
**UNIVERSITÀ DI GENOVA
SCUOLA DI SCIENZE SOCIALI
DIPARTIMENTO DI ECONOMIA**



Tesi di laurea magistrale in
Economics and Data Science

Markup as a Measure of Competition: A Theoretical and Empirical Analysis with Application to Liguria

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anno accademico 2025/2026

Abstract

This thesis investigates markups as indicators of market power and competition. It combines the theoretical foundations of pricing above marginal cost, evidence from the United States and Italy, and production-function methods developed by De Loecker and Warzynski. The empirical application uses a 2015-2024 panel of Ligurian manufacturing firms and implements a value-added Levinsohn-Petrin production function with the Akerberg-Caves-Frazer correction and a *translog* specification through Stata's *markupest* command. The final sample contains 3,849 firm-year observations for 601 firms. The average estimated markup is 1.387 and the median is 1.319; mean markups decline to a minimum in 2020 and then rise to 1.458 in 2024, while substantial heterogeneity remains across manufacturing sectors.

Abstract (Italiano)

Questa tesi analizza i markup come indicatori del potere di mercato e della concorrenza. Integra i fondamenti teorici della fissazione dei prezzi al di sopra del costo marginale, l'evidenza empirica relativa agli Stati Uniti e all'Italia e i metodi basati sulla funzione di produzione sviluppati da De Loecker e Warzynski. L'applicazione empirica utilizza un panel di imprese manifatturiere liguri relativo al periodo 2015–2024 e stima una funzione di produzione in valore aggiunto mediante il metodo di Levinsohn–Petrin, con la correzione di Akerberg–Caves–Frazer e una specificazione *translog*, attraverso il comando *markupest* di Stata. Il campione finale comprende 3.849 osservazioni relative a 601 imprese. Il markup medio stimato è pari a 1,387 e la mediana a 1,319; i markup medi diminuiscono fino a raggiungere il valore minimo nel 2020, per poi aumentare fino a 1,458 nel 2024, mentre permane una notevole eterogeneità tra i settori manifatturieri.

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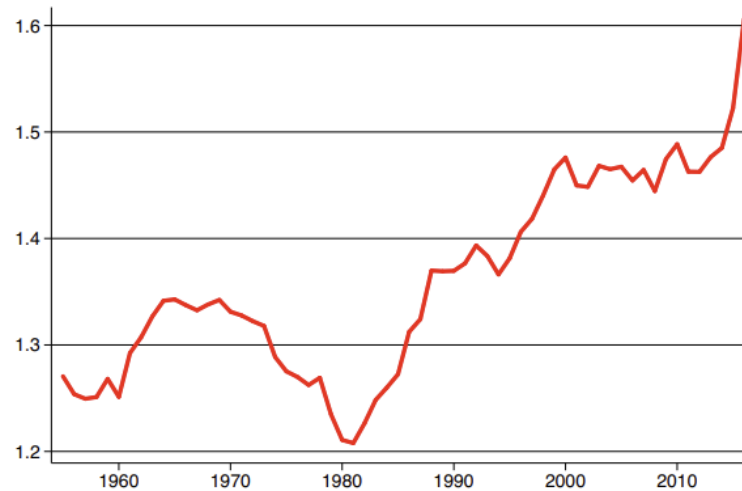
I. Introduction

Competition shapes the prices consumers pay, the incentives firms face to invest and innovate, and the distribution of income generated by production. When firms can sustain prices above marginal cost, their decisions may affect resource allocation and the gains that consumers and workers receive from economic growth. These concerns have renewed interest in whether market power has increased and in how it can be measured with firm-level data. This thesis examines the usefulness and limitations of markups as measures of competition, combining theoretical analysis and evidence from the United States and Italy with an empirical application to Ligurian manufacturing over 2015-2024.

A markup is the ratio of a firm's output price to its marginal cost, the cost of producing an additional unit. It equals one in the benchmark of perfect competition and exceeds one when price is above marginal cost. This makes it a useful indicator of pricing power, but its interpretation requires care. A price-cost margin can help finance fixed costs, product development, and other investments; it is not equivalent to a pure profit rate. Concentration measures answer a different question by describing how activity is distributed across firms, and depend on the definition of the relevant market. Understanding competition therefore requires relating estimated markups to the technologies, products, and market conditions that generate them.

The recent debate owes much to De Loecker, Eeckhout and Unger (2020), who document a rise in the sales-weighted aggregate markup of US publicly traded firms from approximately 1.21 in 1980 to 1.61 in 2016. As Graph I.1 illustrates, this increase follows an earlier period without a sustained upward trend. Their evidence also shows that the aggregate change is uneven: the upper tail of the markup distribution expands while the median remains broadly stable, and economic activity shifts toward firms with higher markups. An aggregate increase can consequently reflect both changes within firms and changes in their relative economic importance.

Graph I.1: Average markups in the US



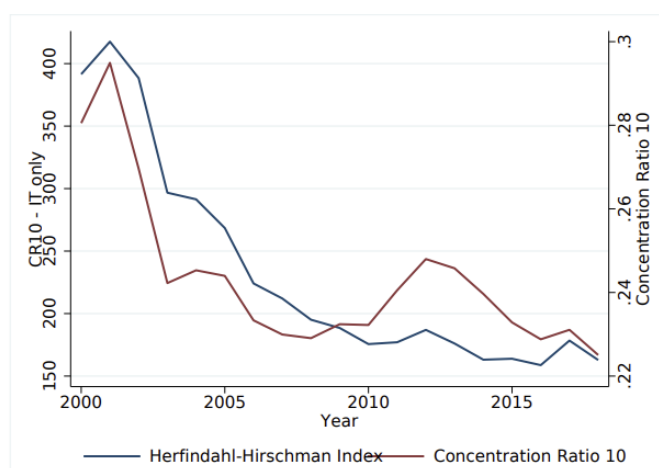
Source: De Loecker, Eeckhout and Unger (2020).

Autor et al. (2020) develop this distributional perspective through the rise of superstar firms. Their analysis links the declining aggregate labor share to the growing weight of highly productive firms with relatively high markups and low labor shares. This mechanism makes firm heterogeneity central to the interpretation of aggregate trends. It also raises a question that matters throughout this thesis: to what extent do higher markups reflect advantages in productivity and product appeal, and to what extent do they signal weaker competitive constraints? Markups alone cannot distinguish these explanations or determine their net welfare consequences.

Industry studies reinforce the need for a qualified interpretation. Döpper et al. (2025) estimate rising markups across US consumer products between 2006 and 2019, associated with falling marginal costs and reduced consumer price sensitivity. Grieco, Murry and Yurukoglu (2024), by contrast, find declining markups in the US automobile industry over 1980-2018 alongside gains in consumer welfare. These demand-based studies examine different markets and periods, but together show why a single aggregate trajectory cannot be assumed to describe every activity. Changes in costs, preferences, and product quality matter for the relationship between markups and economic welfare.

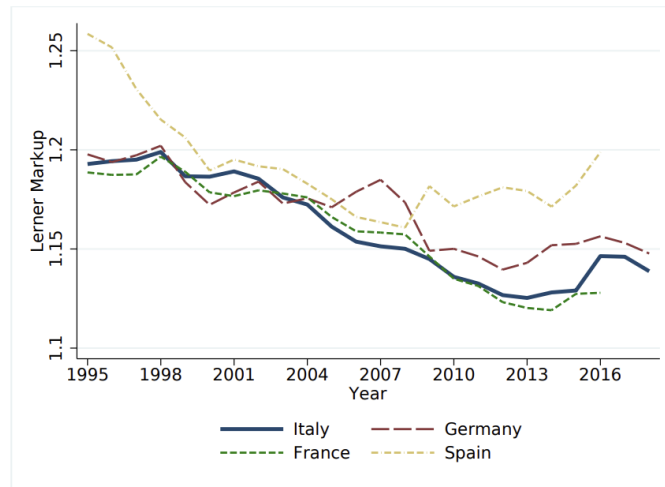
The Italian evidence provides the closest reference for the regional application. Ciapanna et al. (2022) combine national accounts with firm-level data and find relatively stable or slightly declining aggregate markups, substantial sectoral heterogeneity, and a larger role for changes within firms than for reallocation toward high-markup producers. The published analysis emphasizes that sample selection is a major reason for differences from results based on listed companies. Graph I.2 reports concentration indices for Italy, while Graph I.3 presents accounting-based macro markups for Italy, France, Germany, and Spain. These indicators provide background for the comparison; their different definitions and coverage preclude treating them as directly comparable estimates of the same price-cost wedge.

Graph I.2: Concentration indices in Italy



Source: Ciapanna et al. (2022), Figure 2(d); CADS, CERVED Group.

Graph I.3: Country-level markups



Source: Ciapanna et al. (2022), Figure 3; Eurostat national accounts.

Italy's productive structure, with its large presence of small and medium-sized enterprises and differences across regions, makes the level of aggregation particularly important. National averages cannot establish whether manufacturing firms in Liguria display the same distribution or evolution of markups. The motivation for this study is to examine that regional evidence and to assess what standard accounting data can reveal about competition when detailed product prices and quantities are unavailable. Manufacturing offers a defined empirical scope spanning activities such as food production, chemicals, fabricated metals, machinery, and transport equipment. The application does not cover most of the region's service economy, and a firm's location in Liguria does not imply that its customers or competitors are confined to the region.

The empirical analysis asks how estimated markups are distributed across the selected firms and how they evolve between 2015 and 2024. It then examines differences across manufacturing sectors and associations with firm size and labor productivity. Comparison with the national evidence asks whether the regional patterns are qualitatively similar, while accounting for differences in samples, periods, and estimation methods. The contribution is a regional application of established methods that connects these descriptive findings to the broader debate about markup measurement.

A central empirical obstacle is that marginal cost is rarely observed in company accounts. The production approach developed by De Loecker and Warzynski (2012) makes estimation possible by dividing a flexible input's output elasticity by its expenditure share under cost minimization. Its practical appeal is that it can use accounting information without estimating a separate demand system for each product market. Its validity nevertheless depends on the production technology and the assumptions governing input choices. Firms may adjust inputs in response to productivity information that is unavailable to the researcher, making ordinary least squares an unreliable way to estimate production elasticities.

The control-function literature addresses this simultaneity problem. Olley and Pakes (1996) use investment decisions to recover information about unobserved productivity; Levinsohn and Petrin (2003) extend the approach to intermediate inputs, which can remain informative when investment is infrequent or zero. Akerberg, Caves and Frazer (2015) show that the earlier procedures may fail to identify the labor coefficient and propose an alternative estimation strategy. The Ligurian application combines the Levinsohn-Petrin proxy approach with the Akerberg-Caves-Frazer correction. It uses Stata's `markupest` and `prodest` framework, drawing on Rovigatti (2020) and Rovigatti and Mollisi (2018).

The data come from an AIDA (Bureau van Dijk) extract of 2,585 Ligurian manufacturing firms with annual accounts covering 2015-2024. After imposing a minimum of 15 employees at the firm-year level, requiring positive and non-missing estimation variables, and excluding a singleton sector-year cell, the final dataset contains 3,849 firm-year observations for 601 firms across 22 two-digit ATECO sectors. The sample remains predominantly composed of smaller employers above the threshold: median employment is 30, and 73.8 percent of observations fall in the 15-49 employee band.

The specification uses value added as output, personnel expenditure as the labor input, tangible fixed assets as capital, and raw-material and service expenditure as the productivity proxy. A translog production function allows estimated elasticities to vary with firms' input combinations. Logged variables are centered within sector-year groups, and the markup calculation restores the observed personnel-cost share of value added after

this normalization. The resulting estimates are summarized using unweighted means, medians, and distributional comparisons. This procedure describes the firms observed in the dataset rather than constructing a measure weighted by their contribution to regional sales.

The main results reveal estimated markups above one for most observations, together with considerable dispersion. Across all firm-years, the mean is 1.387 and the median is 1.319. The 10th and 90th percentiles are 1.046 and 1.751, respectively, and about 6 percent of estimates are below one. The higher mean than median indicates a right-skewed distribution. These are model-based estimates from the value-added specification: their levels should not be treated as directly observed price-cost ratios or converted into statements about pure profits. The mean changes only slightly, to 1.380, when the tails are winsorized at the 1st and 99th percentiles, suggesting that the overall average is not explained solely by the most extreme observations.

The annual pattern shows a decline followed by a recovery rather than a continuous increase. Mean markups move from 1.391 in 2015 to a minimum of 1.322 in 2020, before rising to 1.458 in 2024. The endpoint change amounts to approximately 4.8 percent of the initial markup ratio. The median also increases over the full period, from 1.332 to 1.385, although the gap between mean and median widens in 2022, when dispersion is highest. Among the 216 firms observed in every year, the mean rises from 1.397 to 1.516. The recovery therefore also appears among continuing sample firms, but this selected subset cannot eliminate concerns about survival and composition.

Sectoral differences are substantial. Among sectors with broader sample coverage, chemicals have a mean markup of 1.781 and other non-metallic mineral products 1.625, compared with 1.233 for fabricated metal products. Estimated markups are also positively associated with log labor productivity, measured from value added per employee and centered within sector and year. The correlation is 0.384, and average markups rise from 1.251 in the lowest relative-productivity quintile to 1.624 in the highest. This association is compatible with differences in efficiency and product differentiation, but it does not identify their effects. Value added enters both the productivity measure and the markup

calculation, creating a shared accounting component. The results therefore do not establish the reallocation mechanism associated with superstar firms.

The comparison with Banca d'Italia is most informative about heterogeneity and the absence of an uninterrupted increase. In the common observation window, 2015-2018, the Ligurian mean falls from 1.391 to 1.355. This is compatible with the national study's picture of limited aggregate movements, without establishing identical regional and national trajectories. The subsequent regional recovery lies outside that study's period. Moreover, the national production-function benchmark uses gross output and a variable-cost bundle, whereas this thesis uses value added and personnel cost; aggregation weights also differ. A numerical gap between their estimates cannot, by itself, establish a regional premium in market power.

Several limitations constrain the interpretation. The panel is unbalanced, excludes observations below 15 employees, and derives from an extract of firms classified as active in June 2026. Earlier exits may therefore be under-represented, and changes in the annual sample can reflect missing data or movement across the employment threshold as well as economic entry and exit. Many sector-year cells contain few observations, making some comparisons sensitive to individual firms. The results cannot be generalized to all Ligurian enterprises, especially microenterprises and services, and their unweighted averages do not track an economically weighted regional aggregate.

Measurement and identification impose further limits. Centering nominal accounting variables within sector and year removes common log levels but is not a genuine price deflator; firm-specific prices, quality, and input-price differences remain. Personnel expenditure combines employment, hours, wages, and workforce composition, and its use as a flexible input requires assumptions about labor adjustment. The proxy estimator also relies on restrictions on productivity and the timing of input decisions. Although the translog permits heterogeneous elasticities, its coefficients are pooled across manufacturing industries. These restrictions, and the distinction between value-added and gross-output measures, make estimated levels dependent on the chosen specification.

