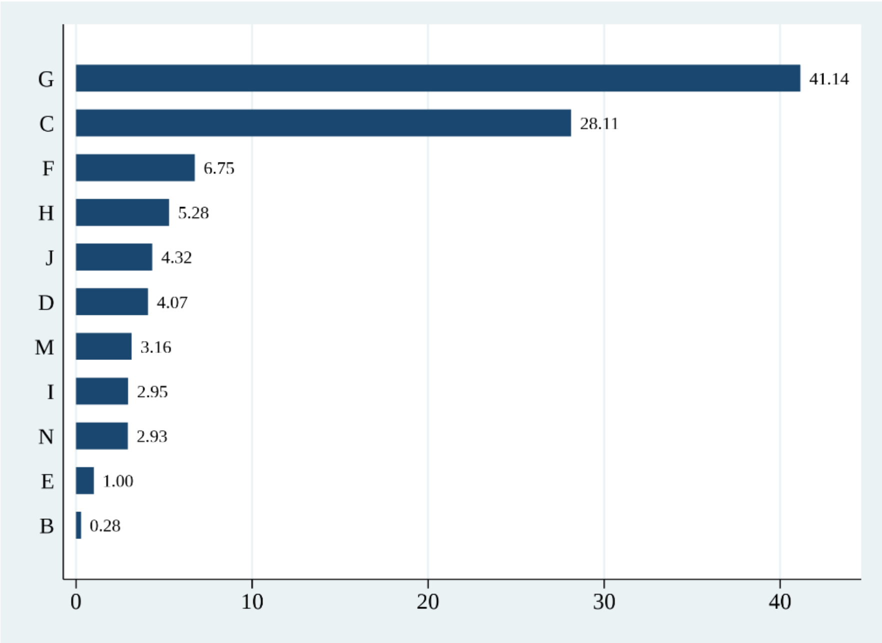
The mining and quarrying (B) sector's markups exhibit a somewhat erratic behaviour during the estimation sample. Given its minimal economic significance (less than 1% of total output) and few firm-year observations, fluctuations in this sector are strongly influenced by firm-level heterogeneity and should be interpreted with caution.

Panel iii) presents sector D (electricity, gas, steam, hot and cold water, cold air), which shows a consistent decline in markups compared to 2007 and ends up with markups considerably below their pre-crisis levels. This pattern likely reflects the joint impact of regulatory controls, high capital intensity, and the limited ability of firms to revise prices freely in response to cost fluctuations (Banco de Portugal 2022, November). Given the small share of sector D in aggregate output, this ongoing decline has had a limited impact on the overall economy.

Sector-level patterns can also be linked to the current evidence available in Portugal, as discussed in Chapter 4.1 at the economy level. Consistent with the results of Alves and Figueira (2019) and Amador and Soares (2012), this thesis finds that the wholesale and retail trade (G) sector exhibits the lowest average markups, reflecting intense competition in a highly fragmented sector. Moreover, service-related activities typically exhibit higher markups than manufacturing activities. Summing up, although there are variations in levels, the relative ranking of sectors and the presence of substantial cross-sector heterogeneity are coherent with the existing Portuguese evidence.

To complement the sector analysis, *Figure 4* reports the contribution of each sector to total output. This highlights that sectors with stable markups are predominant in the economy, whereas those with more pronounced increases have a lesser impact on aggregate trends. The combination of sector behaviour and output weights explains why the economy-wide markup remains stable for most of the sample despite heterogeneous sector behaviour.

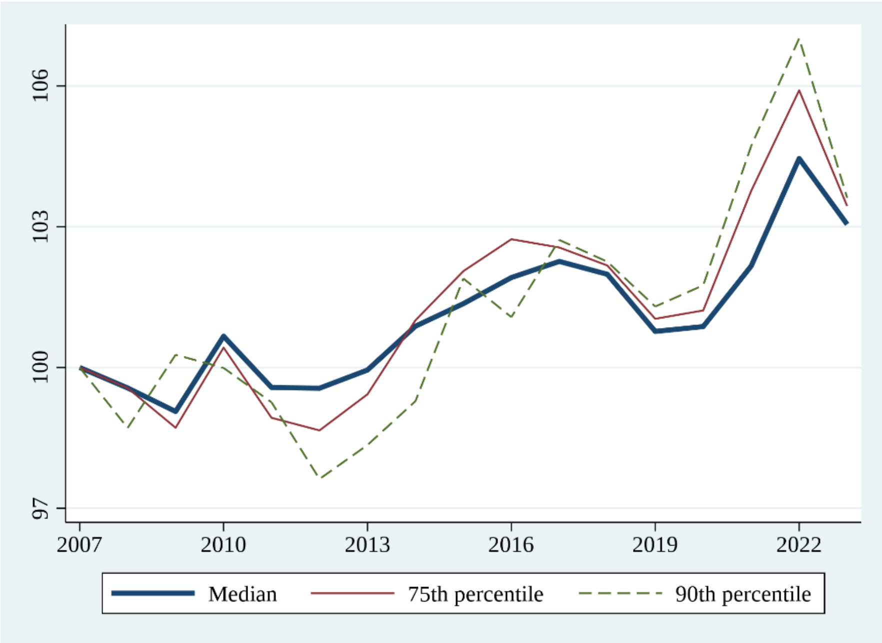
Figure 4: Sector shares of total output in the Portuguese non-financial economy (average over sample).



