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The Implication of Market Power on Labour Share of Value-added: Evidence from Estonia

Master's Thesis

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DECLARATION

I have written this master's thesis independently. All viewpoints of other authors, literary sources and data from elsewhere used for writing this paper have been referenced.

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ABSTRACT

Contrary to the long-held stylised fact of growth — stability of labour share, recent empirical evidence has shown a decline in labour share and a rise in market power due to the reallocation of economic activities towards large firms. This observed phenomenon might be partly responsible for rising inequalities. Markups — a proxy for measuring market power may vary across industries, and a more disaggregated study of markups is needed to understand its implications on the labour share of value-added. This study examines the effect of market power on the labour share of value-added at the firm level using data from various industries in Estonia between 2013 and 2020. Our findings show that while there is a slight rise in the labour share of value-added, there is an overall decline in markups across all the five industries under investigation — resource, consumer manufacturing, material manufacturing, technological manufacturing, and retail/wholesale. Also, while we establish that there is a reallocation of economic activities from firms with lower markups to firms with higher markups, the within-industry decline of surviving firms' markups due to the increase in competition arising from the net entry effect outweighs the reallocation effect. Hence, a decline in aggregate markups. Furthermore, we perform a regression of markups on investment in intangible capital, and our result shows that the higher markups over marginal cost can be associated with higher profits (market power). Finally, we investigate markups' impact on the labour share of value-added. Consistent with the literature, we find an inverse relationship between markups and the labour share of value-added.

Keywords: Market power, markup, labour share of value-added, intangible capital

CERCS: S180 Economics, econometrics, economic theory, economic systems, economic policy

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1. INTRODUCTION

The noticeable decline in labour share across many countries in the past decades has attracted the research community's attention. As highlighted by Dao et al. (2017), the labour share of income has been on a downward trend since the 1980s in advanced economies, and this observed trend is not different in some emerging and developing economies in the past decades. The evidence of a declining labour income share in many developed European countries is well documented by Arpaia et al.(2009). They observed that in many EU countries, the labour share peaked in the 1970s and early 1980s but has since declined. Bentolila & Saint-Paul (2003) and Autor et al. (2020) presented a similar observation about labour income share in OECD countries. The observed phenomenon in recent decades is contrary to the long-held Kaldor (1961) "stylised fact" of growth regarding the relative stability of the labour share, which Keynes described as "a bit of a miracle " (John Maynard Keynes, 1939, p. 49).

This observation, coupled with evidence of widening income inequality across the globe, has attracted much public discourse and remains a topical subject among policymakers in recent times. This is so because inequality can fuel social discontent and political unrest. Bhattarai (2016), in his study on theories of redistribution and share of labour income, highlighted a rising Gini coefficient among OECD countries with a significant increase in most Western European countries from about 0.29 to 0.39 between the years 1960 and 2015.

While much has been done to understand the causes of the declining labour income share, mainly using aggregate data, with only a few studies utilising firm-level data, factors like an increase in trade openness, globalisation, outsourcing and technological innovation, as posited by Bloise et al. (2022), Dimova (2019) and Siegenthaler & Stucki (2015) or increase in automation as highlighted by Tiwari (2022) and Acemoglu & Restrepo (2019) can not solely explain the noticeable decline in labour share across the globe.

A novel explanation of the cause of the decline in labour share is provided by De Loecker & Eeckhout (2017) and De Loecker et al. (2020). They argue that the decline in labour share is primarily influenced by dominant firms with significant market power, characterised by high markups and relatively low labour shares on an individual basis — "superstar firms" (Autor et al., 2020). Therefore, as a result of the reallocation of economic activities from smaller firms to these "superstar firms", as found by both De Loecker et al. (2020) and Autor et al. (2020) in at least for the US, labour share on the aggregate declines.

The two notable studies on market power in advanced and emerging EU countries are Weche & Wambach (2021) and IMF's World Economic Outlook (2019). While the IMF's World Economic Outlook (2019) study the macroeconomic implications of the rise in markups of some selected EU member states, Weche & Wambach (2021) compare the pre and post-financial crisis (The Great Recession) average markups of all the EU member states. However, regarding the estimated average markups in CEE member states, the conclusions are starkly contrasting. Weche & Wambach (2021) observe an overall decline in mark-ups within CEE countries, whereas the IMF's World Economic Outlook (2019) indicates an increase in markups. The difference in their findings perhaps is caused by the number of CEE countries included in their analysis and the aggregation level of the analysis, since both Weche & Wambach (2021) and IMF's World Economic Outlook (2019) used data from the same source (Orbis database) and the same method of markup estimation suggested by De Loecker (2011) and Loecker & Warzynski (2012) — while Weche & Wambach (2021) use firms-level data from eight CEE countries, IMF's World Economic Outlook (2019) used data from nine CEE countries plus two emerging countries outside CEE .