Finally, the descriptive comparisons do not identify the causes of the changes observed around the pandemic or subsequent cost disturbances. The analysis does not estimate demand, define antitrust markets, measure pure profits, or calculate consumer welfare. Annual and sector summaries are reported as point estimates without confidence intervals, so their differences should not be presented as established statistical effects. Comparisons with alternative inputs and functional forms, suitable price indices, sales weights, and uncertainty estimates would help assess robustness. The evidence supports a finding of heterogeneous estimated markups and a recent recovery in the selected manufacturing sample, while leaving open whether these movements reflect changes in competition, costs, demand, or measurement.

The thesis proceeds as follows: Chapter 2 develops the theoretical relationship between competition, market power, and markups. Chapter 3 presents the production-function approach and alternative functional forms. Chapters 4 and 5 review the US and Italian evidence, respectively. Chapter 6 explains the data construction and econometric implementation in Stata. Chapter 7 presents the Ligurian results, their comparison with previous studies, and their limitations. Chapter 8 concludes with the implications for interpreting markups and for further research.

II. Theoretical Foundations of Market Power and Competition

II.1 Competition, Market Power and Markups

Competition is one of the central concepts in economic theory. In its most general meaning, competition refers to the process through which firms interact in markets by setting prices, choosing quantities, improving quality, innovating, and attempting to attract consumers. A competitive market structure is usually associated with efficient allocation of resources, lower prices, higher product quality, and stronger incentives for firms to improve productivity. The benchmark model is perfect competition. In a perfectly competitive market, firms are price takers: each individual producer is too small to influence the market price. Products are homogeneous, information is complete, entry and exit are free, and

firms maximize profits subject to the available technology. Under these conditions, firms produce up to the point where price equals marginal cost:

$$P = MC$$

This condition is central because it implies allocative efficiency. If price equals marginal cost, the value consumers attach to the last unit produced equals the cost of producing it. No mutually beneficial reallocation remains possible. However, perfect competition is a theoretical benchmark rather than a complete description of most real-world markets. Firms often sell differentiated products, face entry barriers, possess technological advantages, or operate in markets where strategic interaction matters. In these situations, firms may acquire market power. Departures from this competitive benchmark give rise to market power, which can be defined as the ability of a firm to set prices above marginal cost. A firm with market power is not simply a passive price taker; rather, it has some discretion over its pricing decisions. The degree of market power depends on several factors, including the elasticity of demand, the number and strength of competitors, product differentiation, barriers to entry, economies of scale, and consumer switching costs.

The theoretical opposite of perfect competition is monopoly. A monopolist faces the entire market demand curve and chooses the level of output that maximizes profits. Since the monopolist recognizes that selling more units requires lowering the price, the profit-maximizing price is above marginal cost. This creates a wedge between what consumers pay and what it costs to produce an additional unit. Between perfect competition and monopoly there are several intermediate market structures. In oligopolistic markets, a small number of firms compete strategically. In monopolistic competition, many firms compete but sell differentiated products. In both cases, firms may possess some degree of market power, even if they do not behave as pure monopolists. Therefore, market power should not be understood only as the existence of a monopoly. It may also emerge in markets with

several firms if products are differentiated, entry is difficult, or consumers face switching costs.

This pricing discretion can be summarized by the markup, one of the most direct measures of market power. It is defined as the ratio between price and marginal cost:

$$\mu = P/MC$$

where μ is the markup, P is the price, and MC is marginal cost.

Under perfect competition, price equals marginal cost and the markup is equal to one:

$$\mu = 1$$

When firms possess market power, price exceeds marginal cost and the markup is greater than one:

$$\mu > 1$$

The markup therefore measures the wedge between the price charged to consumers and the cost of producing an additional unit. A higher markup indicates that the firm is able to charge a price further above marginal cost, which suggests stronger pricing power.

The markup is particularly relevant because it provides a firm-level measure of competition. Traditional measures such as concentration ratios or the Herfindahl-Hirschman Index focus on market structure, while markups focus directly on pricing behavior. A market may be concentrated but still competitive if firms compete

aggressively; conversely, a market may contain many firms but still allow high markups if products are strongly differentiated or consumers face switching costs.

A closely related measure is the Lerner Index, defined as:

$$L = (P - MC)/P$$

The Lerner Index measures the proportional difference between price and marginal cost. It ranges from zero under perfect competition to higher values when firms have greater market power. If $P = MC$, then $L = 0$. If price is substantially higher than marginal cost, the index increases.

The Lerner Index is directly related to the markup. Since

$$\mu = P/MC$$

the Lerner Index can also be written as:

$$L = 1 - 1/\mu$$

This relationship shows that the markup and the Lerner Index capture the same underlying concept: the ability of firms to price above marginal cost. In standard monopoly theory, the Lerner Index is also related to the price elasticity of demand. A profit-maximizing monopolist facing demand elasticity ϵ sets price according to the inverse elasticity rule:

$$L = 1/|\epsilon|$$

Here $|\epsilon|$ denotes the absolute value of the price elasticity of demand. This expression shows that market power is limited by demand elasticity. When demand is very elastic, consumers

respond strongly to price increases, and the firm cannot charge a large markup. When demand is inelastic, consumers are less responsive, and the firm can sustain higher prices above marginal cost.

II.2 Market Structures and Sources of Market Power

Different market structures imply different degrees of pricing power. In perfect competition, the individual firm faces a perfectly elastic demand curve and has no pricing power. Any attempt to raise price above the market price would cause consumers to switch to competitors. In monopoly, the firm faces the market demand curve and chooses the price-output combination that maximizes profits. The monopolist restricts output relative to the competitive level and charges a price above marginal cost.

In oligopoly, pricing power depends on the nature of strategic interaction. If firms compete *à la Cournot*, each firm chooses quantities while considering the output decisions of rivals. If firms compete *à la Bertrand*, each firm chooses prices. When products are homogeneous and firms compete in prices, competition can be intense even with few firms. However, if products are differentiated, firms retain some pricing power because consumers do not view all products as perfect substitutes. In monopolistic competition, firms sell differentiated products and each firm faces a downward-sloping demand curve. Even though entry may reduce profits in the long run, firms can still charge prices above marginal cost because product differentiation weakens direct price competition. This theoretical framework shows that market power does not depend only on the number of firms. It also depends on how firms compete, how consumers perceive products, and how easy it is for new firms to enter the market.

Across these market structures, pricing power becomes persistent when competitive pressure is limited. One of the main sources of persistent market power is the presence of barriers to entry. If new firms can freely enter a market, high profits attract entrants, which increases supply and reduces prices. If entry is difficult, incumbent firms may sustain high markups for longer periods. Barriers to entry can take several forms. Legal barriers include patents, licenses, regulation, and exclusive rights. Technological barriers arise when

production requires large fixed costs, specialized knowledge, or access to advanced technologies. Strategic barriers may be created by incumbent firms through advertising, exclusive contracts, control of distribution networks, or acquisitions of potential competitors. Economies of scale are another important source of market power. If average costs decline with firm size, large firms can produce at lower cost than potential entrants. This may generate natural monopoly tendencies, especially in sectors with high fixed costs and low marginal costs. In digital markets, network effects are particularly important. A product or platform becomes more valuable when more users adopt it. As a result, early advantages may become self-reinforcing. Once a platform reaches a dominant position, new entrants may find it difficult to attract users, even if they offer similar or better services.

Entry barriers are only part of the explanation. Product differentiation is another key source of market power. Firms can differentiate their products through quality, branding, design, location, customer service, technology, or reputation. When products are differentiated, consumers do not treat them as perfect substitutes. This allows firms to raise prices without losing all demand. The strength of market power depends on the elasticity of residual demand faced by the firm. If consumers can easily switch to close substitutes, demand is elastic and the firm's markup is limited. If consumers are loyal to a brand or face high switching costs, demand is less elastic and markups can be higher. Product differentiation is therefore central to understanding why firms may possess market power even in markets with many competitors. A restaurant, a clothing brand, a software platform, or a professional service provider may face many rivals, yet still retain pricing power because its product or service is not perceived as identical to others.

II.3 Dynamic Competition and Welfare

The relationship between market power and innovation is complex. Static theory often emphasizes the inefficiency generated by markups, because prices above marginal cost reduce output and consumer welfare. However, dynamic theories recognize that temporary market power may provide incentives for innovation. Firms invest in research, development, branding, and new technologies because they expect to earn profits from

successful innovation. If competition immediately eliminated all profits, firms might have weaker incentives to innovate. From this perspective, some degree of market power may be compatible with dynamic efficiency. This argument is associated with Schumpeterian competition. In Schumpeter's view, competition is not only price competition among existing firms, but also a process of creative destruction in which new technologies replace old ones. Firms innovate in order to gain temporary monopoly power, but that power is eventually challenged by new innovators. Nevertheless, market power may also reduce innovation if dominant firms become protected from competition. Once firms acquire a strong position, they may prefer to defend existing rents rather than innovate. They may also acquire potential competitors, create entry barriers, or use their control over data and networks to prevent disruption. Therefore, the welfare interpretation of markups depends on their source. High markups may reflect successful innovation and superior products, but they may also reflect weak competition, entry barriers, or rent extraction. These dynamic considerations do not remove the static welfare costs of market power. Market power has important welfare implications. The most direct effect is allocative inefficiency. When firms set prices above marginal costs, output is lower than the socially efficient level. Some consumers who value the good above its marginal cost but below the monopoly price are excluded from the market. This creates a deadweight loss.

Market power also redistributes surplus from consumers to firms. Higher prices reduce consumer surplus and increase producer surplus. If the additional producer surplus reflects economic rents rather than productive efficiency, market power may worsen inequality. Moreover, market power can affect input markets. If firms reduce output because of high markups, they may demand fewer inputs, including labor. This can reduce employment and weaken wage growth. In this sense, product-market power may have consequences for the labor market and income distribution. Market power may also reduce aggregate productivity if it protects inefficient firms or limits the entry of more productive competitors. Conversely, if high-markup firms are highly productive, market power may coexist with high measured productivity. The central issue is whether productivity gains are passed on to consumers and workers or captured primarily as profits.

II.4 Interpreting Markups alongside Profits and Concentration

Interpreting these welfare effects requires distinguishing markups from profits. Although markups are closely related to market power, they are not identical to profits. A firm may charge a high markup because it has high fixed costs. In this case, the markup may be necessary to cover overhead, research and development, advertising, or capital expenditures. Therefore, a high markup does not always imply excessive profits. For this reason, markup analysis should be combined with evidence on profitability, cost structure, investment, and market dynamics. If markups rise together with profit rates, this provides stronger evidence of increasing market power. If markups rise only because fixed costs rise, the interpretation is more ambiguous. This distinction is particularly important in modern industries with high fixed costs and low marginal costs, such as digital services, pharmaceuticals, and software. In these sectors, marginal costs may be very low, so markups can be high even when firms need to recover large upfront investments. Therefore, markups are best understood as an indicator of pricing power, while their welfare interpretation requires additional economic analysis.

The same caution applies when markups are compared with concentration measures such as the concentration ratio or the Herfindahl-Hirschman Index. These measures capture the distribution of market shares among firms. A highly concentrated market is one in which a small number of firms account for a large share of sales. However, concentration and market power are not the same. A concentrated market may still be competitive if firms compete aggressively. Similarly, a fragmented market may still display high markups if products are highly differentiated or consumers face switching costs.

Markups provide a complementary measure because they focus directly on the price-cost wedge. While concentration describes market structure, markups describe pricing outcomes. A complete analysis of competition should therefore consider both dimensions. This distinction is especially relevant when comparing countries or sectors. Differences in market definition, product differentiation, and data availability can make concentration measures difficult to interpret. Markups, by focusing on firm behavior, offer a more direct

measure of market power, although they also present measurement challenges because marginal costs are not directly observed.

Taken together, this theoretical framework establishes why markups are useful for studying competition. A markup above one indicates that firms price above marginal cost, which is the defining feature of market power. The markup therefore provides a bridge between microeconomic theory and empirical analysis. At the same time, markups must be interpreted carefully. High markups may reflect market power, but they may also arise from innovation, fixed costs, product quality, or technological differences. For this reason, the empirical analysis of markups must be complemented by evidence on profitability, firm size, sectoral heterogeneity, productivity, and reallocation.

The following chapters build on this theoretical foundation. The empirical evidence from the United States shows how rising markups may be associated with superstar firms, increasing profits, and declining labor shares. The Italian evidence provides a contrasting case in which markups appear more stable and sectorally heterogeneous. Together, these cases illustrate the importance of studying markups not as isolated numerical indicators, but as part of a broader analysis of competition, market structure, and economic performance.

III. Methodologies for Measuring Markups

The empirical estimation of markups is one of the main challenges in industrial organization and applied microeconomics because marginal costs are generally not observed. Three broad approaches dominate the literature. Accounting methods infer margins from financial statements, but accounting costs need not coincide with marginal costs. Demand-system methods derive markups from estimated price elasticities and assumptions about firms' strategic interaction, which requires detailed market-level information. This thesis follows the third approach, production-function estimation. The method developed by De Loecker and Warzynski is especially useful because it recovers

firm-level markups from production data and firms' cost-minimization conditions without imposing a specific model of product-market conduct.

III.1 The Production-function Approach to Markup Estimation

The De Loecker-Warzynski methodology relies on firms' first-order conditions for variable input demand. Under cost minimization, the markup can be expressed as:

$$\mu_{it} = \theta_{it}^X (\alpha_{it}^X)^{-1}$$

where θ_{it}^X denotes the output elasticity of the selected variable input and α_{it}^X denotes the expenditure share of that input in total revenue. Operationally, the method requires estimating the production function, recovering the relevant output elasticity, and measuring the firm-level expenditure share. Its main advantage is that it does not require an explicit assumption about the form of product-market competition.

Production-function estimation is complicated by simultaneity and endogeneity because firms choose inputs after observing information about their own productivity. The Olley-Pakes (1996) estimator addresses this problem by using investment as a proxy for unobserved productivity. Under the assumption that investment rises monotonically with productivity, the investment rule can be inverted to recover the unobserved component. Controlling for that component reduces the bias caused by the correlation between input choices and productivity, although the method can be difficult to apply when investment is zero or lumpy.

The Levinsohn-Petrin (2003) estimator addresses simultaneity and endogeneity by using intermediate inputs, such as materials or energy, as a proxy for unobserved productivity. The idea is that firms adjust their use of intermediate inputs after observing productivity shocks, so these inputs contain information about the firm's productivity level.

Unlike investment, intermediate inputs are usually positive and vary more smoothly over time. By recovering productivity through intermediate input demand, the estimator controls for the correlation between input choices and unobserved productivity, reducing the bias that would affect ordinary least squares estimation.

The Akerberg-Caves-Frazer (2015) estimator addresses simultaneity and endogeneity by extending the control-function approach used by Olley-Pakes and Levinsohn-Petrin. Its main contribution is to solve the identification problem that arises when labor and intermediate inputs are chosen simultaneously. Instead of identifying labor in the first stage, ACF estimates a first-stage function that absorbs unobserved productivity, and then identifies the production-function parameters in a second stage using assumptions on the timing of input choices and the law of motion of productivity. In this way, the estimator controls for the correlation between input choices and productivity shocks while improving the identification of input elasticities.