4.3 Distribution of Firm-level Markups

Beyond average markups found across the economy and within specific sectors, changes in market power may be concentrated on certain firms. *Figure 5* shows how the distribution of firm-level markups changed over time under the baseline specification. It presents the median, 75th percentile, and 90th percentile of the firm-level markup distribution, all indexed to the year 2007. The percentiles for the levels are in Appendix B.2.

Figure 5: Distribution of firm-level markup indices: median, 75th percentile, and 90th percentile (Class-Quintile baseline, 2007=100).



Before 2020, the median markup followed a broadly cyclical trend showing the behaviour of the economy-wide index discussed in Chapter 4.1. The movements suggest that the fluctuations result from widespread shifts rather than from a small set of dominant firms.

Additionally, dispersion gradually increases over time, particularly post-2019, as the upper tail grows faster than the median. The 75th and 90th percentiles undergo more significant contractions during crises and display more pronounced expansions during recovery periods. This pattern indicates that firms with higher markups face greater exposure to demand volatility and competitive pressures, thereby increasing distributional dispersion throughout the economic cycle.

From 2021 to 2022, the upper percentiles increased at a steeper rate than the median, suggesting that the earlier observed rise in aggregate markups was driven disproportionately by firms at the higher end of the markup distribution. This finding is consistent with evidence from other economies indicating that cost pass-through and pricing power were unevenly distributed across companies during the post-COVID inflationary period (Meier and Reinelt 2024).

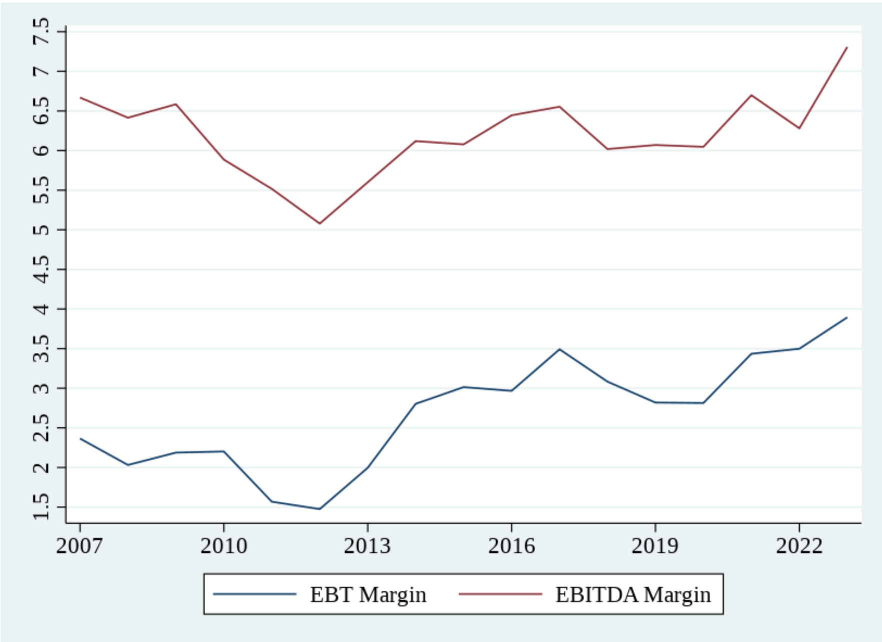
In 2023, all percentiles decline from their 2022 peaks, indicating a partial return to typical pricing patterns. However, dispersion remains higher than pre-COVID-19 levels, suggesting that certain variations in market power distribution may last beyond the immediate inflationary impact.

The distributional evidence supports the perspective that markup movements in Portugal are cyclical and heterogeneous, with macroeconomic shocks impacting firms asymmetrically rather than evenly throughout the distribution.

4.4 Profit Margins and Profitability Dynamics

Markup estimates based on production functions reveal the difference between prices and marginal costs, providing a way to measure market power. In contrast, profit margins reflect the company's actual profitability relative to its revenues and are influenced by average costs, including fixed costs, depreciation, and financing expenses. While they are conceptually distinct, analysing profit margins alongside markups offers important complementary knowledge into firms' pricing and cost structures over the business cycle. *Figure 6* illustrates the evolution of median EBITDA and EBT profit margins among firms in the estimation sample from 2007 to 2023.

Figure 6: Median EBT and EBITDA profit margins.



The gap between EBITDA and EBT margins emphasises the relevance of financing and depreciation costs in shaping firms' total profitability. Throughout the sample period, earnings before tax (EBT) margins were consistently lower than earnings before interest, taxes, depreciation and amortisation (EBITDA) margins. This indicates that the median firm's interest expenses and capital-related costs were a non-negligible financial burden. The disparity widens during downturns and narrows during recoveries, highlighting the cyclical characteristics of financial constraints.