Since markups vary for different industries, a more disaggregated study of markups in emerging markets would be definitive. Estonia provides an interesting case study because of its well-established statistical system, quality data, and the significant economic reforms it has undergone since the collapse of the Soviet Union in 1991. Trąpczyński et al. (2016) highlighted that Estonia maintained a competitive lead among the CEE countries from 2007 to 2014. Also, Runiewicz-Wardyn (2018) noted that Estonia and the Czech Republic had the highest level of labour productivity and took the top positions among the CEE countries in the Global Competitive Index 2016-2017. Runiewicz-Wardyn (2018) further reveals that Estonia offers the highest institutional environment quality and the most competitive financial market among the CEE countries. Trąpczyński et al. (2016), who describe Estonia as an innovation-driven country, found that Estonia was one of the countries with the highest GDP per capita among the CEE countries. More importantly, the European Bank for Reconstruction and Development (EBRD) transition progress qualities indicators from 2016 to 2021 show that Estonia continues to maintain the highest position among CEE countries in competitiveness, inclusiveness, well-governance, resilience and is only second to the Czech Republic in terms of integration from 2020 to 2021[1]. Despite the small market size of Estonia, it has a remarkable performance in all

[1] See *Figure C 7* of Appendix C for EBRD transition quality indicators.

the critical transition indicators, making it a suitable candidate when choosing an emerging CEE country for a study.

This thesis, therefore, seeks to answer the following research questions: (i) How does the aggregate labour share evolves in Estonia — an emerging CEE country. (ii) What was the trend of markups and labour share at the firm-level in Estonia prior to the COVID pandemic. (iii) Does the level of markups charged by firms in Estonia signify the existence of market power in the industries under consideration[2]. (iv) Are the changes in aggregate markups in each of the five industries under consideration caused by within-industry changes in markups of firms without any change in the firms' market share or changes in reallocation of economic activities among firms in the industry or changes in the net entry of firms in the industry. (v) What is the effect of markups on labour share of value-added at the micro-level in Estonia.

Answering these research questions will help us contribute to empirical studies in the following ways: (i) Provide an industry-specific insight into the trend of labour of value-added and markups in Estonia. (ii) Contribute to the growing literature on market power implication on labour share by exploring and comparing evidence from different techniques of markups estimation at the firm-level.

1.1. OBJECTIVES

The main aim of this thesis is to explore the implication of market power on labour share of value-added using firm-level data of a catching-up country (Estonia) as a case study. The objectives of this thesis are:

i) To analyse the trends of labour share of value-added at the industry level in Estonia
ii) To analyse the trends of markups and their implications on market power.
iii) To decompose the changes in the level of aggregate markups of industries into within-industry effects, between-industries effects, and net-entry effects.
iv) To analyse the effect of markups on labour share at the firm-level in Estonia.

The remainder of this thesis is structured as follows. Section 2 reviews related literature, and section 3 describes the data used for our study. In section 4, we explain the empirical strategy

[2] Note that in this thesis we are considering five industries for our analysis based on our own classification of firms using their NACE 2-digit codes. See section 3 for the motivation behind this classification of industries. The industries under consideration are the resources industry, consumer manufacturing industry, material manufacturing industry, technological manufacturing industry and the retail/wholesale industry.

employed in this thesis. We present our empirical findings in section 5. Finally, section 6 draws the conclusion and discussion of the results.

2. REVIEW OF LITERATURE ON THEORY AND EVIDENCE OF LABOUR SHARE OF INCOME

The labour income share (or labour share) is part of national income or value-added allocated to labour compensation. In practice, the labour share is normally measured by taking the ratio of total labour compensation or labour costs to nominal GDP or nominal value added. A measure of employees' compensation compared to a simple measure of "wages and salaries" provides a better measure because it incorporates other forms of non-wage compensations like commissions, bonuses, tips, family allowances, employers' contribution to social security programs, and pension plans (Guerriero, 2012). This measure still suffers from various limitations, as pointed out by Krueger (1999). In pointing out the complexity of measuring the various components of the labour share, which might cause variation in the outcome of the research results, (Krueger, 1999, p. 45) posed the following questions:

> *" Who is a worker? Should CEO's and business owners be included? What is included in compensation? Should the corporate officers' stock options count as labor earnings? Is the return to investment in human capital counted as labor or capital income? How should retired workers who receive continuing health insurance coverage be treated?"*

Addressing these issues, the adjustment of self-employed has become the most topical issue in the literature on labour share estimation. According to Razgūnė & Lazutka (2015), if the employee compensation measure is used without regard to self-employment, it may underestimate the actual labour share since self-employment may mask the pervasiveness of informal employment. This is a notable drawback when analysing labour share over an extended period or in a cross-country study of labour share. To count for measurement error due to self-employed individuals, the OECD, the US Bureau of Labor Statistics, and the EU KLEMS adjust labour compensation by assuming that the average wage of self-employed individuals is equal to that of employees in the same sector (Schneider, 2011). Schneider pointed out that this might result in measurement error since the wages of self-employed and employees may differ substantially across different sectors and countries. A possible solution is to analyse the manufacturing sector only where self-employment is relatively few (Guerriero, 2019). In this paper, we compute labour share using compensation of employees from firm-level data, which is less prone to issues arising from mixed-income due to self-employed individuals as posited by Paul & Isaka (2020).