The Wooldridge system-GMM approach addresses simultaneity and endogeneity by reformulating the control-function method as a single-step generalized method of moments estimation. Instead of estimating the production function in separate stages, it uses moment conditions and lagged input variables as instruments for potentially endogenous inputs. This allows the estimator to control for the correlation between input choices and unobserved productivity shocks. Compared with earlier proxy-variable estimators, the Wooldridge approach improves efficiency and makes statistical inference more straightforward because the parameters are estimated within one unified GMM framework.

III.2 Cobb-Douglas and Translog Specifications

In production-function estimation, the choice of the functional form determines how the relationship between inputs and output is represented. This is particularly important in the estimation of markups because markups are obtained from the comparison between an input's output elasticity and its expenditure share. Therefore, the way in which output elasticities are modeled directly affects the resulting measure of market power.

The Cobb-Douglas production function is one of the most commonly used specifications. In its basic form, it can be written as:

$$Q_{it} = A_{it} L_{it}^{\beta_l} K_{it}^{\beta_k} M_{it}^{\beta_m}$$

where Q_{it} is output, L_{it} is labor, K_{it} is capital, M_{it} represents intermediate inputs, and A_{it} captures firm-level productivity. In logarithmic form, the same function becomes:

$$q_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \omega_{it} + \varepsilon_{it}$$

The main advantage of the Cobb-Douglas specification is its simplicity. The coefficients are directly interpreted as output elasticities. For example, β_l measures the percentage change in output associated with a one percent increase in labor. However, this specification imposes strong restrictions. In particular, output elasticities are assumed to be constant across firms and over time. This means that all firms are assumed to share the same production technology, regardless of differences in size, sector, organization, or input intensity.

This assumption can be restrictive in empirical studies of market power. If firms differ substantially in their production technologies, a Cobb-Douglas specification may attribute technological differences to differences in markups. Since the output elasticity is constant, variation in estimated markups mainly comes from variation in input expenditure shares.

The translog production function provides a more flexible alternative. It extends the Cobb-Douglas specification by including squared terms and interaction terms among inputs. A simplified translog specification can be written as:

$$\begin{aligned} q_{it} = & \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} \\ & + \beta_{ll} l_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{mm} m_{it}^2 \\ & + \beta_{lk} l_{it} k_{it} + \beta_{lm} l_{it} m_{it} + \beta_{km} k_{it} m_{it} \\ & + \omega_{it} + \varepsilon_{it} \end{aligned}$$

Unlike the Cobb-Douglas function, the translog specification allows output elasticities to vary across firms and over time. For example, the output elasticity of labor depends not

only on the labor coefficient itself, but also on the firm's use of capital and intermediate inputs. This makes the translog function more suitable when firms are heterogeneous and when the relationship between inputs and output is not constant across producers.

The choice between Cobb-Douglas and translog therefore reflects a trade-off between simplicity and flexibility. Cobb-Douglas provides a clear and easily interpretable framework, but it imposes restrictive assumptions on technology. Translog is more flexible and better suited to capture heterogeneous production technologies, but it requires more parameters and greater data richness. In the context of markup estimation, this distinction is crucial because the estimated output elasticities form the basis for measuring the wedge between prices and marginal costs.

IV. Evidence of Market Power in the United States

The United States is central to the debate on the evolution of market power because evidence of rising markups has emerged alongside increasing concentration, higher profitability, and a declining labor share. These developments have encouraged the view that successful firms capture a growing share of economic income. However, the empirical literature also shows that these indicators answer different questions. Concentration describes the distribution of activity across firms; a markup measures the wedge between price and marginal cost; economic profits measure income remaining after all production costs, including the required return on capital. Their joint evolution is informative, but none establishes the causes or welfare consequences of changing competition on its own.

This chapter examines the aggregate evidence developed by De Loecker, Eeckhout and Unger (2020) alongside six complementary contributions. Autor et al. (2020) connect concentration and labor shares through the growth of superstar firms; Barkai (2020) separates economic profits from capital income; and Covarrubias, Gutiérrez and Philippon (2020) investigate whether concentration reflects efficiency or barriers to competition. Basu

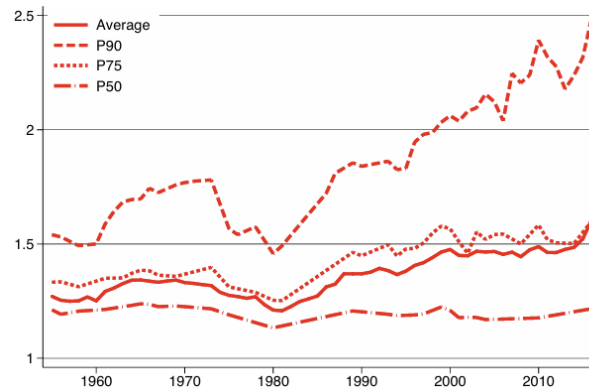
(2019) assesses the measurement assumptions underlying aggregate markup estimates. Demand-based evidence from Döpper et al. (2025) and Grieco, Murry and Yurukoglu (2024) then shows how markup trends differ across product markets. Together, these studies support an interpretation of US market power that takes firm heterogeneity, technology, and measurement seriously.

IV.1 The Rise and Reallocation of Markups

De Loecker, Eeckhout and Unger (2020) provide an influential account of rising markups using financial statements for publicly traded firms. Their production-function approach recovers output elasticities and compares them with expenditure shares, following the cost-minimization logic discussed in Chapter 3. In their baseline estimates, the sales-weighted average price-to-marginal-cost ratio rises from approximately 1.21 in 1980 to 1.61 in 2016. Prices therefore move from around 21 percent to around 61 percent above estimated marginal cost. These figures concern their particular sample and specification; they should not be read as directly observed margins for every firm operating in the United States.

The distribution behind the average is essential to understanding this result. As illustrated in Graph IV.1, the rise is concentrated toward the upper end of the markup distribution, while the median changes relatively little. A higher aggregate markup consequently need not describe the experience of the typical firm. Many firms may continue to operate with relatively narrow price-cost wedges while a smaller group accounts for a growing share of high-markup activity. This distinction also explains why comparisons based only on an unweighted firm average can differ from those based on the economic importance of firms.

Graph IV.1: Percentiles markup distribution



Source: De Loecker, Eeckhout and Unger (2020).

The aggregate trend reflects both changes in firms' own markups and changes in their sales weights. When a firm with an above-average markup expands, the sales-weighted average increases even if its markup remains unchanged. Conversely, a rise in an individual firm's markup has little effect on the aggregate when that firm accounts for few sales. De Loecker, Eeckhout and Unger (2020) emphasize reallocation toward high-markup firms as a major contributor to the increase. Their findings therefore concern the changing distribution of economic activity as well as pricing behavior within firms.

Autor, Dorn, Katz, Patterson and Van Reenen (2020) develop this mechanism through the superstar-firm hypothesis. Their principal US evidence uses the Economic Census from 1982 to 2012 and covers manufacturing, retail trade, wholesale trade, services, utilities and transportation, and finance. Coverage of the latter two sectors starts in 1992. The establishments represented account for approximately 80 percent of US employment and GDP. The authors construct consistent industry classifications and link establishments belonging to the same firm, allowing them to examine concentration and factor shares beyond the publicly listed companies available in financial databases (Autor et al., 2020, pp. 657-658).

In their framework, differences in productivity or product quality become more consequential for market shares. Firms with superior products or lower costs expand disproportionately, so sales become concentrated in a smaller number of successful

producers. These firms can charge lower prices than less efficient competitors while retaining higher markups because their marginal costs are lower. Large investments in software, organizational capabilities, and other scalable assets can reinforce this advantage. The label superstar therefore refers to a combination of scale and economic performance; it does not by itself establish that a firm's position results from exclusionary conduct.

The connection to labor income follows from differences in firms' labor shares. Under cost minimization, competitive input markets, and a variable labor input, the labor expenditure share is related to the output elasticity of labor divided by the markup. Holding that elasticity fixed, a higher markup implies a lower labor share. Fixed labor requirements can also make labor shares lower at larger firms because overhead costs are spread over more output. When activity shifts toward firms with low labor shares, the aggregate labor share falls even if the labor share of the average firm changes little. The relevant weights depend on the denominator: a labor share measured against value added aggregates using value-added weights, while a payroll-to-sales ratio uses sales weights.

Autor et al. (2020) find evidence consistent with this mechanism. Sales concentration rises across a broad range of industries, and industries with larger increases in concentration experience larger declines in labor shares. A substantial part of the aggregate decline comes from reallocation between firms. The unweighted mean labor share changes relatively little in manufacturing and rises in much of non-manufacturing, even as activity shifts toward firms with lower shares. Their markup results likewise show a larger increase in size-weighted measures than in unweighted firm averages. Outside manufacturing, limited information on intermediate inputs means that payroll relative to sales plays an important role, so the empirical measures are not identical across sectors.

An especially important finding is that concentrating industries also tend to exhibit faster productivity growth and innovation. Autor et al. (2020) interpret this as evidence that technological dynamism contributes to the growth of superstar firms. Their model can generate greater concentration when competition becomes more demanding: stronger selection reallocates activity toward efficient producers. Thus, rising concentration and a falling aggregate labor share can coexist with efficiency gains. The evidence supports the

reallocation mechanism but does not provide a definitive causal test of the technological explanation, as the authors explicitly acknowledge (Autor et al., 2020, pp. 703-704).

This qualification changes the interpretation of the US evidence. The expansion of highly productive firms is not sufficient to conclude that competition has weakened. At the same time, an initially efficient firm may subsequently use its position to impede entry or protect rents, a possibility that Autor et al. (2020) do not rule out. Jan Eeckhout's *The Profit Paradox* (2021) emphasizes the broader concern that corporate success can coexist with weaker outcomes for workers and consumers. Establishing when this concern applies requires evidence on profits, investment, and the ability of other firms to challenge incumbents, in addition to the distribution of markups.

IV.2 Profits, Labor Share and Business Dynamism

Profitability provides a complementary test because high markups do not necessarily translate into high economic profits. The difference between price and marginal cost must also finance fixed costs, overheads, and investments whose benefits extend beyond current production. De Loecker, Eeckhout and Unger (2020) address this issue by examining profitability as well as markups, and report rising profit rates alongside their markup estimates. This strengthens the interpretation that the increase is not entirely absorbed by overhead expenses. Nevertheless, the distinction between accounting income, compensation for capital, and pure profits remains crucial for assessing the magnitude of economic rents.

Barkai (2020) makes this distinction the focus of his analysis of the US non-financial corporate sector from 1984 to 2014. A conventional division of value added into labor and non-labor income assigns all income remaining after labor compensation to capital. This procedure combines the cost of using capital with any profits earned beyond that cost. Barkai instead estimates capital costs directly, multiplying the value of each type of capital by its required rate of return. This user cost incorporates financing costs, depreciation, expected changes in capital prices, and taxation. Pure profits are the residual after

subtracting labor compensation, estimated capital costs, and net taxes on production and imports from gross value added.

The central finding is that the decline in labor's share (see Graph IV.2) is accompanied by a decline in the capital-cost share. In the main specification, the fitted labor share falls by about 11 % and the capital share by about 22 % over 1984-2014. These are proportional changes in the shares, not percentage-point declines. The fitted pure-profit share rises by 13.5 percentage points of gross value added. That figure is a change in the share of income assigned to pure profits; it is neither a markup nor the level of the profit share in 2014 (Barkai, 2020, Table I). The results challenge explanations in which the observed decline in labor's share is simply offset by greater expenditure on capital inputs.

Barkai's explanation depends partly on the substantial fall in the required return on capital. Although cheaper capital could encourage firms to accumulate enough additional assets to increase total capital costs, the measured expansion of the capital stock does not offset the decline in its user cost. Both measured factor-cost shares consequently fall, leaving a larger residual. This is consistent with firms retaining a growing share of value added as economic rents. It also explains why treating all non-labor income as remuneration for productive capital can conceal a change in the distribution of income between production costs and profits.

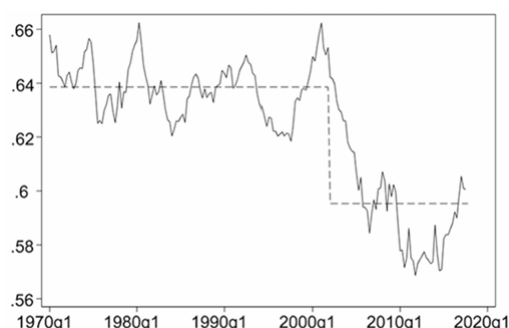
The treatment of intangible capital is a central robustness issue. If productive assets are omitted, their required remuneration can be incorrectly counted as pure profits. Barkai (2020) incorporates existing estimates of omitted intangibles and examines alternative assumptions about investment, depreciation, and capital-price changes. These exercises do not eliminate the rise in pure profits; scenarios that explain most of it require very large stocks of missing capital. This provides evidence against omitted intangibles as a complete explanation within the scenarios considered. It does not make the residual directly observable: its level and trend remain conditional on the measurement of assets and required returns.

At the industry level, Barkai (2020) also finds that increases in concentration are associated with larger reductions in the labor share. This complements Autor et al.'s evidence,

although the papers emphasize different aspects of the same broad pattern. Autor et al. examine which firms receive a larger weight in aggregate activity, while Barkai asks how value added is divided after the cost of capital has been estimated. The concentration regressions establish an association rather than an exogenous effect of weaker competition. Moreover, lower labor shares can coexist with rising wages if value added grows faster than compensation, and product-market markups do not directly measure employers' wage-setting power.

Covarrubias, Gutiérrez and Philippon (2020) extend the analysis to the joint behavior of concentration, productivity, prices, investment, and firm dynamics. Their distinction between good and bad concentration separates two broad mechanisms. Concentration can increase because efficient firms expand through lower costs, better technology, or stronger economies of scale. Alternatively, it can increase because barriers to competition protect incumbent firms. The authors combine Economic Census concentration measures, corporate financial data, and industry and aggregate statistics to assess which mechanism better matches different periods and industries. Their objective is to evaluate several observable implications together, rather than infer competition from concentration alone.

Graph IV.2: labor share



Source: Covarrubias, Gutiérrez and Philippon (2020)

The distinction has testable consequences. An expansion driven by productive efficiency should tend to associate concentration with higher productivity and lower prices. It should also generate investment consistent with firms' growth opportunities, especially among

industry leaders. By contrast, entrenched positions can sustain high profits without a comparable expansion of productive capacity. Covarrubias, Gutiérrez and Philippon (2020) therefore examine investment relative to Tobin's Q, which relates firms' market valuation to the replacement cost of their capital. Weak investment despite high valuations can indicate that the value of incumbents reflects protected rents rather than profitable opportunities to expand production.

Their evidence supports efficiency-related concentration during the 1990s, when concentration is associated with productivity growth, declining prices, and strong investment, including investment in intangibles. After 2000, these relationships change: concentration growth is associated with weaker productivity growth and stronger price growth, investment relative to Q declines, and incumbents' market shares become more persistent. They also report that entry becomes much less responsive to Q after the late 1990s, while exit rates remain broadly stable. This pattern is more consistent with reduced competitive pressure than with concentration driven principally by the exit of inefficient firms (Covarrubias, Gutiérrez and Philippon, 2020, pp. 4-6 and 20-22).