Additionally, profit margins display dynamics that contrast with those of markups. Markups react promptly to swings in pricing relative to marginal costs, whereas profit margins tend to adjust more slowly, showing the influence of fixed and quasi-fixed costs. During economic recessions, revenues decline rapidly while average costs remain high, leading to a larger reduction in profit margins than in markups. Conversely, in recovery phases, margins improve only gradually as firms spread fixed costs across increased output levels and take advantage of better financing conditions.

The aftermath of the pandemic clearly highlights this distinction. During 2021-2022, markups rose significantly, suggesting a greater disparity between prices and costs. However, the recovery of profit margins has been more inconsistent. EBITDA margins rebound strongly, indicating enhanced operational profitability and effective cost pass-through at the production level. The recovery in EBT margins, however, is more subdued, indicating the lagged effects of increasing interest rates and elevated financing costs as the sample period ends. This difference emphasises that greater pricing power does not automatically lead to a proportional increase in net profitability.

As of 2023, profit margins continue to exceed their levels before the pandemic; however, unlike markups, there has been no return to previous stability. As marginal pricing power returns to normal, the average cost structures of firms, which encompass efficiency gains and contractual pricing agreements, continue to support profitability.

The comparison between markups and profit margins supports their conceptual complementarity. The fact that both measures show coherent, yet distinct dynamics, strengthens the idea that the estimated markups reflect significant variation in firms' pricing behaviour rather than byproducts of the estimation methodology.

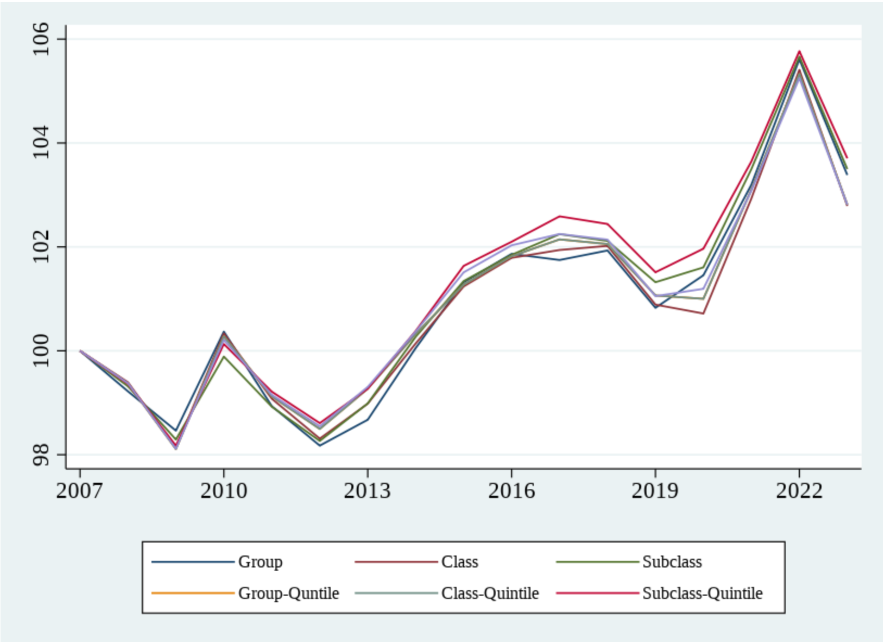
5 Robustness

This chapter assesses the robustness of the markup estimates against alternative specifications in the construction of output elasticities and considers the effects of percentile trimming applied to extreme firm-level observations.

As discussed in Chapter 3 the flexible cost-share approach of Raval (2023a) allows for various sensible aggregation schemes that balance technological homogeneity with within-group heterogeneity. The grouping strategy directly affects the estimated output elasticities and, consequently, the level of markups. However, they should not alter the underlying time-series dynamics if the estimated patterns reflect economic forces rather than modelling choices.

The baseline results presented in Chapter 4 rely on the Class-Quintile specification. *Figure 7* illustrates the evolution of the economy-wide markup index across six different specifications: Group, Class, Subclass, and their corresponding Quintile variants. All series are normalised to 100 in 2007 to facilitate comparison.

Figure 7: Economy-wide markup index under alternative specifications (2007=100).