The distribution of production factors shares is most often traced back to Ricardo (1817), who described the laws that regulate this distribution as "the principal problem in Political Economy" (Ricardo, 1817, p. 5). Kaldor (1955) outlined "a bird's eye view" on the implications of the different theories that tried to solve this "principal problem". In reviewing the various distribution theories of shares, Kaldor classifies the theories into four main groups – Ricardian or Classical Theory, Marxian, Neo-Classical or Marginalist Theory and Keynesian Theory. Kaldor (1955) analysed these theories based on the empirical evidence of the "historical constancy" of labour income across different countries. Kaldor (1955, pp. 83–84) asserted that:

> *"... no hypothesis as regards the forces determining distributive shares could be intellectually satisfying unless it succeeds in accounting for the relative stability of these shares in the advanced capitalist economies over the last 100 years or so, despite the phenomenal changes in the techniques of production, in the accumulation of capital relative to labour and in real income per head."*

Kaldor compared Ricardo's and Marx's work and pointed out that both Ricardo and Marx believed in the inequality of wages to marginal productivity and that the supply price of labour is constant (inelastic). Ricardo's assumption of the variability of the relative share of labour due to the demand of labour being determined by capital accumulation is described as a contradiction of empirical research by Kaldor (1955) in his analysis due to the famous "historical constancy" of wage share. On the other hand, Marx believes that wages are determined at the subsistence level, and at any time, an excess supply of labour results in a falling labour share. In Marx's theory, wages can only increase if workers collectively pressure capitalists through unionisation to relinquish part of the "surplus value". Kaldor (1955) pointed out that constancy of wage share will only be achieved under this hypothesis if the wage increase is enough to compensate for the increase in output per head.

On the other hand, the neo-classicals or the marginalist value and distribution theory assumes that all factors under competitive conditions will receive remuneration at their marginal product. The implication of this gives rise to the marginal productivity theory, which assumes that input prices are equal to their marginal products in a competitive condition. The neo-classicals also employed the principle of "limited substitutability" rather than the principle of substitution as employed by Ricardo. As pointed out by Kaldor (1955), the entire approach of the neo-classicals to provide answers to the relative stability of factor share is premise on the assumption that factor shares are determined by the marginal rate of substitution between capital and labour — "the constancy of relative shares is evidence of a unity-Elasticity of Substitution between Capital and Labor" (Kaldor, 1955, p. 91).

However, the recent empirical evidence of the decline in labour share across countries and industries has shifted the scientific community's attention from trying to understand the mechanisms that explain the constancy in labour share to understanding the determinants of the decline in labour share.

One hypothesis for the noticeable decline in labour income share is a within-firm substitution of labour for capital. Most prominently among those who explore this hypothesis are Karabarbounis & Neiman (2014), who found the elasticity of substitution between labour and capital to be around 1.25. Based on this result, they argued that the price decrease in investment goods had led to the substitution of labour for capital, and this explained about half of the observable global decline in labour share. While the hypothesis of Karabarbounis & Neiman's (2014) argument is based on the high elasticity of substitution between labour and capital, numerous studies such as Acemoglu & Restrepo (2019), Antràs (2004) and Knoblach et al. (2020), among many others, have found the elasticity of substitution between capital and labour to be less than one.

As argued by some researchers, another possible cause of the declining labour income shares is globalisation. A study by Autor et al. (2013) found that Chinese import competition was responsible for the decrease in employment and wages in the US manufacturing industries between 1990 and 2007. That is, firms in advanced economies with high wages offshore to countries with low wages, like China. This leads to reduced employment in those advanced countries, resulting in a decline in wages and aggregate labour share. Using data from 87 countries, Doan & Wan (2017) found evidence of exports hurting labour share, which is more significant in advanced countries, while imports positively affect labour share. However, they found little evidence of FDI influencing labour share.

In conclusion, it is essential to emphasise that labour income share, or labour share, is an important measure used to assess the allocation of national income or value added to labour compensation. The measure of employees' compensation is a better measure than a simple measure of wages and salaries as it incorporates other forms of non-wage compensation. However, this measure suffers from various limitations, such as the complexity of adjusting for self-employed people, which might cause variation in the research outcome. Using firm-level data is less prone to issues of imprecisely measured income resulting from self-employment, especially in the manufacturing sector where self-employment is few. While there are a few factors that most researchers agree are contributing to the declining labour share, there is less consensus on the relative importance of these factors and their specific mechanisms.

3. DATA AND VARIABLES: DEFINITIONS AND DESCRIPTION

The data used in this study is the structural business statistics (EKOMAR) data for 2013 to 2020. The structural business statistics (EKOMAR) data is a survey data of enterprises in Estonia launched in 2013. The survey provides statistical information on the structure, performance, and development of these enterprises, including data on the number of employees, turnover, profit and loss, investment, and other financial and structural indicators. While in the earlier years, the sample was stratified by industry sector, the sample in recent years consists of all enterprises except for a few micro-enterprises. This makes the sample size much more significant and a better representation of the population. The sample used in this paper is limited to only enterprises from five (5) industries — the resources industry, consumer manufacturing, material manufacturing, technological manufacturing, and retail/wholesale industries. While classifying the industries into these five industries is not straightforward, it is worth of it because we are able to get a clearer picture and compare the trends of labour share in industries where there is the least chance of having self-employed individuals (technological manufacturing and material manufacturing) with the industries that may suffer from such limitations (retail/wholesale industry and to some extend the resource industries)[3] .