The authors further use principal components analysis to summarize industry differences. Computer manufacturing is strongly associated with the efficiency-related component, while telecommunications, banking, and airlines are more closely associated with the component interpreted as barriers to competition. Some industries exhibit both characteristics: intangible assets can support productivity and also make entry more difficult. The classification is useful for organizing a large set of correlations, but the statistical components do not constitute independent causal identification of entry barriers. The paper's interpretation rests on the joint consistency of the observed patterns with its theoretical predictions.

This account qualifies the technological interpretation of superstar firms without removing its relevance. Differences in time periods, industry coverage, and measures can explain part of the contrast between Autor et al. (2020) and Covarrubias, Gutiérrez and Philippon (2020). A positive relationship between concentration and productivity over a longer interval need not characterize the period after 2000. The papers also differ in their

interpretation of international comparisons, so they do not establish a single harmonized account of US exceptionalism. For the purposes of this thesis, their common implication is that the competitive significance of concentration depends on what happens to productivity, prices, investment, and entry at the same time.

IV.3 Interpretation and Measurement Debate

The preceding findings depend on quantities that are difficult to observe, particularly marginal costs and the required remuneration of capital. Basu (2019) organizes the measurement debate around three approaches: inferring markups from profits under assumptions about returns to scale, estimating production relationships using multiple inputs, and recovering markups from the cost-minimization condition for a single input. All exploit firms' input decisions, but they require different assumptions about technology, factor costs, utilization, and aggregation. His review assesses the evidence available in 2019; it provides a framework for evaluating subsequent studies rather than a direct assessment of the later product-market papers discussed below.

Basu's critique focuses partly on the consistency between microeconomic estimates and aggregate income accounts. Very high markups must be reconciled with the remuneration of labor and capital, the scale properties of production, and the measured importance of pure profits. He argues that some large estimates imply implausible aggregate outcomes under the assumptions used to interpret them. However, heterogeneity matters for this comparison: an arithmetic average of firm markups cannot automatically be treated as the markup of a representative firm. Basu (2019) explicitly calls for checks at the firm level, where the relationships among markups, elasticities, and factor shares can be examined consistently.

Accounting classifications create another difficulty. Cost of goods sold and selling, general and administrative expenses do not necessarily correspond to stable economic categories of variable and fixed inputs. If similar activities move between these accounting categories over time, a falling measured input share can appear as a rising markup even without a corresponding change in pricing power. Basu (2019) consequently stresses the

importance of consistently defined input measures and of checking how estimated elasticities respond to the treatment of overheads. The cost-minimization formula alone cannot establish that a particular accounting expenditure is an appropriate empirical input.

The denominator of output also matters. A gross-output markup and a value-added markup are different objects when production uses intermediate inputs; converting between them requires information about those inputs and the production structure. Basu's aggregate illustration, based on changes in intermediate-input shares, implies a much smaller increase in markups than the most prominent firm-level estimates. He presents this as suggestive because it assumes a constant average output elasticity and a stable covariance between firm markups and input shares. His overall conclusion is that the evidence available at the time cannot reliably distinguish stable markups from a modest increase. A modest increase could still have substantial consequences for factor shares; rejecting a very large increase does not imply that market power is economically irrelevant.

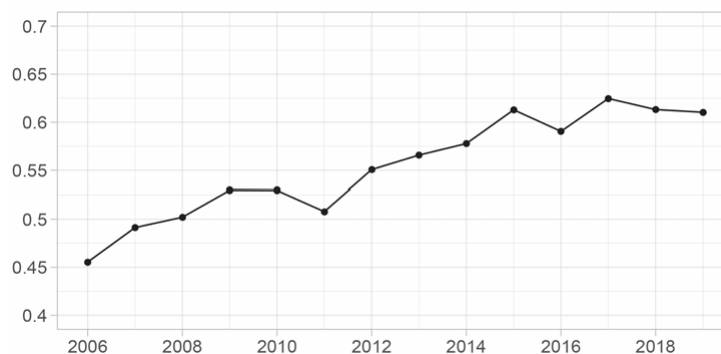
Demand-based studies offer a different way to investigate these issues. They use observed prices, quantities, and consumer choices to estimate substitution patterns, then infer marginal costs from an assumed model of firms' pricing decisions. This avoids the need to recover output elasticities from corporate accounts, but introduces assumptions about demand and strategic conduct. These studies also frequently report the Lerner index, which divides the difference between price and marginal cost by price. The price-to-marginal-cost ratio used elsewhere in this thesis instead divides price by marginal cost. The two measures are related nonlinearly, so their levels and percentage changes cannot be compared directly, and converting an average index need not give the average of the converted firm or product measures.

Döpfer, MacKay, Miller and Stiebale (2025) apply this approach to 133 consumer-product categories in the United States over 2006-2019, including food, household products, and personal-care goods. They combine NielsenIQ retail scanner information with household purchasing and demographic data, estimating separate random-coefficients logit demand models for each category and year. Their 1,862 models allow consumer preferences to change over time. Markups are recovered under Nash-Bertrand price

competition among manufacturers, with retailers assumed to apply passive cost-plus pricing. Under this treatment of the vertical relationship, retail margins form part of the cost faced by manufacturers in selling their products.

The paper finds a broad increase in product-level margins. Its headline trend takes the median Lerner index within each category and year and then averages across categories. This statistic rises from approximately 0.45 in 2006 to around 0.60 toward the end of the sample, an increase the authors summarize as about 30 percent. These numbers are fractions of price, not prices expressed as multiples of marginal cost. The rise extends across the distribution and is driven mainly by changes within products, rather than a shift of purchases toward products that already had higher margins (Döpfer et al., 2025, pp. 2478-2480). The difference from the reallocation emphasis in aggregate firm-level studies concerns both the unit of analysis and the sample period.

Graph IV.3: mean of within-category median markups over time (Lerner index)



Source: Döpfer, MacKay, Miller and Stiebale (2025)

The authors attribute the increase primarily to falling marginal costs and lower consumer price sensitivity. Real prices are only about 2 percent higher in 2019 than in 2006, while estimated marginal costs fall at an average annual rate of approximately 2.1 percent. Product-specific demand elasticities decline in absolute magnitude by about 30 percent. Counterfactual exercises allowing marginal costs and price sensitivity to change, while holding other factors fixed, reproduce much of the estimated markup trend. Changes in

market concentration and observable consumer demographics have less explanatory power for that trend. The deeper cause of declining price sensitivity remains less certain: reduced shopping time and coupon use provide suggestive evidence, rather than a definitive causal explanation (Döpfer et al., 2025, pp. 2465-2466).

Higher margins nevertheless coexist with rising estimated consumer surplus in these markets. Cost reductions and changing preferences can improve consumers' outcomes even while firms retain a larger price-cost wedge. The gains are uneven across income groups, and the authors estimate that consumer surplus would have been 18 percent higher in 2019 under a counterfactual that scales margins back to their 2006 levels. Thus, an improvement relative to the past can coexist with a loss relative to a lower-markup counterfactual. These welfare calculations concern the products covered and remain conditional on the estimated demand system. Likewise, maintaining Nash-Bertrand conduct throughout means that the exercise does not separately identify changes in collusion or other forms of strategic behavior.

Grieco, Murry and Yurukoglu (2024) provide a contrasting result for the US new automobile market between 1980 and 2018. Their demand model combines market shares, prices, and vehicle attributes with household demographics, purchases, and stated second choices. Exchange-rate variation helps identify the response of demand to prices, and marginal costs are recovered assuming Nash-Bertrand pricing by multiproduct manufacturers. The median Lerner index falls from 0.325 in 1980 to 0.185 in 2018, despite an increase in real vehicle prices. The result demonstrates why higher observed prices, particularly for products whose characteristics change substantially, are not sufficient evidence of higher markups (Grieco, Murry and Yurukoglu, 2024, pp. 1201-1203).

Their welfare analysis attributes most of the improvement in consumer outcomes to higher product quality and better production technology. The contribution of expanding import competition and additional vehicle models is smaller in their counterfactual exercises. The share of efficient surplus accruing to consumers rises from 62 percent to 82 percent; efficient surplus here includes consumer surplus, producer surplus, and deadweight loss. Estimated average consumer surplus per household increases by approximately \$8,000 in

2015 dollars over the sample period. These estimates illustrate the importance of accounting for improvements in vehicle characteristics, including attributes that standard product datasets do not directly measure.

The automobile study also compares its results directly with production-based estimates and explains why the methods can disagree. Corporate accounts may combine domestic and foreign sales, financing operations, parts production, and other activities. Samples of listed firms may omit manufacturers that sell in the US market, while accounting costs can mix variable expenses with overheads. Revenue-based output measures and pooled production elasticities introduce additional difficulties. Conversely, the demand approach depends on its specification of consumer substitution and pricing conduct. The authors find declining margins under several conduct assumptions held fixed over time, but do not estimate historical changes in conduct or analyze the adjacent financing, parts, dealership, and labor markets (Grieco, Murry and Yurukoglu, 2024, pp. 1236-1239 and 1249-1250).

The contrast between automobiles and consumer products demonstrates substantial sectoral heterogeneity, rather than a universal US markup trajectory. Autor et al. identify the importance of reallocation, Barkai provides evidence of rising residual profits, and Covarrubias, Gutiérrez and Philippon connect the post-2000 concentration pattern to weaker competitive pressure. Basu shows why the magnitude of aggregate markup growth remains sensitive to measurement. The demand studies then establish that even the sign of the markup trend can differ across markets, and that a welfare assessment requires information about costs, quality, and demand in addition to the price-cost wedge.

These lessons guide the application to Liguria. The US results supply hypotheses about heterogeneity and the relationship between markups, productivity, and firm size, but do not supply a directly comparable numerical benchmark for regional manufacturing firms. The Ligurian estimates use value added and personnel costs, while several US studies use gross revenues or product-level demand data. Sector-year normalization also leaves differences in firm prices, wages, quality, and product mix unresolved. Mean and median markups, differences across sectors, and changes in the composition of the sample must therefore be interpreted together. The evidence reviewed here supports using

estimated markups as one indicator of competitive conditions, with causal and welfare conclusions tied to the additional information that the data can sustain.

V. Evidence of Market Power in Italy

The Italian case provides an important contrast to the evidence on market power in the United States. While the U.S. literature documents a substantial increase in markups since the 1980s, the empirical evidence for Italy points to a more stable and heterogeneous pattern. This difference is relevant because it shows that the evolution of market power cannot be interpreted as a uniform phenomenon across advanced economies. Instead, markup dynamics depend on the structure of the productive system, the composition of firms, sectoral specialization, institutional features, and the data used for estimation.

Italy is particularly interesting because its economy differs significantly from the United States. The Italian productive system is characterized by a strong presence of small and medium-sized enterprises, family-owned firms, local production networks, and marked regional heterogeneity. These features may limit the emergence of very large “superstar firms” comparable to those observed in the United States. At the same time, Italy has long faced structural problems related to low productivity growth, limited firm scaling, weak investment, and territorial disparities. The study of markups therefore provides a useful perspective for understanding whether these weaknesses are associated with insufficient competition, excessive market power, or other structural factors.

The main empirical reference for the Italian case is the Bank of Italy study by Ciapanna, Formai, Linarello and Rovigatti, which examines market power using both macroeconomic and microeconomic data. Their analysis compares Italy with the largest euro area economies and then studies Italian firms using detailed firm-level datasets. The main conclusion is that, unlike in the United States, Italian markups do not display a strong increasing trend. Rather, they remain broadly stable or slightly decreasing over the period considered.

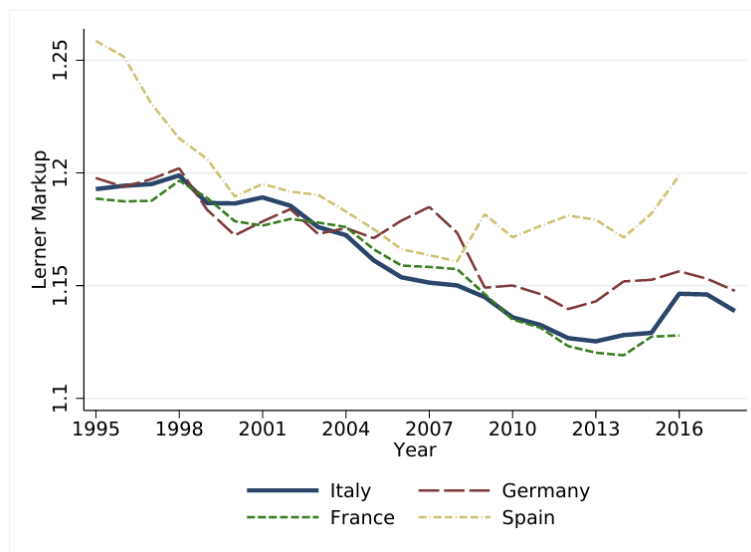
V.1 Productive Structure and the European Context

The interpretation of markup dynamics in Italy requires consideration of the country's productive structure. Italy is dominated by small and medium-sized enterprises, many of which operate in traditional manufacturing sectors, local services, tourism, construction, and specialized industrial districts. Compared with the United States, the Italian economy has fewer very large listed corporations and a more fragmented firm distribution. This structure has ambiguous implications for competition. On one hand, fragmentation may limit the ability of firms to exercise strong market power at the national level. A large number of small firms competing in local or sectoral markets can generate competitive pressure and keep markups relatively low. On the other hand, fragmented markets may also be associated with limited productivity growth, insufficient economies of scale, and difficulties in adopting advanced technologies.

Another distinctive feature of Italy is regional heterogeneity. Productive conditions differ substantially between Northern and Southern regions, as well as across coastal, industrial, rural, and metropolitan areas. Regional specialization affects the nature of competition. For example, manufacturing districts may exhibit strong competition among firms producing similar goods, while some local service sectors may display higher markups due to limited tradability and local market power.

For these reasons, the Italian case cannot be reduced to a simple question of whether markups are high or low. The relevant issue is how market power varies across sectors, firm types, and territories. Against this structural background, the macroeconomic evidence suggests that Italy has not experienced the same rise in markups observed in the United States. Using national accounts data, the Bank of Italy study compares Italy with Germany, France, and Spain over the period 1995–2018. The analysis focuses on industry and market services, excluding financial services and real estate, which are often treated separately because of their specific accounting and regulatory characteristics.