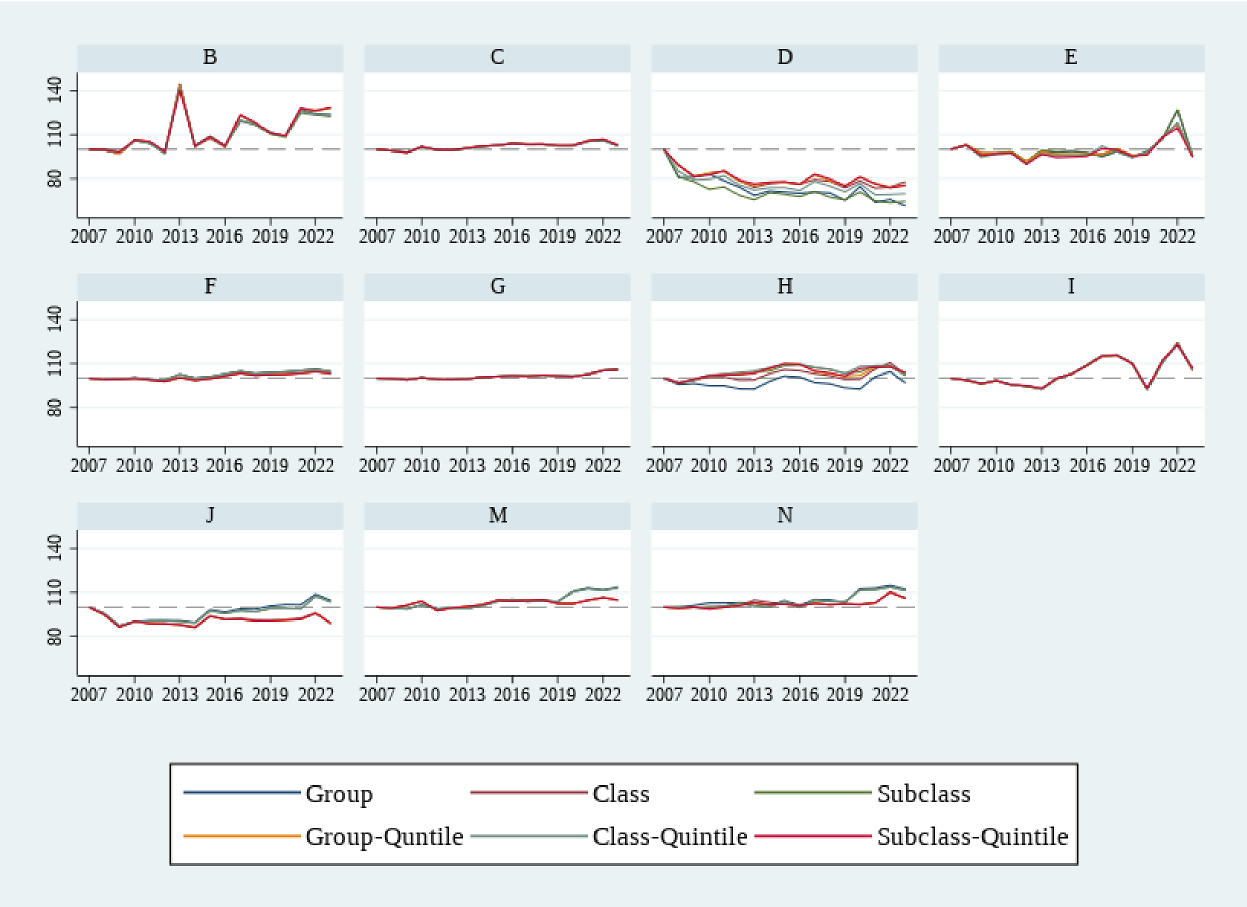
The time-series dynamics exhibit a striking resemblance across all specifications. The cyclical behaviour observed before 2020 shows a decline during the Global Financial Crisis and the sovereign debt crisis, followed by a gradual recovery during the post-2013 expansion, as evidenced across all six series. Moreover, the temporary compression in 2020, which aligned with the COVID-19 shock, was followed by a marked growth in 2021-2022 and partial normalisation in 2023, and this pattern is stable across all specifications.

The alternative specifications imply differences in markup levels, which follow a systematic pattern only within families of aggregation schemes. Specifically, when considering specifications that do not account for productivity quintiles, broader technological pooling (Group) results in higher average markups compared to more detailed industry classification (Class and Subclass), reflecting stronger homogeneity assumptions in elasticity estimation.

When grouping firms by their labour-augmenting productivity quintiles, the estimated markups are consistently lower than those of their pooled counterparts, indicating that accounting for productivity differences significantly lowers estimated elasticities. Although the markup index levels slightly differ across specifications due to variations in estimated elasticities, the timing, magnitude, and persistence of the main movements remain consistent.

Figure 8 illustrates sector-level markup indices under the specifications mentioned above. Each panel corresponds to one sector of economic activity.

Figure 8: Sector-level markup indices under alternative specifications (2007=100).



Across all specifications, the classification of sectors by long-run trend: stable, rising, or declining, remains unchanged. Large sectors like manufacturing (C), construction (F), and trade (G) present consistent trends across aggregation schemes, whereas smaller sectors are more volatile but contribute little to aggregate results.

Finally, robustness to extreme firm-level observations is assessed by contrasting baseline results with untrimmed markup indices reported in Appendix B.3. Firm-level markups are calculated as the ratio of estimated output elasticities to the revenue shares of intermediate inputs. When the shares of intermediate inputs are very small, this mapping can yield unrealistically high markups, especially in capital-intensive, heavily regulated sectors. To reduce the effect of these observations, baseline results adjust the firm-level markup distribution by trimming at the 1st and 99th percentiles before aggregation.

While untrimmed estimates result in substantially higher levels and extreme fluctuations in a few sectors, particularly in water and waste services (E) sector, the qualitative time-series trends for the aggregate economy and for the majority of sectors stay unchanged.

The robustness exercises suggest that the main empirical results presented in Chapter 4 are not driven by aggregation choices or by the treatment of extreme observations. Instead, they indicate widespread and consistent trends in markup dynamics across specifications.