We adjusted variables under consideration for the effects of inflation in our data by using the values in 2015 as the base year for estimating the deflators. To avoid the influence of outliers on our analysis, we identified and treated outliers in our data using the Stata command —

[3] NB: The five industries under study in this thesis are constituted using NACE 2-digit codes are:
Resource industry: NACE 2-digit code in the range: 1 to 5, 7 to 9 & 35 to 39.
Consumer manufacturing: NACE 2-digit in the range: 10 to 15, 18 & 31 to 32
Material manufacturing: NACE 2-digit in the range: 16 to 17 & 19 to 25
Technological manufacturing: NACE 2-digit in the range: 26 to 30 & 33
Retail industry: 45 to 47

BACON (Weber, 2010), which employs Mahalanobis distance to detect outliers in multivariate data. After treating outliers, we have 77,436 observations in our data.

The consumption data of Estonia extracted from the gross domestic product of Estonia from Statistics Estonia database tables — "RAA0061: gross domestic product by expenditure approach (esa 2010) by Component, Year, Quarter and Indicator" is also used in our analysis. The data provide information on private consumption expenditure, general government final consumption expenditure and final consumption expenditure of non-profit institutions serving households from 1995 to 2020. Deflated consumption expenditure (Chain-linked volume (the reference year 2015), million euros) is used to estimate the rental rate of capital using Glover & Short (2020) approach.

We highlighted the trend of aggregate labour in six Central and Eastern European (CEE) countries — Estonia, the Czech Republic, Slovakia, Latvia, Lithuania, and Bulgaria, from 1998 to 2022 using data from AMECO database tables (series ALCD0). The AMECO database adjusts labour share estimates by assuming that the proportion of self-employed individuals stays the same over time and that the income share of self-employed individuals equals the compensation of employees[4]. As shown in *Figure 1*, there is an overall increase in the labour share across all the six CEE countries, with Estonia having an increase of about 4.8 percentage points between 1998 and 2022 despite the notable declines between 1998 – 2002 (Post-Asian Financial Crisis), between 2010 – 2012 (Post-Global Financial Crisis) and between 2020 – 2022 (COVID19 crisis). The overall increase in the labour share in these countries belies what is observed in many advanced economies such as the USA, France, Germany, the UK and Japan (Autor et al., 2020). Notwithstanding the overall increase in labour share in these CEE countries, the labour share is still lower than in other advanced economies (Tiwari, 2022). Therefore, Tiwari (2022, p. 10) describes the increase in labour share in Estonia as "catching-up to the levels observed in the OECD countries."

[4] The labour share, as estimated in the AMECO database is based on the formula:

$$Labour\ share = \frac{\frac{compensation\ of\ employees}{number\ of\ employees} \times total\ employment}{gross\ domestic\ product\ at\ market\ prices} \times 100$$

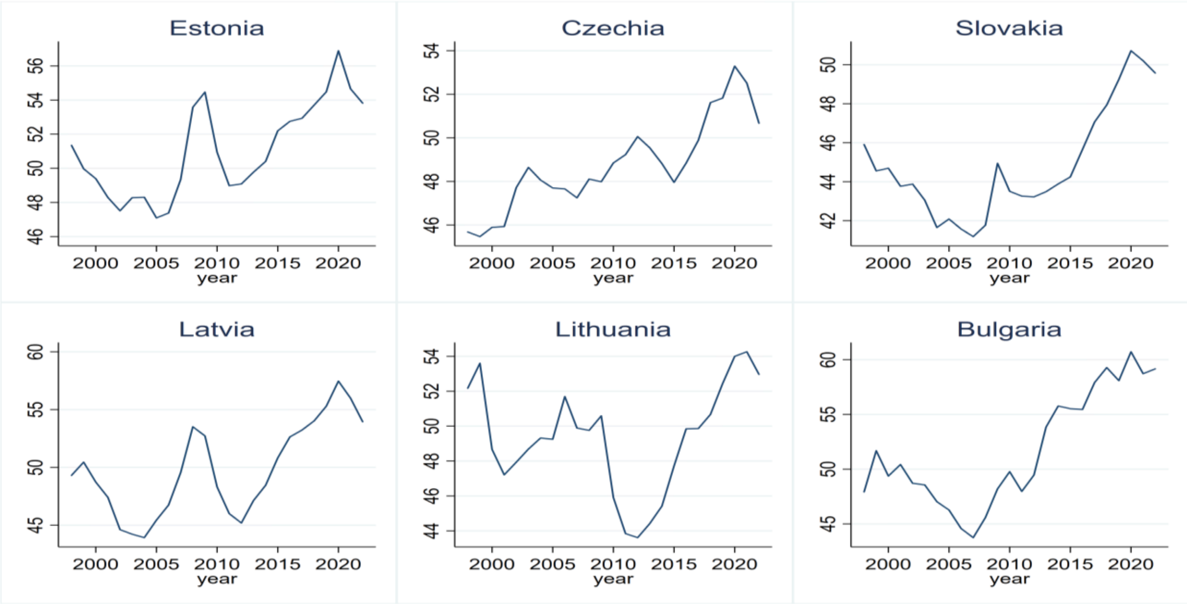

Figure 1. CEE Countries Comparison: Labour Share country

Source: AMECO Database

In the study of aggregate productivity and labour share implications of automation by Tiwari (2022), reallocation from less productive non-adopters of automation towards more efficient adopters of automation is highlighted as one of the possible causes of the increase in aggregate labour share in Estonia. We find the overall decrease in markups across industries due to an increase in competition as one of the factors contributing to the increase in the aggregate labour share of value-added. Other possible factors include an increase in trade openness and international integration, favouring catching-up and developing countries positively regarding labour share.