Graph V.1: Country-level markups



Source: National Accounts, Eurostat

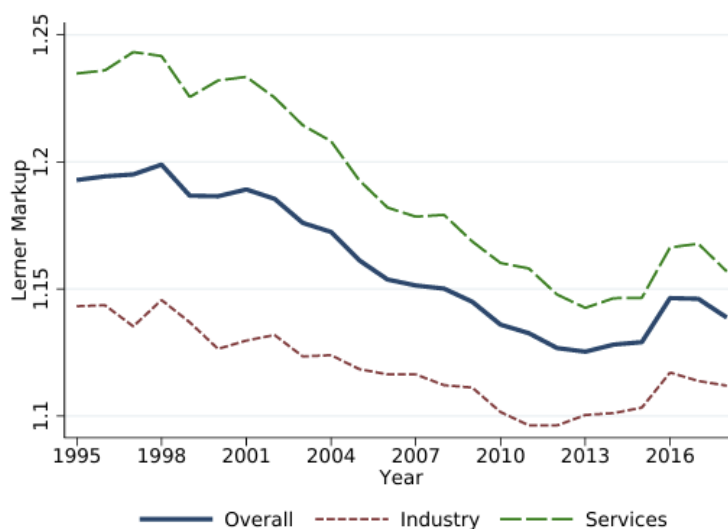
The results show that average markups in Italy are relatively low and stable. Markups computed from macro data settle around 1.1 in Italy, France, and Germany, while Spain displays slightly higher levels, around 1.2. These values are substantially lower than those estimated for the United States in the literature on rising market power.

The Italian evidence therefore suggests that the broad macroeconomic symptoms associated with rising U.S. market power are less pronounced in the euro area. In particular, the Bank of Italy study shows that the main euro area economies do not display a comparable increase in concentration, markups, or profit shares. This does not imply that market power is absent in Italy, but rather that its aggregate dynamics are more limited and less concentrated among dominant firms.

The macro evidence also reveals that markup dynamics differ across sectors. The aggregate series hides considerable heterogeneity between industry and services. Manufacturing sectors generally show lower markups, while services tend to display higher values. This pattern is consistent with the fact that manufactured goods are more exposed to

international competition, while many services are less tradable and more locally segmented.

Graph V.2: Aggregated markups, Italy, 1995-2018



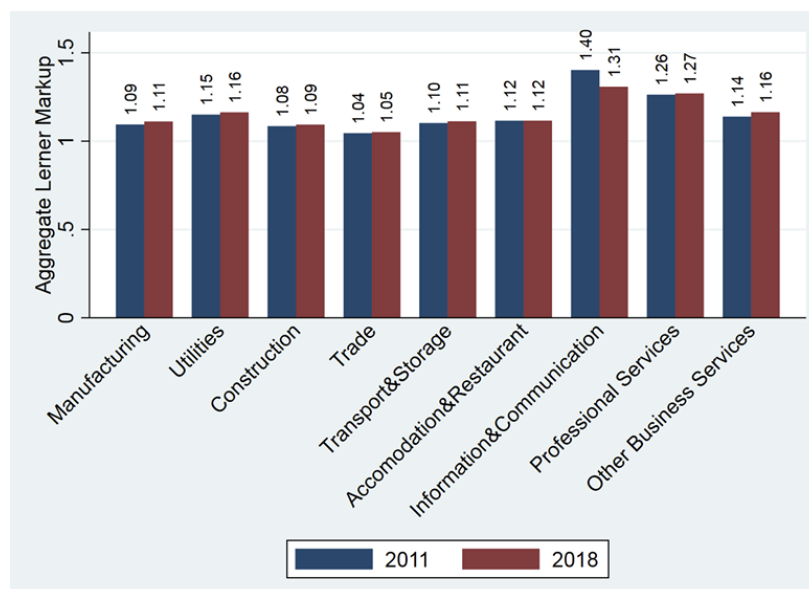
Source: Ciapanna, Formai, Linarello, Rovigatti

V.2 Sectoral and Firm-level Evidence

A central result of the Italian evidence is that aggregate markup stability masks substantial sectoral heterogeneity. Markups differ significantly across industries, both in levels and in dynamics. Services generally exhibit higher markups than manufacturing. Within services, information and communication activities and professional services tend to display relatively high markup levels. These sectors often rely on intangible assets, specialized knowledge, reputation, digital infrastructure, or professional barriers, all of which can support higher pricing power. By contrast, retail trade tends to display lower markup levels and flatter dynamics. This may reflect stronger competitive pressure, lower barriers to entry, and the presence of many firms operating in similar markets. Manufacturing also tends to show lower markups, partly because many manufacturing firms are exposed to

international competition. Export-oriented sectors face pressure from foreign competitors, which limits their ability to raise prices above marginal costs.

Graph V.3: Aggregate markups by sector



Source: Ciapanna, Formai, Linarello, Rovigatti

The presence of sectoral heterogeneity is important for the interpretation of aggregate markup measures. A stable aggregate markup does not imply that all sectors are equally competitive. Some sectors may experience increasing market power, while others may face stronger competition. Therefore, a complete analysis of markups in Italy requires disaggregated evidence at the sectoral and firm level.

Firm-level evidence provides a more detailed view of market power in Italy. The Bank of Italy study relies on two main sources of firm-level data: ASIA-Frame and CERVED. ASIA-Frame is an integrated dataset produced by Istat and covers the universe of Italian firms active for at least six months in a given year. Its main advantage is representativeness: it includes a broad population of firms and therefore avoids the selection problems associated with datasets limited to listed companies. Using this source,

the analysis confirms that Italian markups remained relatively stable in recent years. CERVED data, by contrast, cover limited liability companies and provide richer balance-sheet information. This makes it possible to estimate markups using production-function methods, as in the international literature. Although CERVED covers fewer firms than ASIA-Frame, it is useful because it contains detailed accounting variables such as revenues, labor costs, capital, intermediate inputs, investment, and depreciation. The use of both datasets strengthens the reliability of the Italian evidence. ASIA-Frame provides broad representativeness, while CERVED allows the application of production-function techniques. Across both sources, the main conclusion remains consistent: Italian markups do not show the strong upward dynamics observed in the United States.

These micro data also make it possible to decompose changes in the aggregate markup. In the U.S. literature, a large part of the rise in aggregate markups is explained by reallocation: high-markup firms gain market share, and their growing weight increases the aggregate markup. This mechanism is closely related to the rise of superstar firms.

In Italy, the decomposition results are different. The Bank of Italy study finds that the within-firm component is the most important driver of markup dynamics, while the reallocation component is quantitatively smaller. This means that changes in Italian markups are mainly explained by changes in firms' own pricing behavior rather than by a large shift of market shares toward high-markup firms. This finding is crucial because it suggests that Italy does not exhibit the same superstar-firm dynamics observed in the United States. Larger and more innovative firms may still have higher markups on average, but they do not appear to drive a broad aggregate increase in market power. In other words, high-markup firms in Italy have not expanded their market shares enough to generate the type of reallocation-based increase observed in the U.S. economy.

The limited role of reallocation is consistent with the structure of the Italian productive system. Many Italian firms remain small, and relatively few firms reach the scale necessary to dominate national or international markets. This reduces the likelihood of a U.S.-style

pattern in which a small number of very large firms reshape the aggregate markup distribution.

V.3 Interpretation and Implications for Liguria

The Italian results differ from some earlier international studies that reported a sharp increase in markups in Italy. In particular, De Loecker and Eeckhout's global analysis suggested that Italy experienced one of the strongest increases in markups among European countries. The Bank of Italy study argues that this discrepancy depends mainly on two methodological issues: sample selection and the assumption of common technology parameters across countries. The sample-selection problem is particularly important. Studies based on listed firms may be appropriate for countries such as the United States, where publicly traded corporations represent a large share of economic activity. In Italy, however, listed firms represent only a small and highly selected fraction of the economy. They are generally larger, more capital-intensive, and less representative of the typical Italian firm. Therefore, using only listed companies may overstate markup levels and produce misleading aggregate dynamics. The second issue concerns technology parameters. If studies impose common production elasticities across countries, they may ignore important differences in national production structures. Italian firms may use different technologies, input combinations, and organizational models than U.S. firms. Estimating country-specific technology parameters is therefore essential for obtaining reliable markup measures. By using more representative data and country-specific estimation, the Bank of Italy study provides a more cautious interpretation of Italian market power. Its findings suggest that Italy has not experienced a general rise in market power comparable to that observed in the United States.

Taken together, the Italian evidence points to relative stability in aggregate market power rather than a generalized rise in markups. That stability does not imply perfect competition: sectoral heterogeneity remains substantial, with services generally displaying higher markups than manufacturing and some knowledge-intensive activities recording particularly high values. Nor does Italy show the clear superstar-firm mechanism found in the United States, because reallocation toward a small group of dominant firms plays a

more limited role. The comparison also shows why data selection and institutional context matter. Evidence based only on listed firms can distort the picture of an economy dominated by small and medium-sized enterprises, while common technology parameters may conceal national differences in input use and organization. Markups must therefore be interpreted together with firm size, sectoral composition, ownership structure, production technology, and the representativeness of the underlying sample.

These conclusions provide the national background for the regional analysis of Liguria. Since Italian markups are characterized by sectoral heterogeneity and strong differences across firms, a regional perspective is particularly relevant. Liguria has a productive structure with specific characteristics, including port activities, logistics, tourism, maritime services, local commerce, and small manufacturing. These sectors may exhibit different degrees of market power. For example, services linked to local demand may display higher markups than tradable manufacturing activities, while logistics and port-related sectors may be influenced by infrastructure constraints and local market structure. The national evidence suggests that the analysis of Liguria should not simply replicate aggregate Italian conclusions. Instead, it should examine whether the region's sectoral composition produces specific markup patterns. The relevant question is whether Ligurian firms follow the national pattern of stable and moderate markups, or whether some regional sectors exhibit stronger signs of market power. This regional extension is therefore important because it connects the national debate on competition with the concrete productive structure of a specific territory.

VI. Stata Methodology and Econometric Implementation

This chapter translates the production-function approach discussed in Chapter 3 into the empirical workflow used for Ligurian firms. The objective is to recover a markup for each firm and year without observing marginal cost directly. The implementation follows the micro approach of De Loecker and Warzynski (2012), as operationalized by Rovigatti's

markupest command. It first estimates a value-added production function while controlling for unobserved productivity and then combines the estimated output elasticity of labor with the firm's observed labor expenditure share.

VI.1 Data Construction and Sector-year Normalization

The unit of observation is a firm-year. Output is measured by value added, labor input by total personnel cost, capital by tangible fixed assets, and the proxy for unobserved productivity by the sum of raw-material and service expenditure. Personnel cost is used instead of the number of employees in the production function because it is the expenditure on the variable input that enters the De Loecker-Warzynski first-order condition. Employment remains important for the minimum-size rule and for the descriptive labor-productivity analysis in Chapter 7. All monetary variables are expressed in thousands of euros in the source data.

Table VI.1: Variables used in the empirical implementation

Economic measure	Stata variable	Role in the analysis
Value added	value_added	Production-function output
Personnel cost	labor_cost	Flexible labor input and observed input share
Tangible fixed assets	capital_tangible	Predetermined state variable
Raw materials + services	intermediate_input	Levinsohn-Petrin proxy for productivity
Employees	employees	Size threshold and labor-productivity denominator
ATECO 2007, two digits	sector2	Sector-year normalization groups

Source: Author's elaboration.

The data construction begins by importing the second worksheet of the AIDA/BvD manufacturing file with the *allstring* option. This choice preserves firm identifiers with leading zeroes and allows the text code 'n.d.' to be converted explicitly to a missing value before numeric conversion. The first worksheet row contains headings and is removed; continuation rows without both a company name and BvD identifier are also excluded. The

BvD code identifies firms, while the first two digits of the ATECO 2007 code identify manufacturing sectors.

The source is organized in wide form, with separate columns for each variable from 2024 back to 2015. Stata's reshape long command converts it to a panel indexed by *firm_id* and year. The employee threshold is applied at the firm-year level: observations with missing employment or fewer than 15 employees are removed, but a firm can remain in other years in which it satisfies the threshold. This detail matters because the resulting panel is unbalanced and because the analysis represents medium-sized and larger manufacturing activity rather than the full population of Ligurian firms.

Intermediate input expenditure is constructed as raw materials plus services. Logs and expenditure shares require strictly positive values, so observations with missing or nonpositive value added, personnel cost, tangible capital, or intermediate inputs are dropped. Sector-year groups with only one observation are also removed because a within-cell normalization would contain no comparative information. Finally, *xtset firm_id year* declares the panel structure used by *markupest*.

Because actual firm-level output and input price deflators are unavailable, the code centers each logged variable within its two-digit ATECO sector and year. For a generic variable *X* and a firm *i* belonging to sector *s* in year *t*, the transformation is:

$$\tilde{x}_{ist} = \ln(X_{ist}) - \text{mean}_{st}[\ln(X)] = \ln(X_{ist} / \text{GM}_{st}[X])$$

where GM denotes the sector-year geometric mean. The transformed output, labor, capital, and proxy variables are *d_ln_va*, *d_ln_l*, *d_ln_k*, and *d_ln_m*. The do-file verifies numerically that every transformed variable has a zero mean within each sector-year cell. This removes common sector-year log levels and focuses estimation on relative differences among firms operating in the same broad industry and year.

The transformation must not be interpreted as a genuine price deflator. It cannot remove firm-specific output prices, differences in product quality, or input-price heterogeneity within a sector. Consequently, the estimated productivity component is closer to revenue productivity than to a pure quantity-based measure of technical efficiency. The production-

function coefficients are pooled across manufacturing sectors after this centering. This provides enough observations for a translog ACF estimation, but it also imposes a common coefficient vector across industries.

VI.2 Production Function, Productivity and Endogeneity

In the value-added specification, logged output depends structurally on labor and capital, while intermediate inputs serve as a proxy rather than as an additional production input. A simplified translog representation is:

$$\tilde{q}_{it} = \beta_l \tilde{l}_{it} + \beta_k \tilde{k}_{it} + \beta_{ll} \tilde{l}_{it}^2 + \beta_{kk} \tilde{k}_{it}^2 + \beta_{lk} \tilde{l}_{it} \tilde{k}_{it} + \omega_{it} + \varepsilon_{it}$$

The persistent component ω_{it} is firm productivity: it captures the amount of output a firm can generate from a given combination of observed inputs. It can reflect technology, organization, management, know-how, product mix, or other persistent advantages that are observed by the firm but not by the econometrician. The term ε_{it} captures a transitory shock and measurement error. Total factor productivity is therefore not a simple ratio such as value added per employee. Labor productivity uses only one input, whereas TFP measures output conditional on the joint use of labor and capital.

Because output is measured in nominal value added and firm-level prices are not observed, ω_{it} may also contain demand and price effects. A firm selling a higher-quality product at a higher price can appear more productive even without producing more physical output from the same inputs. This limitation is important when productivity and market power are interpreted together. This interpretation of productivity also explains why ordinary least squares would estimate the production function consistently only if labor and capital were uncorrelated with the unobserved productivity term. That assumption is implausible because managers generally have more information about current productivity than the researcher. Consider a firm that observes an improvement in technology, organization, or demand. The productivity shock directly raises output, but it can also induce the firm to hire more workers, increase hours, or expand its wage bill. Employment is therefore partly a response to productivity, not an externally assigned input.