6 Conclusion

This thesis analyses changes in market power within the Portuguese non-financial corporate sector from 2007 to 2023, using firm-level data and a production-based framework to estimate markups. By applying the flexible cost-share approach of Raval (2023a), the analysis provides new evidence on the behaviour of markups throughout the business cycle, highlighting pronounced cyclical fluctuations linked to major macroeconomic shocks rather than a smooth secular trend. The results show substantial heterogeneity across sectors and firms, with aggregate dynamics mainly driven by large sectors that exhibit stable pricing patterns. In contrast, times of greater volatility are characterised by sector-specific disturbances and important contributions from firms in the upper tail of the markup distribution.

Despite its advantages, this dissertation is subject to several limitations inherent to the empirical framework adopted. First, the grouping strategy relies on the assumption that differences in labour-to-intermediate input cost ratio reflect variation in labour-augmenting productivities. If relative input prices vary substantially across firms, this ratio may be capturing price heterogeneity rather than technological differences. This concern is mitigated by grouping firms within relatively homogeneous sectors and by estimating elasticities in expectation, nonetheless it remains an important caveat for the interpretation of group-level elasticities. Second, the analysis relies on accounting data to proxy for economic costs, which may introduce measurement issues, as accounting measures typically exclude opportunity costs and other implicit costs relevant to firms' pricing decisions. This limitation is especially relevant in capital-intensive sectors or those subject to regulation, where fixed costs, network structures, and regulatory pricing schemes can lead to discrepancies between accounting and economic marginal costs. Third, the production-based framework assumes average-cost minimisation and constant returns to scale, which may be restrictive in sectors characterised by scale economies or network effects. In such cases, a portion of the price–cost wedge might reflect scale-related or regulatory rents rather than market power alone. Finally, intangible capital is measured at book value, implicitly assuming that fiscal and economic depreciation are equivalent. When the economic lifespan of intangible assets exceeds what accounting conventions suggest, their actual economic value might be undervalued, which could affect cost and markup measurement, especially in knowledge-intensive sectors.

These shortcomings point to several directions for future research. Broadening the analysis to include firm-level data for 2024 and 2025 would yield significant information about whether the partial decline in markups seen in 2023 marks the end of a post-pandemic normalisation process or whether markups have continued to adjust and reverted to pre-COVID-19 levels. Moreover, expanding the framework to accommodate non-constant returns to scale or distinct elasticities of substitution would allow for richer heterogeneity across sectors and firm types. Finally, incorporating improved measures of economic capital, especially regarding intangible assets, or explicitly accounting for variation in relative input prices would strengthen the identification of production technologies and deepen understanding of the sources of markup heterogeneity.

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Appendix A – Data Construction and Sample Characteristics

This appendix provides additional information on data construction and sample characteristics, complementing the discussion in Chapter 3.

A.1 Construction of Capital Stock Price Indices

Sector-specific capital stock price indices were constructed to recover the nominal value of tangible capital stock.

As the capital stock series in Gouveia and Pereira (2022) are measured in 2020 prices, to obtain its nominal value, the real capital stock is multiplied by the ratio of the specific sector-year price index of capital stock to the price index of capital stock in 2020 (100 by definition by setting the base year as 2020 for the price index). Formally, the nominal capital stock for sector s in year t is given by:

$$K_{s,t}^{Nominal} = K_{s,t}^{Real\ (2020)} * \frac{I_{s,t|2020}^{K_{chain}}}{I_{s,2020|2020}^{K_{chain}}}, \tag{36}$$

where $I_{s,t|2020}^{K_{chain}}$ denotes the chain-linked capital stock price index for sector s, in year t, with 2020 as the base year ($I_{s,2020|2020}^{K_{chain}} = 100$).

To determine the capital stock price indices, we used the annual capital stock by sector, available at the INE's website, both at current and previous-year prices. Annual link relatives are computed as:

$$I_{s,t|t-1}^{K} = \frac{K_{s,t}^{current\ prices}}{K_{s,t}^{previous\ year's\ prices}}. \tag{37}$$

To allow the price indices to be fixed-based, using the definition in Silvestre (2007), the fixed-based chain-index for sector s, for a given base year, is given by:

$$I_{s,t|base}^{K_{chain}} = I_{s,t|t-1}^{K} * I_{s,t-1|t-2}^{K} * I_{s,t-2|t-3}^{K} * \dots * I_{s,base+1|base}^{K}, \tag{38}$$

with $I_{s,base|base}^{K_{chain}} = 100$.

A.2 Evolution of the Number of Firms by Sector

Table A.1 reports the evolution of the number of firms in the estimation sample by sector from 2007 to 2023. The table documents changes in IES filing coverage over time and provides context for the aggregated results. Differences in the number of firms across sectors reflect structural characteristics of the Portuguese economy, and data availability should not be interpreted as a measure of economic relevance.

Table A.1: Evolution of the number of firms per sector.