4. EMPIRICAL STRATEGY

4.1. Markup Estimation using the Production Approach

Calculating concentration measures in a market is easy with tools like the Herfindahl-Hirschman Index (HHI) or the combined market share of the biggest n firms (CRn). However, figuring out the markups of prices over marginal costs is more complex because we cannot easily observe marginal costs or prices themselves.

We estimated markups using the production approach employed by De Loecker et al. (2020). The method involves firm-level markup estimation using cost minimisation of variable production input that may have a potential dynamic implication. One advantage of using this method in our study is that we do not need information on prices and quantities of firms' output, which are notably lacking in our data. Also, the approach does not restrict how firms must compete nor assume a particular demand system that the products must adopt.

Markups are estimated as a ratio of an input's output elasticity to its revenue share, as outlined below. Consider a firm i that produces output Q_{it} in period t with capital K_{it} as an input with adjustment cost (dynamic input) and variable inputs — labour L_{it} (potential dynamic implications) and materials M_{it}. The production function of the firm is defined as:

$$Q_{it} = Q_{it}(L_{it}, K_{it}, M_{it}, \omega_{it}) \tag{1}$$

Whereby, ω_{it} is the unobserved productivity of the firm (technical efficiency of factors of production) and $Q_{it}(.)$ is continuous and second-order differentiable with respect to the inputs. Employing cost minimisation problem of the firm:

$$\min_{w,r,p^m \geq 0} w_{it}L_{it} + r_{it}K_{it} + p_{it}^m M_{it} \;\; s.t.\; Q_{it} = Q_{it}(L_{it}, K_{it}, M_{it}, \omega_{it}) \tag{2}$$

the Lagrangian function becomes:

$$\mathcal{L}(L_{it}, K_{it}, M_{it}, \lambda_{it}) = w_{it}L_{it} + r_{it}K_{it} + p_{it}^m M_{it} + \lambda_{it}\big(Q_{it} - Q_{it}(.)\big) \tag{3}$$

Where, w_{it}, p_{it}^m and r_{it} respectively represent the factor prices of labour, material input and capital, and λ_{it} is the Lagrangian multiplier which is a measure of marginal cost of production inputs.

The first-order condition with respect to labour input gives the expression:

$$\frac{\partial \mathcal{L}(L_{it}, K_{it}, M_{it}, \lambda_{it})}{\partial L_{it}} = w_{it} = \lambda_{it}\frac{\partial Q_{it}(.)}{\partial L_{it}} \tag{3}$$

Multiplying equation (3) by $\frac{L_{it}}{Q_{it}}$ and rearranging terms, we will get the following expression for markup:

$$\mu_{it} = \theta_{it}^L \left(\frac{w_{it}L_{it}}{P_{it}^Q Q_{it}}\right)^{-1} \tag{4}$$

Where P_{it}^Q is the price of output, $\mu_{it} = \frac{P_{it}^Q}{\lambda_{it}}$ is the markup (the ratio of price over the marginal cost), $\theta_{it}^{L} = \frac{\partial Q_{it}(.)}{\partial L_{it}} . \frac{L_{it}}{Q_{it}}$ is the output elasticity of labour input and $\frac{w_{it}L_{it}}{P_{it}^{Q}Q_{it}}$ is the revenue share of labour. Hence, μ_{it} is equal to one if the output elasticity of labour input is equal to the revenue share of labour[5]. Both the cost of labour input ($w_{it}L_{it}$) and revenue from output ($P_{it}^{Q}Q_{it}$) can be observed directly from our data. Hence, we only need to estimate θ_{it}^{L} from the production function of a firm. To estimate the production function, we follow the control function approach of Ackerberg et al.(2015), as outlined in Appendix A. We have used the output elasticity of labour input in the cost minimisation process to outline how markups are obtained with this approach because the approach allows the use of output elasticity of at least one variable input of production. Theoretically, the markups must be the same for each variable input of production because marginal cost must be the same for every variable input in the cost minimisation process.

Despite the advantages of the production approach of estimating markups, it has shortcomings. Hence, we also estimated markups using the so-called "A Flexible Cost Share Approach" adopted by Raval (2023). The cost-share approach of markup estimation relies on two key assumptions — cost minimisation and constant returns to scale to estimate markups by equating the variable cost of production to a firm's marginal cost of production. This is particularly important to account for the limitations of Loecker & Warzynski (2012) and De Loecker et al. (2020) production function approach of markup estimation. One of the notable shortcomings De Loecker et al. (2020) approach to markup estimation, as pointed out by both Doraszelski & Jaumandreu (2020) and Raval (2023), is the possibility of the existence of non-neutral productivity (productivity being different across firms), which can lead to systematically different output elasticities of inputs in different firms — since neutral productivity assumes the same output elasticities of input for different firms or plants. This is particularly so because these productivity differences augment labour (Doraszelski & Jaumandreu, 2020; Raval, 2023). Hence, markups estimated without considering the difference in firms' productivity might not be consistent.