In the simple production function $q_{it} = \beta_l l_{it} + \omega_{it} + \varepsilon_{it}$, the positive response of labor to productivity implies $\text{Cov}(l_{it}, \omega_{it}) > 0$. The omitted productivity component is contained in the regression error, so the OLS labor coefficient absorbs both the causal contribution of labor and part of the productivity advantage:

$$\text{plim } \hat{\beta}_l^{OLS} = \beta_l + \text{Cov}(l_{it}, \omega_{it}) / \text{Var}(l_{it})$$

Under this simplified positive-covariance case, the labor elasticity is biased upward. In a multivariate production function the exact bias also depends on the covariance among inputs, but inconsistency remains. The problem is often called simultaneity or input-choice endogeneity: productivity affects the chosen number of employees, while labor also affects output. Firm and year fixed effects cannot fully solve it because the relevant productivity shock varies within firms over time and is observed before flexible inputs are chosen.

The attached application uses personnel cost rather than headcount as l_{it} , but the same mechanism applies. A positive productivity shock can raise the wage bill through hiring, hours, skills, or wages. This endogeneity matters twice: it biases the production-function coefficient and, because the estimated elasticity is the numerator of the markup, it can also bias the inferred price-cost wedge. De Loecker and Warzynski (2012) show empirically that controlling for unobserved productivity can materially change estimated markups.

VI.3 Levinsohn-Petrin Estimation with the ACF Correction

The control-function approach addresses this simultaneity by using an observable input that responds to productivity. Levinsohn and Petrin (2003) use intermediate inputs because they are usually positive and adjust more continuously than investment. Conditional on the predetermined capital stock, intermediate-input demand is assumed to be monotonic in productivity:

$$m_{it} = m_t(k_{it}, \omega_{it}) \Rightarrow \omega_{it} = h_t(k_{it}, m_{it})$$

The inverse function h_t acts as a control for ω_{it} . The Stata specification sets *pmethod(lp)*, uses *d_ln_m* as the proxy, and approximates the first-stage control function with a third-degree polynomial through *poly(3)*. Capital is the state variable because the current capital stock is largely determined before the current flexible-input shock.

Akerberg, Caves, and Frazer (2015) show that labor may not be identified in a conventional first stage when labor and the proxy are chosen at the same time. The *acf* option therefore delays identification of the labor coefficient to the second stage and uses timing assumptions plus a first-order Markov process for productivity. The empirical specification is thus best described as an LP proxy strategy combined with the ACF identification correction.

The *trans* option activates a translog technology. Unlike a Cobb-Douglas model, the resulting labor elasticity varies with each firm's input mix. With labor and capital in the value-added function, its schematic form is $\theta_{it}^l = \beta_l + 2\beta_{ll}\tilde{l}_{it} + \beta_{lk}\tilde{k}_{it}$. This flexibility is valuable for heterogeneous firms, although it increases the number of parameters and makes estimates more sensitive in small samples. A fixed seed, 20260721, makes the pseudo-random elements of the nonlinear estimation reproducible.

VI.4 Markup Construction, Reproducibility and Interpretation

For a flexible input chosen through cost minimization, the firm's first-order condition implies that the markup equals the output elasticity of that input divided by its expenditure share. Using labor, the firm-year markup is:

$$\mu_{it} = \theta_{it}^l / \alpha_{it}^l, \quad \alpha_{it}^l = \text{personnel cost}_{it} / \text{value added}_{it}$$

The *markupest* command estimates *markup_demeaned* using *d_ln_l* and *d_ln_va*. Internally, however, exponentiating these separately centered logs produces a normalized share rather than the observed accounting share. The do-file therefore constructs both quantities:

$$\alpha_{it}^d = \exp(d_ln_l_{it} - d_ln_va_{it}), \quad \alpha_{it}^{obs} = \text{labor_cost}_{it} / \text{value_added}_{it}$$

and rescales the markup as $\mu_{it}^{final} = \mu_{it}^{demeaned} \times (\alpha_{it}^d / \alpha_{it}^{obs})$. This retains the output elasticity from the normalized production function but restores the actual personnel-cost share in the markup denominator. Because the same first-stage residual correction multiplies both share definitions, the rescaling also preserves *markupest*'s corrected option. In the command's implementation, *corrected* automatically requests first-stage residuals and multiplies the input share by $\exp(\hat{\epsilon}_{it})$ before computing the markup.

For reproducibility, the final Stata command specifies *method(dlw)*, the firm and year identifiers, *d_ln_va* as output, *d_ln_l* as both the flexible input and markup input, *d_ln_k* as the state variable, and *d_ln_m* as the proxy. The options *valueadded*, *pmethod(lp)*, *prodestoptions("poly(3) acf trans")*, *corrected*, and *verbose* reproduce the chosen estimator. The code then saves the complete firm-year dataset and exports annual and sector-year summaries containing the number of estimates, mean, median, and standard deviation.

The exported file contains the variables needed to audit the markup calculation, but it does not save an estimated firm-level ω_{it} series. Chapter 7 therefore distinguishes the productivity controlled for during production-function estimation from an additional descriptive measure, value added per employee. A separate analysis of TFP would require predicting and saving the productivity term after *prodest* and, ideally, using sector-specific output and input price indices. Finally, estimated markups should be read as model-based price-cost wedges. Values above one are consistent with market power, but their level can also reflect technology, input measurement, fixed-cost recovery, product quality, or functional-form assumptions.

VII. Application to Liguria

This chapter applies the methodology to manufacturing firms located in Liguria. The scope is narrower than the regional discussion in Chapter 5: the underlying file does not cover tourism, retail, or most port and logistics services. It captures manufacturing activities, including food, fabricated metals, machinery, transport equipment, and the repair and installation of machinery. The results therefore describe competition-related patterns within Ligurian manufacturing rather than the regional economy as a whole.

VII.1 Data and Estimation Sample

The raw AIDA (Bureau van Dijk) extract, exported on 10 June 2026, contains 2,585 Ligurian firms classified in ATECO 2007 manufacturing divisions 10-33. Its wide annual accounts cover 2015-2024 and report employment, sales revenue, value added, personnel

cost, tangible assets, raw materials, services, and other balance-sheet items. Monetary amounts are in thousands of current euros.

The potential panel contains 25,850 firm-years, but employment is reported in only 14,514. The 15-employee threshold leaves 3,903 observations for 607 firms. Positivity requirements for value added, personnel cost, tangible capital, and intermediate inputs remove 53 observations and six firms; dropping one singleton sector-year cell yields the final 3,849 firm-years, 601 firms, and 22 two-digit ATECO sectors.

The panel is unbalanced: the median firm contributes eight years, 216 appear in all ten, and 101 only once. Coverage grows from 291 observations in 2015 to 473 in 2024. Because the AIDA search retained firms classified as active in June 2026, earlier years may under-represent firms that exited. Annual changes therefore mix within-firm developments, threshold movements, data availability, and sample selection rather than identifying causal effects.

Of the 601 firms, 335 are located in the province of Genoa (55.7 %), 158 in La Spezia (26.3 %), 71 in Savona (11.8 %), and 34 in Imperia (5.7 %); three are coded only at the regional level. Genoa and La Spezia therefore account for 82 % of firms in the selected sample.

Table VII.1 summarizes the main variables after all estimation filters. Because the data are strongly right-skewed, the median and interquartile range are more representative of a typical firm-year than the arithmetic mean.

Table VII.1: Descriptive statistics for the estimation sample, 2015-2024

Variable	Mean	Median	P25	P75
Employees	64.5	30.0	19.0	51.0
Sales revenue	44,853.6	5,627.1	2,471.5	14,027.5
Value added	7,912.2	1,904.9	996.0	4,042.9
Personnel cost	3,591.6	1,371.8	740.6	2,522.2
Tangible fixed assets	16,992.2	861.3	181.3	2,863.1
Intermediate inputs	32,864.5	3,536.5	1,257.3	10,373.3
Value added per employee	77.1	59.9	43.5	85.8

Note: N = 3,849 firm-years. Employees are headcounts; other variables are in thousands of current euros. P25 and P75 denote quartiles; intermediate inputs equal raw materials plus services. Source: AIDA(BvD); author's calculations.

The employment distribution shows that the 15-worker threshold does not create a sample dominated by large corporations. The mean is 64.5 employees, but the median is 30 and the interquartile range is 19-51. Of all firm-year observations, 73.8 % fall in the 15-49 employee band, 22.4 % in the 50-249 band, and only 3.7 % have 250 or more employees. A small upper tail therefore raises the mean substantially, while most observations describe small and medium-sized production units above the imposed cutoff.

The same asymmetry is visible in accounting size. Mean annual sales revenue is 44.9 million euros, almost eight times the median of 5.6 million euros. Mean value added is 7.9 million euros compared with a median of 1.9 million euros. At the 75th percentile, revenue is 14 million euros and value added 4 million euros, so the very large gap between mean and median is generated by a relatively small number of high-scale observations. For this reason, unweighted average levels should not be read as the size of a representative Ligurian manufacturer.

Revenue and value added play different roles. Revenue measures gross sales of goods and services and therefore includes the value of purchased intermediate inputs embodied in output. Value added measures the portion of production remaining after intermediate consumption and is the output concept used in the production-function estimation. A firm can consequently record high revenue but much lower value added if raw-material and

service purchases are large. In the estimation sample, intermediate inputs average 32.9 million euros but have a median of 3.5 million euros; personnel cost has a mean of 3.6 million euros and a median of 1.4 million euros. Tangible fixed assets are even more skewed, with a mean of 17 million euros and a median below 0.9 million euros.

The annual medians suggest moderate nominal expansion rather than a large change in typical employment. Between 2015 and 2024, median sales revenue rises from 5.44 million euros to 6.05 million euros, median value added from 1.71 million euros to 2.13 million euros, and median employment from 29 to 30 workers. Median value added per employee increases from 55.9 thousand euros to 68.3 thousand euros. Revenue and value added both weaken in 2020 and recover afterward. These comparisons are in current prices and come from a changing set of firms, so they mix inflation, composition, and real performance; they are descriptive rather than measures of real growth.

VII.2 Distribution and Evolution of Estimated Markups

Across all firm-years, the unweighted mean markup is 1.387 and the median is 1.319. Interpreted literally, a markup of 1.387 means that price is estimated to be 38.7 percent above marginal cost. The mean exceeds the median, indicating a right-skewed distribution. The 10th and 90th percentiles are 1.046 and 1.751, while the 99th percentile is 2.873. Approximately 5 % of observations exceed two.

All reported markups are positive, but 6 % fall below one; the minimum is 0.751 and the maximum is 7.326. Values below one should not automatically be treated as economically impossible observations. They may arise from temporary pricing below marginal cost, measurement error, unusual value-added accounting, or imperfectly estimated elasticities. No observations were trimmed from the supplied output, so both tails remain in the summaries. The 1st-99th-percentile winsorized mean is 1.380, close to the untrimmed mean, suggesting that the overall level is not driven solely by the most extreme estimates.

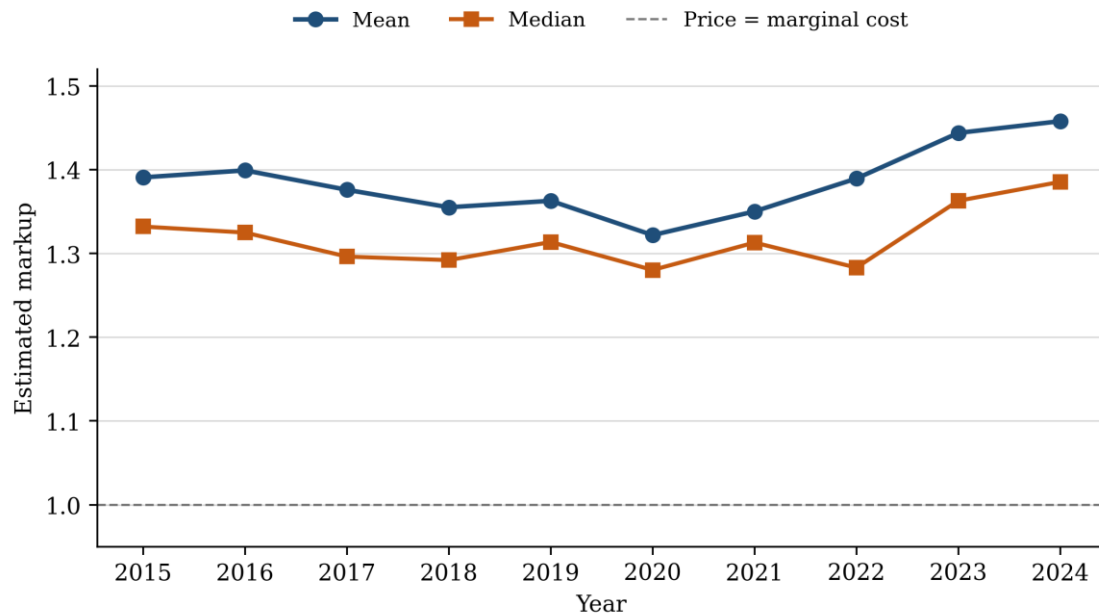
Table VII.2: Annual summary of firm-level markups

Year	Observations	Mean	Median	S. d.
2015	291	1.391	1.332	0.351
2016	328	1.399	1.325	0.356
2017	349	1.376	1.296	0.375
2018	368	1.355	1.292	0.366
2019	376	1.363	1.314	0.328
2020	390	1.322	1.280	0.296
2021	411	1.350	1.313	0.317
2022	426	1.389	1.283	0.533
2023	437	1.444	1.363	0.401
2024	473	1.458	1.385	0.368

Source: Author's calculations.

Viewed over time, the annual series is not monotonic. The mean is 1.391 in 2015 and 1.399 in 2016, then gradually declines to 1.355 in 2018. After a small increase in 2019, it reaches its sample minimum of 1.322 in 2020. From 2021 onward the mean rises, reaching 1.444 in 2023 and the sample maximum of 1.458 in 2024. The absolute difference between 2015 and 2024 is 0.067, corresponding to a 4.8 percent increase in the markup ratio. The median follows a broadly similar pattern and rises from 1.332 to 1.385 over the same interval.

Graph VII.1: Mean and median markups in Ligurian manufacturing, 2015-2024



Source: Author's calculations

The gap between the mean and median is informative. In 2022 the mean returns to 1.389 while the median remains at 1.283 and the standard deviation rises to 0.533, the largest annual dispersion in the sample. The 2022 increase in the mean is therefore concentrated in the upper part of the distribution rather than shared uniformly across firms. The sharp movements around 2020-2022 coincide with the pandemic and subsequent input-price disruptions, but the available design cannot identify those events as causes.

As a composition check, the 216 firms observed in every year have a mean markup of 1.397 in 2015 and 1.516 in 2024. The increase is therefore also visible in the balanced subset and is not generated only by the growing number of observations. Nevertheless, balanced firms are a selected group of survivors, so this comparison remains a sensitivity exercise rather than a causal estimate of a common trend.