Year \ Sector	B	C	D	E	F	G	H	I	J	M	N
2007	545	28,384	105	430	22,798	56,885	12,917	17,841	2,780	13,828	4,943
2008	553	28,022	107	446	22,854	56,969	13,071	18,018	2,987	14,633	5,208
2009	533	26,773	117	463	21,337	55,761	12,928	17,969	3,058	14,722	5,302
2010	500	24,946	124	448	19,309	51,629	11,755	16,584	3,002	14,487	4,961
2011	479	24,657	139	513	18,149	50,878	11,469	16,812	3,148	14,860	4,931
2012	432	23,493	163	508	15,673	48,669	10,814	14,945	3,229	14,714	4,849
2013	415	23,189	150	532	14,778	47,351	10,429	13,269	3,273	14,624	4,825
2014	400	24,228	165	534	15,897	49,320	11,148	13,912	3,573	15,735	5,279
2015	393	24,813	172	537	16,341	50,427	11,166	14,720	3,767	16,387	5,537
2016	407	25,685	168	560	17,186	52,601	11,221	16,257	3,963	17,107	5,795
2017	411	26,228	169	562	18,227	53,811	11,301	18,064	4,202	17,791	6,043
2018	400	26,396	174	575	19,206	54,376	11,243	19,672	4,473	18,534	6,342
2019	389	26,324	187	590	20,231	54,429	11,306	20,488	4,722	19,242	6,676
2020	387	25,387	189	601	21,687	53,658	9,328	17,500	4,985	19,651	5,558
2021	383	25,567	174	620	22,839	54,387	9,696	18,289	5,286	20,321	5,937
2022	384	26,287	175	632	24,132	56,138	10,908	20,739	5,708	21,578	6,647
2023	382	26,109	183	627	25,133	56,742	12,620	23,209	6,171	22,435	7,493

Appendix B – Supplementary Results

This appendix complements the empirical results presented in Chapters 4 and 5 by reporting additional outputs from the markup estimation that are not shown in the main text.

B.1 Absolute Markup Levels

While the main text focuses on markup indices normalised to 2007 to highlight movements over time, this section provides markup levels for completeness. Table B.1 displays the economy-wide markup levels for each specification outlined in Chapter 5. Table B.2 reports sector-level markup levels for the baseline Class–Quintile specification only, since alternative specifications produce comparable results, as detailed in the robustness analysis.

Standard errors, reported in parentheses below each estimate, are computed using a firm-level clustered bootstrap with 500 replications, as described in Chapter 3.3.

Table B.1: Economy-wide markup level (all specifications), 2007-2023.

Year	Group	Group–Quintile	Class	Class–Quintile	Subclass	Subclass–Quintile
2007	1.083	1.045	1.078	1.045	1.075	1.045
	(0.012)	*(0.008)*	*(0.012)*	*(0.008)*	*(0.010)*	*(0.008)*
2008	1.075	1.039	1.071	1.038	1.068	1.038
	(0.010)	*(0.007)*	*(0.010)*	*(0.007)*	*(0.008)*	*(0.007)*
2009	1.067	1.025	1.060	1.025	1.056	1.025
	(0.012)	*(0.006)*	*(0.012)*	*(0.006)*	*(0.008)*	*(0.006)*
2010	1.087	1.048	1.077	1.047	1.077	1.047
	(0.015)	*(0.007)*	*(0.008)*	*(0.007)*	*(0.008)*	*(0.007)*
2011	1.072	1.035	1.067	1.035	1.067	1.036
	(0.011)	*(0.007)*	*(0.008)*	*(0.006)*	*(0.008)*	*(0.007)*
2012	1.064	1.027	1.060	1.029	1.060	1.029
	(0.012)	*(0.006)*	*(0.007)*	*(0.005)*	*(0.007)*	*(0.006)*
2013	1.069	1.034	1.067	1.037	1.067	1.037
	(0.010)	*(0.006)*	*(0.005)*	*(0.004)*	*(0.005)*	*(0.004)*
2014	1.084	1.046	1.081	1.048	1.079	1.049
	(0.011)	*(0.005)*	*(0.009)*	*(0.005)*	*(0.007)*	*(0.006)*
2015	1.098	1.058	1.093	1.058	1.093	1.060
	(0.010)	*(0.006)*	*(0.008)*	*(0.005)*	*(0.007)*	*(0.005)*
2016	1.104	1.064	1.098	1.064	1.098	1.066
	(0.010)	*(0.005)*	*(0.008)*	*(0.005)*	*(0.007)*	*(0.005)*
2017	1.102	1.065	1.103	1.067	1.103	1.068
	(0.007)	*(0.004)*	*(0.006)*	*(0.004)*	*(0.006)*	*(0.004)*
2018	1.104	1.066	1.101	1.066	1.101	1.067
	(0.007)	*(0.005)*	*(0.006)*	*(0.005)*	*(0.006)*	*(0.005)*
2019	1.092	1.054	1.093	1.056	1.091	1.056
	(0.006)	*(0.004)*	*(0.006)*	*(0.004)*	*(0.006)*	*(0.004)*
2020	1.099	1.052	1.096	1.055	1.096	1.057
	(0.011)	*(0.005)*	*(0.007)*	*(0.005)*	*(0.007)*	*(0.005)*
2021	1.118	1.076	1.116	1.077	1.114	1.077
	(0.006)	*(0.004)*	*(0.005)*	*(0.004)*	*(0.005)*	*(0.004)*
2022	1.144	1.101	1.139	1.100	1.137	1.099
	(0.007)	*(0.005)*	*(0.006)*	*(0.005)*	*(0.006)*	*(0.005)*
2023	1.120	1.074	1.116	1.074	1.115	1.074
	(0.009)	*(0.004)*	*(0.006)*	*(0.005)*	*(0.006)*	*(0.005)*

Table B.2: Sector-level markup levels (baseline specification), 2007-2023.