Another criticism of the production function approach is its reliance on the revenue production function since quantity output is unobserved in firms' data. This might result in positive biased

[5] Note that the revenue share of labour is different from the labour share of value-added — while the revenue share of labour is the ratio of labour cost to firm's revenue, the labour share of value-added is the ratio of compensation to employees to the value-added of a firm.

output elasticities when markups are different across plants (Doraszelski & Jaumandreu, 2020).

4.2. Markup Estimation using the Flexible Cost-share Approach.

The flexible cost-share approach adopted by Raval (2023) requires two assumptions for the estimation of output elasticities of inputs.

Assumption one: (Cost Minimisation) *On average, the first-order condition for cost minimisation conditions holds for all inputs[6]:*

$$\theta^V = \frac{E(p_{it}^V V_{it})}{E(\lambda_{it} Q_{it})} \tag{5}$$

Where, $p_{it}^V V_{it}$ is the cost of variable input V_{it}, λ_{it} is the marginal cost, Q_{it} is output and θ^V is the output elasticity of the variable input.

A sufficient condition for this assumption is that all inputs are flexible. The assumption also holds if capital is dynamic. In that case, on average, the first-order condition for capital holds.

Assumption two: (Returns to Scale) *There are constant returns to scale.*

The implication of this assumption is that the average cost of production is equal to the marginal cost[7]. This assumption makes it much easier to compute $\lambda_{it} Q_{it}$ from our data since $\lambda_{it} Q_{it}$ becomes the total cost of production. Therefore, the output elasticity of labour input can be estimated as follows:

$$\theta^L = \frac{E(w_{it} L_{it})}{E(w_{it} L_{it} + r_{it} K_{it} + p_{it}^m M_{it})} \tag{6}$$

Using this method of estimating the output elasticity of labour, we can observe all the variables from our data except $r_{it} K_{it}$ which requires an estimation of the rental cost of capital r_{it}. We

[6] Note that equation (4) can also be written as:

$$w_{it} L_{it} = \theta_{it}^L \lambda_{it} Q_{it}$$

Where $\theta_{it}^L = \frac{\partial Q_{it}(.)}{\partial L_{it}} . \frac{L_{it}}{Q_{it}}$ is the output elasticity of labour input. Hence, finding the expected value of $w_{it} L_{it} = \theta_{it}^L \lambda_{it} Q_{it}$ gives the expression:

$$\theta_{it}^L = \frac{E(w_{it} L_{it})}{E(\lambda_{it} Q_{it})}$$

As seen in equation (5) for any input V.

[7] See Varian (2010, pp. 375–377) for mathematical explanation on why marginal cos equals average cost if returns to scale is constant.

estimated the rental cost of capital using consumption data of Estonia by adopting the approach of Glover & Short (2020). Glover & Short estimated the rental rate of capital by setting up a household's problem — maximise household's utility subject to a budget constraint[8].

To account for the possible variation in labour-augmenting productivity across plants, the cost-share of a firm is estimated within groups of firms with similar labour-augmenting productivity as outlined in detail in appendix B.

The good side of this approach is that it does not require firm data on quantities which are mostly unobserved. Also, since the approach only considers the expected costs of inputs, it can withstand any mistakes or imprecisions in measuring those inputs. Finally, the approach relies on labour cost, which is particularly important as it considers the variation in the abilities of workers.

For our analysis, industries' average markups are calculated by weighting firms' markups by the value-added share of firms in the industry. i.e.

$$\mu_{jt} = \sum_{i} w_{ijt}\mu_{ijt} \tag{7}$$

Where μ_{jt} is the weighted average markup of an industry j at time t and w_{ijt} is the weight of each firm i in industry j at time t.

4.3. Decomposition of Aggregate Markup in the Industries

To understand the drivers of the overall change in aggregate markup across the five industries, we perform a decomposition of markups at the industry-level using the decomposition method adopted by Vlokhoven (2021) and De Loecker et al. (2020) by considering how the firm-level distribution of markups have changed within each industry over time. This method of decomposition allows us to understand if the change in aggregate markups is caused by the reallocation of economic activities towards surviving firms with lower markups (decrease in

[8] Note: See Glover & Short (2020, pp. 37–38) for details on the estimation of rental rate of capital. The equation for estimating rental rate of capital base Glover & Short assumptions is as follow:

$$R_{t+1}^{i} = P_{t+1}^{i}\left[\beta^{-1}\left(\frac{c_{t+1}^{i}}{c_{t}^{i}}\right)^{\theta}\frac{P_{t}^{i}}{P_{t+1}^{i}} + \delta - 1\right]$$

Where $R_{t+1}^{i}$is the rental rate of capital of country i at time $t+1$, P is the relative price of investment, c is consumption, β is the time discount factor, and δ is the depreciation rate.