VII.3 Sectoral Heterogeneity, Productivity, and Firm Size

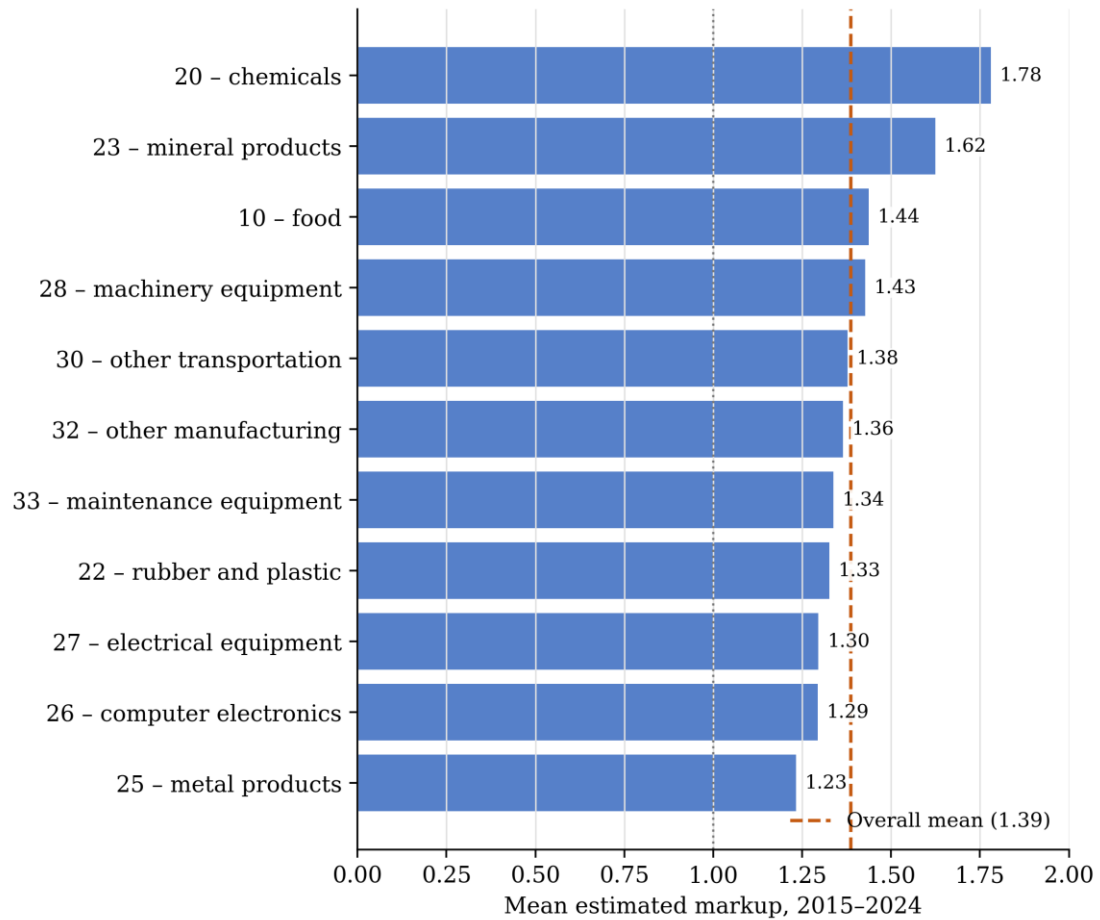
Sectoral comparisons require particular caution. The final data contain 219 sector-year cells; 109 have fewer than ten observations and 73 contain only two to four. Annual estimates for small sectors can therefore change sharply when a single firm enters or leaves the sample. To focus on more informative comparisons, Table VII.3 aggregates the full 2015-2024 period and reports only sectors with at least 100 firm-year observations and 15 distinct firms. This reporting threshold is not part of the production-function estimation; it is used only to make the descriptive sector ranking more reliable.

Table VII.3: Markups by manufacturing sector, 2015-2024

ATECO	Sector	Firms	Obs.	Mean	Median
20	Chemicals	21	162	1.781	1.578
23	Other non-metallic mineral products	18	123	1.625	1.588
10	Food products	74	445	1.437	1.361
28	Machinery and equipment	47	351	1.427	1.412
30	Other transport equipment	43	229	1.378	1.198
32	Other manufacturing	16	128	1.364	1.364
33	Repair and installation of machinery	110	552	1.338	1.256
22	Rubber and plastic products	30	241	1.327	1.303
27	Electrical equipment	28	218	1.296	1.292
26	Computer, electronic and optical products	27	205	1.293	1.242
25	Fabricated metal products	123	755	1.233	1.198

Note: Sectors shown have at least 100 firm-year observations and 15 firms. Source: Author's calculations.

Graph VII.2: Average markups in sectors with broader sample coverage, 2015-2024



Note: Sectors shown have at least 100 firm-year observations and 15 firms. Source: Author's calculations.

Among the sectors with broader coverage, chemicals have the highest mean markup, 1.781, followed by other non-metallic mineral products at 1.625. Food products and machinery and equipment have means of 1.437 and 1.427. At the lower end of the reported group, computer and electronic products, electrical equipment, and fabricated metal products have mean markups of 1.293, 1.296, and 1.233. Repair and installation of machinery, a relevant activity for Liguria's maritime-industrial base, has a mean of 1.338 across 552 observations.

These differences are consistent with meaningful sectoral heterogeneity, but they are not a direct ranking of competitive intensity. Chemicals and mineral products may differ from metal products in product differentiation, fixed-cost requirements, capital intensity, exposure to international trade, and the accounting relation between personnel cost and value added. Because the production-function parameters are pooled and the data do not define product markets, a high sector mean cannot by itself establish anticompetitive conduct. Small sectors excluded from the table are even less suitable for substantive ranking. Firm-level heterogeneity is also evident in relation to productivity and size. Productivity enters the analysis in two distinct ways. First, unobserved TFP is controlled for inside the LP-ACF production-function estimator; this is essential for avoiding the OLS bias described in Chapter 6.2. Second, the available data permit calculation of apparent labor productivity as value added per employee. As reported in Table VII.1, its mean is 77.1 thousand euros per employee and its median is 59.9 thousand euros across firm-years. These nominal levels should not be interpreted as real productivity growth because no genuine output-price deflator is applied.

For a more comparable descriptive exercise, log labor productivity is centered within each sector and year and firms are grouped into relative productivity quintiles. The Pearson correlation between markup and this within-sector-year labor-productivity measure is 0.384; the Spearman rank correlation is 0.382. Mean markups rise monotonically from 1.251 in the lowest relative-productivity group to 1.624 in the highest.

Table VII.4: Markups by within-sector-year labor-productivity quintile

Productivity quintile	Observations	Mean markup	Median markup
1 (lowest)	851	1.251	1.200
2	729	1.289	1.251
3	718	1.340	1.318
4	729	1.423	1.365
5 (highest)	822	1.624	1.497

Source: Author's calculations. Labor productivity is value added per employee.

The positive association admits several interpretations. More productive firms may offer higher-quality or more differentiated products, reduce marginal cost, and retain part of the efficiency gain as a higher markup. Conversely, market power may allow firms to finance intangible investment or organizational improvements. A third possibility is mechanical: value added appears in the numerator of labor productivity and in the denominator of the labor-cost share used to calculate markups. The same accounting movement can therefore raise both measures. The correlation between markups and relative employment is positive but weaker, at 0.214. None of these correlations identifies a causal effect of productivity or size on market power.

VII.4 Comparison with Previous Empirical Evidence

The Ligurian estimates share two features with the Italian evidence in Chapter 5: substantial heterogeneity and no continuous rise in average markups. This resemblance does not establish a common trajectory or a regional premium in market power. The closest reference is Ciapanna, Formai, Linarello and Rovigatti (2022), Banca d'Italia Occasional Paper No. 672, subsequently published in *Empirical Economics* (2024). The comparisons below refer to the 2022 working paper.

In the paper's CERVED sample, the unweighted accounting-based markup for Italian manufacturing is 1.15 in 2018 (Ciapanna et al., 2022, Table 6). The Ligurian mean in the same year is 1.355, compared with 1.387 over 2015-2024. This difference cannot identify a regional premium in market power: the national figure uses a Lerner-based accounting measure, whereas this thesis combines an estimated output elasticity with a labor-cost share. Matching the year removes only one source of non-comparability.

The production-function comparison is closer in principle. Banca d'Italia's baseline uses a sector-year Cobb-Douglas gross-output specification and a variable-cost bundle combining labor and intermediates (Ciapanna et al., 2022, Section 4.2.2). Here, a pooled regional translog uses value added as output, personnel cost as the flexible input, and intermediate expenditure as a productivity proxy. Both the estimated elasticity and its associated expenditure share therefore differ. A larger value-added estimate cannot automatically be read as a larger gross-output price-cost wedge; equivalence requires additional assumptions

about technology and intermediate inputs. Comparisons of levels would require a common specification.

Table VII.5: Design of the comparison with Banca d'Italia

Dimension	Banca d'Italia benchmark	Ligurian application
Firm data and period	CERVED, Italy, 2004-2018	AIDA, Liguria, 2015-2024
Output and flexible input	Gross output; labor and intermediates	Value added; personnel cost
Production technology	Cobb-Douglas by sector and year	Pooled translog after sector-year centering
Firm aggregation	Sales weights	Unweighted means and medians
Comparable calendar window	2015-2018	2015-2018

Note: The national column describes the baseline CERVED production-function comparison, not the Lerner-based statistic cited in the text. Source: Ciapanna et al. (2022), Sections 4.1-4.2; Chapter VI of this thesis.

Sample composition creates a further distinction. The national analysis includes non-listed companies and a broader range of firm sizes and activities, while this application includes only manufacturing observations with at least 15 employees. The regional mean of 64.5 employees and median of 30 show that the resulting sample cannot stand for the many smaller enterprises excluded by construction. Moreover, selecting firms that remained active in June 2026 can leave earlier exits under-represented. These restrictions may affect both markup levels and their evolution, without establishing a predictable direction of bias. The emphasis on representative data in Ciapanna et al. (2022, Section 5) therefore applies to the interpretation of this regional exercise as well as to comparisons based on listed companies.

Aggregation also changes the question being answered. The national firm-level series use sales weights, while their macro aggregates use value-added weights (Ciapanna et al., 2022, Sections 3.1 and 4.1). The Ligurian arithmetic mean instead gives each observed firm equal weight within a year. It describes the average estimate among included firms, rather than the markup associated with the distribution of regional sales. A sales-weighted series could differ if large firms have different markups or change their economic importance. The positive correlation with employment reported in Section 7.3 does not determine the size or even the direction of that difference, because employment is not the same as sales. Regional weights would also have to be interpreted as sample sales shares rather than shares of a fully observed product market.

The common calendar window is 2015-2018. During these years, the Ligurian mean falls from 1.391 to 1.355, a decline of approximately 2.6 percent; the median falls from 1.332 to 1.292. This supports the limited conclusion that the regional estimates show no sustained pre-pandemic increase. It is compatible with the national picture of modest overall movements, although the paths do not coincide: the Italian macro series shows a small recovery after 2014 (Ciapanna et al., 2022, Figure 3). The subsequent Ligurian rise to 1.458 in 2024 is outside the national study's observation period. It therefore neither overturns nor confirms the paper's pre-2019 findings. A current national manufacturing series estimated on comparable data would be needed to establish whether the later regional increase is distinctive.

Distributional comparisons require similar care. The regional mean exceeds the median, and the 2022 rise in the mean accompanies a lower median and unusually high dispersion. This indicates that the movement is not shared evenly across observed firms. However, the national Lerner-based calculations set negative Lerner indices to zero, imposing a markup floor of one, and the ASIA-Frame analysis trims the upper tail (Ciapanna et al., 2022, Sections 4.1 and 4.2.1). The 6 percent of Ligurian observations below one consequently cannot be interpreted as an economic contrast with a national distribution constructed to exclude such values. The small difference between the regional

raw and winsorized means, 1.387 and 1.380, is reassuring about extreme observations alone; it does not resolve differences in measurement or selection.

The evidence on reallocation is especially relevant. Ciapanna et al. (2022, Section 4) attribute most national markup movements to changes within firms, with a limited role for reallocation toward high-markup firms. The balanced Ligurian subset also exhibits an increase, from 1.397 in 2015 to 1.516 in 2024, showing that the regional result is not solely due to the addition of firms to the observed panel. This is a useful point of contact, but a balanced-panel comparison is not the same as the national decomposition. It does not quantify how changing sales weights contribute to a weighted aggregate, and survivor selection prevents it from identifying the contribution of economic entry and exit. The Ligurian evidence thus remains consistent with several mechanisms, including changes within continuing firms, without demonstrating the same mechanism as the national study.

Sectoral heterogeneity is the clearest qualitative similarity. The national result that broad averages conceal differences across activities is echoed within regional manufacturing: chemicals have a mean of 1.781, compared with 1.233 for fabricated metal products. This extends the discussion to differences inside manufacturing, but does not establish that these two industries have the same relative ranking nationally. Nor can this dataset test the manufacturing-services contrast emphasized in Chapter 5, since most services are absent. The pooled coefficients, sparse sector-year cells, and differences in firms' input mixes further limit a competitive interpretation of the regional sector ranking. The finding is evidence of heterogeneity in estimated wedges, rather than independent evidence about the conduct responsible for them.

Comparison with the United States highlights a different scale and distribution of change. De Loecker, Eeckhout and Unger (2020) report a sales-weighted rise from about 1.21 in 1980 to 1.61 in 2016, with a prominent upper tail and reallocation component. The Ligurian increase of 0.067 between 2015 and 2024 is much smaller in absolute terms, and the median also increases over the full period. This is not a valid ranking of competition between Liguria and the United States: the periods, company populations, output measures, and weights differ. The temporary separation between mean and median in 2022 is

nevertheless a reason to investigate which firms account for the regional recovery, rather than infer a common increase for all manufacturers.

Autor et al. (2020) provide a more specific hypothesis: productive firms with high markups gain market share and contribute to changes in aggregate factor shares. The Ligurian correlation of 0.384 between markups and relative labor productivity, together with the rise in mean markups across productivity quintiles, matches the cross-sectional association that such a mechanism could generate. It does not establish a superstar-firm process. The productivity measure is nominal value added per employee, shares of sales have not been decomposed, and value added enters both the productivity measure and the markup calculation. Evidence that high-productivity, high-markup firms subsequently gain sales share would be needed to move from this association to the reallocation hypothesis.

The other US studies help specify what the regional results leave unresolved. Barkai (2020) measures pure profits after accounting for capital costs; a Ligurian markup above one is not evidence of an equivalent pure-profit rate, because fixed costs and capital remuneration have not been deducted. Covarrubias, Gutiérrez and Philippon (2020) assess concentration jointly with productivity, prices, investment, and entry. Without these additional outcomes, the regional correlations cannot distinguish expansion driven by efficiency from protection against competitors. Similarly, the contrasting demand-based findings of Döpper et al. (2025) for consumer products and Grieco, Murry and Yurukoglu (2024) for automobiles caution against assigning one markup trajectory to every industry. Neither study supplies a direct numerical benchmark for the mixed manufacturing activities observed here.