Year	B	C	D	E	F	G	H	I	J	M	N
2007	0.988	1.033	1.434	1.131	1.042	1.018	1.005	1.008	1.231	1.119	1.045
	(0.012)	*(0.004)*	*(0.234)*	*(0.028)*	*(0.005)*	*(0.003)*	*(0.008)*	*(0.008)*	*(0.058)*	*(0.016)*	*(0.011)*
2008	0.986	1.024	1.277	1.167	1.033	1.016	0.973	0.994	1.165	1.111	1.035
	(0.013)	*(0.004)*	*(0.134)*	*(0.033)*	*(0.005)*	*(0.003)*	*(0.014)*	*(0.006)*	*(0.068)*	*(0.012)*	*(0.011)*
2009	0.959	1.008	1.171	1.103	1.035	1.008	0.997	0.970	1.064	1.134	1.044
	(0.011)	*(0.007)*	*(0.096)*	*(0.036)*	*(0.007)*	*(0.006)*	*(0.009)*	*(0.008)*	*(0.042)*	*(0.022)*	*(0.014)*
2010	1.052	1.050	1.199	1.102	1.040	1.022	1.022	0.991	1.111	1.166	1.032
	(0.013)	*(0.005)*	*(0.180)*	*(0.039)*	*(0.010)*	*(0.004)*	*(0.007)*	*(0.005)*	*(0.057)*	*(0.034)*	*(0.013)*
2011	1.038	1.030	1.218	1.106	1.031	1.011	1.032	0.962	1.093	1.093	1.042
	(0.016)	*(0.003)*	*(0.135)*	*(0.034)*	*(0.007)*	*(0.004)*	*(0.015)*	*(0.005)*	*(0.061)*	*(0.015)*	*(0.014)*
2012	0.968	1.028	1.121	1.038	1.020	1.009	1.031	0.954	1.091	1.114	1.058
	(0.026)	*(0.006)*	*(0.093)*	*(0.039)*	*(0.011)*	*(0.005)*	*(0.011)*	*(0.006)*	*(0.051)*	*(0.013)*	*(0.026)*
2013	1.418	1.042	1.081	1.112	1.046	1.013	1.042	0.935	1.081	1.124	1.076
	(0.042)	*(0.007)*	*(0.041)*	*(0.036)*	*(0.009)*	*(0.005)*	*(0.013)*	*(0.006)*	*(0.051)*	*(0.010)*	*(0.031)*
2014	1.009	1.054	1.110	1.092	1.028	1.026	1.068	1.005	1.058	1.139	1.063
	(0.034)	*(0.006)*	*(0.071)*	*(0.044)*	*(0.011)*	*(0.006)*	*(0.014)*	*(0.005)*	*(0.037)*	*(0.010)*	*(0.021)*
2015	1.069	1.061	1.113	1.092	1.040	1.030	1.103	1.038	1.154	1.171	1.066
	(0.041)	*(0.007)*	*(0.074)*	*(0.042)*	*(0.008)*	*(0.005)*	*(0.022)*	*(0.005)*	*(0.025)*	*(0.030)*	*(0.018)*
2016	1.007	1.073	1.093	1.092	1.059	1.036	1.103	1.094	1.128	1.167	1.055
	(0.018)	*(0.007)*	*(0.062)*	*(0.039)*	*(0.007)*	*(0.005)*	*(0.028)*	*(0.006)*	*(0.021)*	*(0.036)*	*(0.012)*
2017	1.218	1.068	1.183	1.095	1.079	1.032	1.051	1.158	1.131	1.171	1.072
	(0.096)	*(0.006)*	*(0.059)*	*(0.020)*	*(0.004)*	*(0.005)*	*(0.008)*	*(0.008)*	*(0.018)*	*(0.031)*	*(0.013)*
2018	1.166	1.069	1.127	1.136	1.063	1.040	1.034	1.166	1.114	1.175	1.062
	(0.056)	*(0.006)*	*(0.070)*	*(0.018)*	*(0.007)*	*(0.005)*	*(0.009)*	*(0.008)*	*(0.034)*	*(0.034)*	*(0.014)*
2019	1.097	1.060	1.079	1.084	1.068	1.034	1.018	1.107	1.115	1.148	1.070
	(0.020)	*(0.006)*	*(0.068)*	*(0.016)*	*(0.004)*	*(0.004)*	*(0.010)*	*(0.007)*	*(0.039)*	*(0.016)*	*(0.013)*
2020	1.078	1.061	1.164	1.096	1.070	1.030	1.025	0.937	1.121	1.146	1.063
	(0.022)	*(0.005)*	*(0.093)*	*(0.048)*	*(0.004)*	*(0.005)*	*(0.026)*	*(0.006)*	*(0.033)*	*(0.013)*	*(0.016)*
2021	1.258	1.092	1.102	1.227	1.078	1.044	1.081	1.128	1.129	1.172	1.075
	(0.025)	*(0.005)*	*(0.063)*	*(0.026)*	*(0.005)*	*(0.004)*	*(0.018)*	*(0.011)*	*(0.047)*	*(0.013)*	*(0.016)*
2022	1.249	1.103	1.063	1.328	1.090	1.072	1.085	1.243	1.179	1.193	1.151
	(0.031)	*(0.010)*	*(0.044)*	*(0.036)*	*(0.007)*	*(0.003)*	*(0.013)*	*(0.010)*	*(0.045)*	*(0.026)*	*(0.024)*
2023	1.262	1.061	1.087	1.081	1.075	1.077	1.040	1.068	1.092	1.173	1.108
	(0.029)	*(0.008)*	*(0.106)*	*(0.043)*	*(0.006)*	*(0.003)*	*(0.039)*	*(0.007)*	*(0.043)*	*(0.022)*	*(0.016)*