"Reallocation effect") or towards surviving firms with higher markups (increase in "Reallocation effect"). In addition, the decomposition method allows us to understand if the change in aggregate markup of an industry is due to changes in the markups of surviving firms within the industry suppose their market shares remain unchanged (within effect). Furthermore, the decomposition method allows for the understanding of the effect of changes in the composition of an industry on the aggregate markup of the industry — the effect of entry and exit of firms in an industry on the aggregate markup of the industry (net entry effect). Therefore, we decompose the aggregate firm-level markup for each industry as follows:

$$\Delta\mu_{jt} = \underbrace{\sum_i m_{jit-1}\Delta\mu_{jit}}_{\text{Within effect}} + \underbrace{\underbrace{\sum_i (\mu_{jit-1} - \mu_{jt-1})\Delta m_{jit}}_{\text{Between effect}} + \underbrace{\sum_i \Delta m_{jit}\Delta\mu_{jit}}_{\text{Covariance effect}}}_{\text{Reallocation effect}}$$
$$+ \underbrace{\sum_{i\epsilon Entry} m_{jit}(\mu_{jit} - \mu_{jt}) - \sum_{i\epsilon Exit} m_{jit-1}(\mu_{jit-1} - \mu_{jt-1})}_{\text{Net Entry effect}} \quad (8)$$

Where μ_{jt} is the weighted average markup of industry j at time t, μ_{jit} is the markup of firm i in industry j at time t and m_{jit} is the value-added share of a firm i in an industry j at time t. Hence, the "Between effect" term measures changes in the aggregate markup of an industry due to changes in the value-added share (market share) of firms while keeping their previous year's markup fixed. An increase in this term indicates an increase in the value-added share or market share of firms with higher markups — increasing the aggregate markup of the industry without increasing the markup of the firms themselves. However, the term "Covariance effect" explains the change in aggregate markup of an industry due to the joint change in value-added share and markup of the firms in the industry. The outcome of the decomposition exercise will provide a disaggregate explanation on the effect of markup on labour share of value-added.

4.4. Effect of Investment in Intangible Capital on Markups

The high markup values observed across the industries might not necessarily be associated with market power because if a firm's production is characterised by increasing returns to scale, where average cost surpasses marginal cost, the firm might set a higher markup to avoid losses. This scenario can arise when marginal cost is lower than fixed cost, and therefore, to cover the fixed cost and avoid bankruptcy, firms charge a markup above marginal cost. Also, high markups might be associated with extensive investment in intangible assets such as research and development (R&D) or information technology (IT) (IMF's World Economic Outlook, 2019). To account for this, we verified if the high markups translate to market power by performing a panel regression of the logarithm of markups on the logarithm of investment in intangible assets (Inv_Int_Cap), i.e.

$$\ln(\mu_{ijt}) = \beta_0 + \beta_1 \ln(Inv\_Int\_Cap)_{ijt} + \chi_i + \lambda_t + \varepsilon_{ijt} \tag{9}$$

Where, μ_{ijt} is the markup of a firm i in industry j at time t, β_0 is the constant term, β_1 which is the coefficient of investment in intangible assets (Inv_Int_Cap) measures the elasticity of markup to change in investment in intangible assets, and χ_i, λ_t and ε_{ijt} are the firm fixed effect, year fixed effect and the error term, respectively.

Therefore, our hypothesis is that:

H0: $\beta_1 = 1$

H1: $\beta_1 \neq 1$

The null hypothesis means a unitary elasticity between markup to investment in intangible assets.

4.5. Effect of Markup on Labour Share of Value-added

We analyse the effects of markups on labour share of value-added in each industry. To examine the degree of response of labour share of value-added to the markup of a firm in each industry, we perform a panel regression analysis of the logarithm of labour share of value-added on the logarithm of markup.

$$\ln(S_{ijt}) = \alpha_0 + \alpha_1 \ln(\mu_{ijt}) + \chi_i + \lambda_t + \varepsilon_{ijt} \tag{10}$$

S_{ijt} is the labour share of value-added of a firm i in industry j at time t, α_0 is the constant term, $\alpha_1$which is the coefficient of markup (μ_{ijt}) measuring the elasticity of labour share to change in markup and χ_i, λ_t and ε_{ijt} are the firm fixed effect, year fixed effect and the error term, respectively.

Hypotheses:

H0: $\alpha_1 = 0$

H1: $\alpha_1 \neq 0$

Whereby the null hypothesis means that markups have no effect on labour share of value-added. i.e. labour share of value-added is perfectly inelastic to changes in markup.

5. RESULTS

5.1. The Trend of Labour Share of Value-added Across the Industries

The weighted aggregate labour share of value-added across the five industries from 2013 to 2020 is presented in *Figure 2*. Overall, the aggregate labour share of value-added has been relatively stable, with a slight rise across all five industries compared to the aggregate labour share in the entire economy, which has seen a much steeper and steady rise post the global financial crisis (Great Recession) until 2020. Also, like in the US (Autor et al., 2020), across all the industries, the average labour share has been smaller compared to the labour share in the broader economy even though Autor et al. (2020) used a rather cruder measure of payroll to sales ratio because "robust firm-level measures of value added are not available from the Economic Census outside of manufacturing" as pointed out by Autor et al. (2020). The possible explanation for the smaller average labour share across these industries compared to that of the entire economy is that the aggregate labour share estimates in the entire economy is influenced by the higher labour share in the services sector as highlighted by De Loecker et al. (2020).