Finally, Raval (2023) finds substantial disagreement between labor- and materials-based markup estimates, including their distributions and time trends. This is directly relevant to a regional application that relies on personnel cost as the flexible input. A credible extension would compare the present estimates with a gross-output specification using intermediate inputs, harmonize the sample and weights with the national benchmark, and examine the overlapping years separately from 2019-2024. These are proposed checks, not results established by the current estimates. The contribution of the Ligurian analysis is

therefore to document regional manufacturing heterogeneity and a recent recovery in the estimated wedge, while leaving open whether the differences from national evidence reflect competition, accounting choices, or sample composition.

VII.5 Limitations and Overall Interpretation

Several limitations define the evidential weight of the Ligurian results. First, the ATECO-year transformation is a normalization, not a genuine price deflator. Firm-specific prices and product quality remain embedded in value added, so both productivity and output elasticities can contain demand-side variation. Second, using personnel cost as the flexible input assumes that labor adjusts sufficiently within the period and that its expenditure is measured consistently. In 6.1 percent of observations personnel cost exceeds value added, often because value added is unusually low; such accounting cases can generate unstable labor shares even though all retained variables are positive.

Third, the translog model is estimated on a pooled regional manufacturing sample. Demeaning controls broad sector-year levels, and the translog makes firm elasticities heterogeneous, but the underlying coefficients remain common across industries. Sector-specific estimation would reduce this restriction but is not credible for many small ATECO cells. Fourth, because the source extraction retains firms classified as active in June 2026, earlier years may under-represent firms that exited before that date. Fifth, the panel is unbalanced and excludes observations below 15 employees, so the estimates are not representative of microenterprises or the full Ligurian business population. Sixth, annual and sector means are unweighted: each firm-year receives equal weight, regardless of its economic size.

Finally, the production approach identifies a price-cost wedge from technology and input shares; it does not estimate consumer demand, define antitrust markets, or isolate the conduct of individual firms. Different flexible inputs and functional forms can produce different markup estimates, as emphasized by Raval (2023). Robustness work should compare Cobb-Douglas and translog specifications, alternative proxy estimators, labor- and materials-based markups where data permit, balanced-panel results, trimming rules, and

sector-specific estimates for sufficiently large samples. Standard errors or bootstrap intervals for annual and sector aggregates would also clarify sampling uncertainty.

Against these limitations, the central empirical finding is that Ligurian manufacturing firms in the selected sample price, on average, above estimated marginal cost. The overall markup of 1.387 is economically meaningful, but the time series does not show a continuous increase. Markups decline through the middle of the sample, reach a low point in 2020, and rise strongly in 2023-2024. The increase from 2015 to 2024 is modest relative to the dramatic long-run U.S. evidence reviewed in Chapter 4, and the short period does not permit a direct comparison with multi-decade national studies.

The results also confirm that an aggregate regional average hides substantial differences across industries and firms. Chemicals and mineral products record higher average markups than fabricated metals and electrical or electronic products among sectors with broader coverage. More productive firms also tend to have higher markups within the same sector and year, although that relationship is descriptive and partly linked to common accounting variables. Taken together, the evidence supports a cautious interpretation: the estimates reveal heterogeneous price-cost wedges and a recent increase, but they do not by themselves establish a generalized deterioration of competition in Liguria.

VIII. Conclusion and Policy Implications

This thesis has examined markups as a bridge between the theory of market power and its empirical measurement. Under perfect competition, price equals marginal cost; a markup above one therefore captures the firm's ability to sustain a price-cost wedge. In practice, however, marginal cost is not observed. The De Loecker-Warzynski approach makes firm-level estimation possible by combining a production-function elasticity with the expenditure share of a flexible input. The comparison between the United States and Italy shows why the resulting estimates must be read in context: a common methodology can reveal a broad rise driven by superstar firms in one economy and relative aggregate stability with strong sectoral variation in another.

The application to Ligurian manufacturing identifies an average markup of 1.387 and a median of 1.319 across 3,849 firm-year observations for 601 firms. The annual path is not a continuous upward trend: the mean declines to its minimum in 2020 and then rises to 1.458 in 2024. The results also reveal pronounced heterogeneity across sectors and a positive association between markups and within-sector-year labor productivity. These patterns are economically informative, but they remain descriptive. The pooled technology, unbalanced panel, current-price accounting data, absence of firm-level deflators, and shared accounting components of the markup and labor-productivity measures prevent a causal interpretation.

The policy implication is therefore one of targeted scrutiny rather than a mechanical presumption that every high markup reflects anticompetitive conduct. Sectoral estimates can help identify areas that deserve closer examination, but a competition assessment should also consider entry conditions, concentration, profitability, investment, product differentiation, trade exposure, and a defensible definition of the relevant market. Regional institutions cannot substitute for national and European competition enforcement, yet they can strengthen competitive conditions by reducing administrative barriers, improving transport and digital infrastructure, supporting skills and innovation diffusion, and making it easier for productive firms to enter and expand. Such measures are particularly relevant in a region where many firms remain small and sectoral conditions vary widely.

Further research should test robustness with better data and broader coverage. The evidence reveals heterogeneous markups, not a generalized deterioration in competition.

Appendix

d_ln_va	Coefficient
d_ln_l	.9419944
d_ln_k	.0721461
d_ln_lXd_ln_l	.0142644
d_ln_lXd_ln_k	-.0120865
d_ln_kXd_ln_k	.0062657

Production function estimations (labor and capital elasticity)

Stata Do-file:

```

6      1. Import the second sheet ("Risultati") of Manifatturiero_liguria.xls.
7      2. Convert the 2015-2024 firm data from wide to long format.
8      3. Keep firm-year observations with at least 15 employees.
9      4. Construct a value-added production-function sample.
10     5. Normalize logged variables as deviations from their ATECO-2/year means.
11     6. Estimate firm-year markups with markupest following Rovigatti (2020):
12         - De Loecker-Warzynski (DLW) micro approach;
13         - value-added production function;
14         - personnel cost as the variable labour input;
15         - tangible fixed assets as capital;
16         - raw materials plus services as the intermediate-input proxy;
17         - Levinsohn-Petrin with ACF correction and a translog specification;
18         - third-degree first-stage polynomial;
19         - correction for first-stage residuals.
20
21
22
23     The script creates an "output" subfolder containing the prepared panel,
24     the markup dataset, CSV exports, and a text log.
25
26     Important interpretation
27     -----
28     The sector-year transformation is a normalization when no actual
29     price indices are available; it is not a genuine price deflator.
30
31     Baseline production-function coefficients are pooled across manufacturing
32     sectors after ATECO-2/year demeaning. This avoids unstable sector-specific
33     ACF/translog estimates in the many small ATECO sectors in this regional
34     file.
35     ****
36     **/
37
38     clear all
39     set more off
40     set linesize 120
41     capture log close _all
42
43
44
45
46     * 0. File names and output folder
47
48     -----
49
50     local excel_file
51     "C:/Users/teobi/Desktop/Tesi_Magi/Manifatturiero_liguria.xls"
52     local excel_sheet "Risultati"
53     local output_dir "C:/Users/teobi/Desktop/Tesi_Magi/output"
54
55     capture confirm file "`excel_file'"
56     if _rc {
57         display as error "File 'excel_file' not found in the current working
58         directory:"
59         display as error "`c(pwd)'"
60         display as error "Change directory with cd or edit local excel_file
61         above."
62         exit 601
63     }
64
65     capture mkdir "`output_dir'"
66     log using "`output_dir'/prepare_va_markupest.log", replace text
67
68     * 1. Import the second worksheet using Excel column letters as variable names
69
70     -----
71
72     * allstring preserves identifiers with leading zeros and the text code
73     "n.d.".
74     * Without firstrow, Stata names variables A, B, ..., FG, which makes the
75     import
76     * robust to the long and repeated AIDA column headings.
77     import excel using "`excel_file'", sheet("`excel_sheet'") allstring clear
78
79     capture confirm variable FG
80     if _rc {
81         display as error "The expected columns A-FG were not imported."
82         display as error "Check that the selected worksheet is 'excel_sheet'."
83         log close
84         exit 111
85     }
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118
119 rename (DH DI DJ DK DL DM DN DO DP DQ) ///
120 (labor_cost2024 labor_cost2023 labor_cost2022 labor_cost2021 ///
121 labor_cost2020 labor_cost2019 labor_cost2018 labor_cost2017 ///
122 labor_cost2016 labor_cost2015)
123
124 rename (EL EM EN EO EP EQ ER ES ET EU) ///
125 (value_added2024 value_added2023 value_added2022 ///
126 value_added2021 value_added2020 value_added2019 ///
127 value_added2018 value_added2017 value_added2016 ///
128 value_added2015)
129
130 *
131 * 2. Clean identifiers and convert financial variables to numeric
132 *
133
134 replace firm_name = trim(firm_name)
135 replace bvd_id = trim(bvd_id)
136 replace tax_id = trim(tax_id)
137 replace ateco6 = trim(ateco6)
138
139 * The BvD identifier uniquely identifies the 2,585 actual firm rows in this
140 * file.
141 isid bvd_id, gen(firm_id)
142
143 * ATECO 2007 at two digits defines the sector used for annual normalization.
144 gen str2 ateco2_string = substr(ateco6, 1, 2)
145 destring ateco2_string, gen(sector2)
146 drop ateco2_string
147 drop if missing(sector2)
148
149 * Convert "n.d." to Stata missing and then destring the yearly series.
150 ds employees* capital_tangible* raw_materials* services* labor_cost*
151 value_added*
152 local numeric_wide `r(varlist)'
153 foreach v of local numeric_wide {
154     replace `v' = "" if lower(trim(`v')) == "n.d."
155     destring `v', replace
156 }

195 * Logs and cost shares require strictly positive, nonmissing observations.
196 gen byte invalid_pf = missing(value_added, labor_cost, capital_tangible,
197 ///
198     intermediate_input)
199
200 ///
201 | value_added <= 0
202 ///
203 | labor_cost <= 0
204 ///
205 | capital_tangible <= 0
206 ///
207 | intermediate_input <= 0
208
209 quietly count if invalid_pf
210 display as text "Rows excluded for missing/nonpositive PF variables: "
211 ///
212 as result %9.0fc r(N)
213
214 drop if invalid_pf
215 drop invalid_pf
216
217 * A mean-deviation rule is not informative in a sector-year cell containing a
218 * single observation, so exclude such cells (one row in the uploaded
219 * workbook).
220 bysort sector2 year: gen int sector_year_n = _N
221 quietly count if sector_year_n < 2
222 display as text "Rows excluded from singleton sector-year cells: "
223 ///
224 as result %9.0fc r(N)
225 drop if sector_year_n < 2
226 drop sector_year_n
227 bysort sector2 year: gen int sector_year_n = _N
228
229 *
230
231 * 5. Logs and ATECO-2/year mean-deviation normalization
232 *
233
234 gen double ln_va = ln(value_added)
235 gen double ln_l = ln(labor_cost)
236 gen double ln_k = ln(capital_tangible)
237 gen double ln_m = ln(intermediate_input)

199
200 * 3. Reshape to a firm-year panel and apply the employee threshold
201 *
202
203 reshape long employees capital_tangible raw_materials services
204 ///
205 labor_cost value_added, i(firm_id) j(year)
206
207 isid firm_id year
208 sort firm_id year
209
210 label variable employees "Employees"
211 label variable capital_tangible "Tangible fixed assets (thousand EUR)"
212 label variable raw_materials "Raw materials and consumables (thousand
213 EUR)"
214 label variable services "Services (thousand EUR)"
215 label variable labor_cost "Total personnel cost (thousand EUR)"
216 label variable value_added "Value added (thousand EUR)"
217 label variable sector2 "ATECO 2007 sector (2 digits)"
218
219 quietly count
220 display as text "Firm-year rows after reshape: " as result %9.0fc r(N)
221
222 * Threshold applied at the firm-year level: missing employment cannot
223 * establish
224 * eligibility and is therefore excluded together with observations below 15.
225 drop if missing(employees) | employees < 15
226
227 quietly count
228 display as text "Rows with at least 15 employees: " as result %9.0fc r(N)
229
230 *
231 * 4. Build the value-added production-function sample
232 *
233
234 * The proxy is total observed intermediate-input expenditure.
235 gen double intermediate_input = raw_materials + services
236 ///
237 if !missing(raw_materials, services)
238 label variable intermediate_input "Raw materials + services (thousand EUR)"
239
240 label variable ln_va "Log value added"
241 label variable ln_l "Log personnel cost"
242 label variable ln_k "Log tangible fixed assets"
243 label variable ln_m "Log intermediate-input proxy"
244
245 * For x in {VA, L, K, M}:
246 * d_ln_x(i,s,t) = ln[x(i,s,t)] - mean_s,t{ln[x(i,s,t)]}.
247 foreach x in va l k m {
248     bysort sector2 year: egen double mean_ln_`x' = mean(ln_`x')
249     gen double d_ln_`x' = ln_`x' - mean_ln_`x'
250
251     * Numerical check: each transformed variable has sector-year mean zero.
252     bysort sector2 year: egen double check_mean_`x' = mean(d_ln_`x')
253     assert abs(check_mean_`x') < 1e-10
254     drop check_mean_`x'
255 }
256
257 label variable d_ln_va "Sector-year demeaned log value added"
258 label variable d_ln_l "Sector-year demeaned log personnel cost"
259 label variable d_ln_k "Sector-year demeaned log tangible fixed assets"
260 label variable d_ln_m "Sector-year demeaned log intermediate inputs"
261
262 * Observed labour share required by the DLW markup formula.
263 gen double labor_share_raw = labor_cost / value_added
264 label variable labor_share_raw "Personnel cost / value added"
265
266 order firm_id bvd_id tax_id firm_name province ateco6 sector2
267 ///
268 sector_description year employees value_added labor_cost
269 ///
270 capital_tangible raw_materials services intermediate_input
271 ///
272 ln_va ln_l ln_k ln_m d_ln_va d_ln_l d_ln_k d_ln_m
273
274 xtset firm_id year
275
276 quietly count
277 display as text "Final positive production-function sample: "
278 ///
279 as result %9.0fc r(N)
280 quietly levelsof firm_id, local(firms_in_pf)
281 local number_of_firms : word count `firms_in_pf'
282 display as text "Distinct firms in final sample: " as result %9.0fc
283 `number_of_firms'

```

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269 compress
270 save "output_dir"/liguria_va_prepared.dta", replace
271
272 *
273 -----
274 * 6. Install/check markupest and estimate corrected DLW markups
275 -----
276 capture which markupest
277 if _rc {
278     display as text "markupest not found; installing it from SSC..."
279     ssc install markupest
280 }
281 which markupest
282
283 * A fixed seed makes the numerical optimization reproducible.
284 set seed 28260721
285
286 * This is the value-added ACF/translog example in the Rovigatti markup
287 * paper, adapted
288 * to the variables in this workbook. LP uses intermediate inputs as the
289 * proxy.
290 capture noisily markupest markup_demeaned, method(dlw)
291 ///
292     id(firm_id) t(year)
293     output(d_ln_va)
294     inputvar(d_ln_l)
295     free(d_ln_l)
296     state(d_ln_k)
297     proxy(d_ln_m)
298     pmethod(lp)
299     valueadded
300     prodestoptions("poly(3) acf trans")
301     corrected verbose
302
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