B.2 Distribution of Firm-Level Markups

In addition to the analysis of markup dispersion presented in Chapter 4.3, this section presents selected percentiles of the firm-level markup distribution in levels, calculated using the baseline specification. The table below presents the 10th, 25th, 50th, 75th, and 90th percentiles, offering a concise overview of pricing power variation across firms.

Table B.3: Distribution of firm-level markup levels (10^{th}, 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentiles).

Percentile / Year	10^{th}	25^{th}	50^{th} (Median)	75^{th}	90^{th}
2007	0.92	0.97	1.01	1.07	1.18
2008	0.92	0.97	1.01	1.07	1.17
2009	0.90	0.96	1.00	1.06	1.18
2010	0.93	0.98	1.02	1.08	1.18
2011	0.92	0.97	1.01	1.06	1.17
2012	0.91	0.97	1.01	1.06	1.15
2013	0.92	0.98	1.01	1.07	1.16
2014	0.92	0.98	1.02	1.08	1.17
2015	0.93	0.99	1.03	1.10	1.20
2016	0.95	1.00	1.03	1.10	1.19
2017	0.95	1.00	1.04	1.10	1.21
2018	0.95	1.00	1.03	1.10	1.21
2019	0.95	0.99	1.02	1.08	1.20
2020	0.93	0.99	1.02	1.09	1.20
2021	0.95	1.00	1.04	1.11	1.24
2022	0.99	1.02	1.06	1.14	1.26
2023	0.95	1.00	1.05	1.11	1.22

B.3 Untrimmed Markup Indices

This section presents additional robustness evidence on the treatment of extreme firm-level observations. *Figure B.1* and *Figure B.2* display markup indices computed without trimming the firm-level markup distribution, using the baseline Class–Quintile specification and normalised to 100 in 2007.

Untrimmed estimates lead to higher levels and greater volatility in a few sectors; nevertheless, the qualitative time-series patterns at both the aggregate and sectoral levels remain consistent with the baseline results discussed in Chapters 4 and 5.

Figure B.1: Economy-wide untrimmed markup index (Class-Quintile baseline, 2007=100).

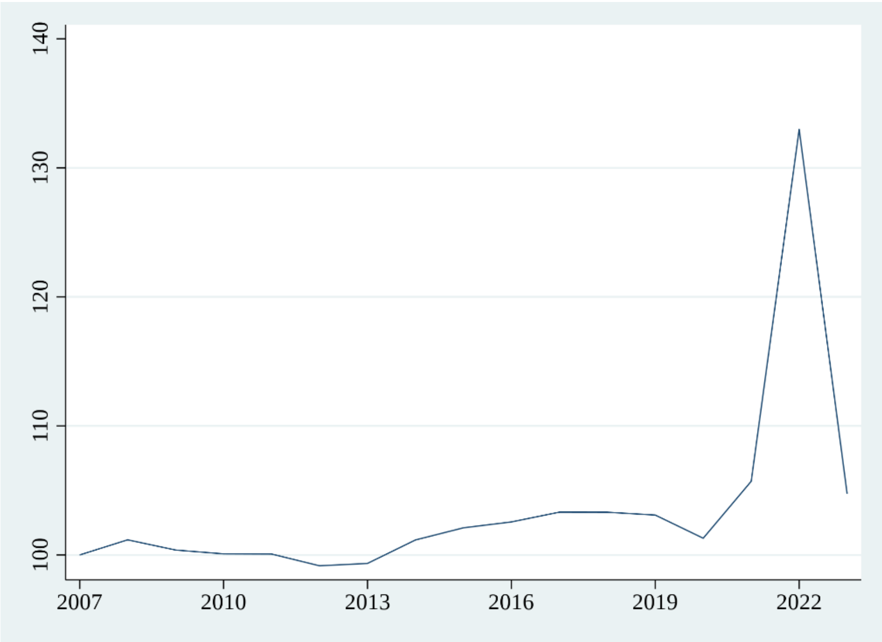

Figure B.2: Sector-level untrimmed markup indices (Class-Quintile baseline, 2007=100).