While consumer manufacturing and the technological manufacturing industries recorded the highest aggregate labour shares of value-added throughout the considered period, the labour share of value-added in the consumer manufacturing industry overtook the technological manufacturing industry around 2016 before it started falling steadily around 2018 to reoccupy the second position in 2020. However, the material manufacturing industry, which has the third highest labour share of value-added throughout the period, has seen a steady increase in aggregate labour share between 2014 and 2016 before it becomes stable in the remainder of the years. The labour share of value-added in the resource industry is only higher than that of the retail/wholesale industry. The resource industry's aggregate labour share of value-added peaked at 0.21 in 2019 before dropping by 23 percentage points to 0.16 in 2020.

It is worth noting that the average labours share in the resource industry and the retail/wholesale industries are extremely low compared to the other three industries. The smaller average values of labour share in the retail/wholesale industry compared to the other industries is similar to

Autor et al. (2020) findings about the US wholesale trade sector where they considered six broad sectors. The established fact that there is an inverse relationship between labour share of value-added and markups in at least the US (De Loecker et al., 2020), the global corporate sector (Karabarbounis & Neiman, 2014) and across advanced economies (IMF's World Economic Outlook, 2019) is likely playing a role in the extremely low values of labour share observed in the resources industry and the retail/wholesale industry since these industries also have higher average markups estimates as highlighted in *Figure 5*.

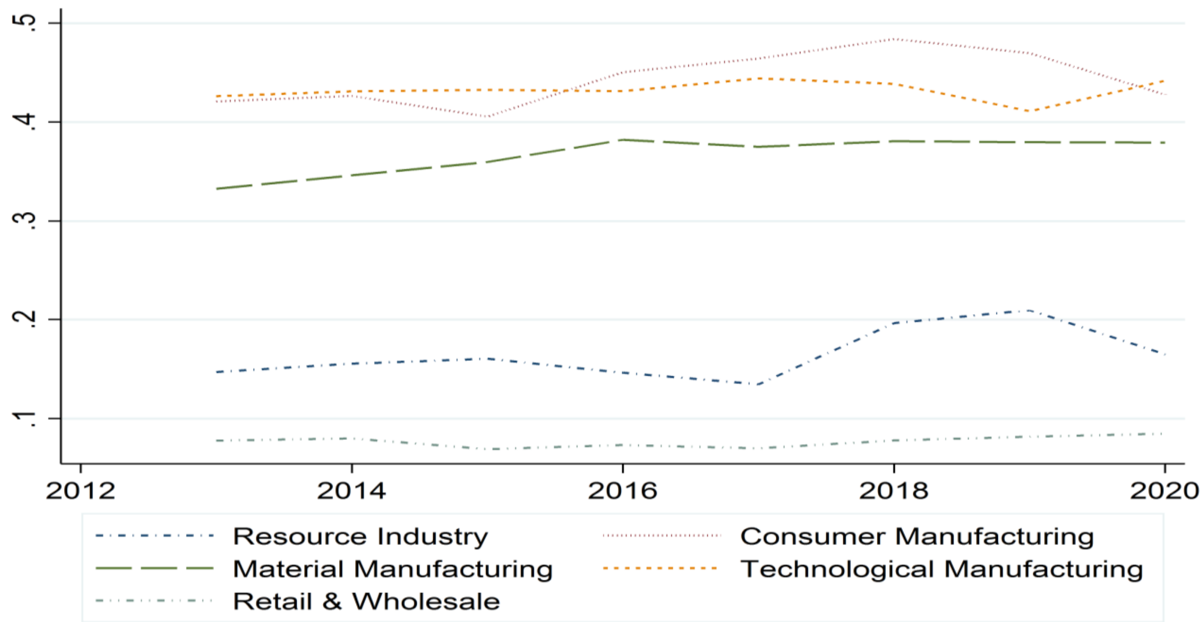

Figure 2. The Trend of Aggregate Labour Share of Value-added by Industry

Source: Author's Calculations using Estonia's firm-level data from the EKOMAR survey.

5.2. Comparing Markup Results from all the Techniques of Markup Estimation

The result of markup estimates using the production function approach (translog production function and Cobb-Douglas production function specifications) and the flexible cost-share method are analysed in this sub-section. While we estimated markups using both the output elasticity of labour and material inputs in the Cobb-Douglas production function specification and the flexible cost-share approaches, markups were estimated with only the output elasticity of labour input in the case of translog production function specification.

Figure 3 compares the trend of aggregate median markups in each industry for all the methods of markup estimation (using output elasticity of labour input) employed in this study. Overall, the aggregate median markups show a similar trend in the material manufacturing, technological manufacturing, and retail/wholesale industries for all three techniques of markup estimations employed, even though they peaked at different periods. However, the resource and consumer manufacturing industries show little difference in the trends of markup estimates from the three techniques in either the earlier periods or the later periods. The difference in the estimates of aggregate markup between the translog and the Cobb-Douglas production functions specifications in the production function approach can be attributed to the difference in their assumptions regarding the underlying production technology and the functional form's flexibility. While the Cobb-Douglas production function assumes a constant elasticity of substitution between production inputs, the translog production function allows for varying elasticity of substitution between inputs. This means the translog production function "permits a larger flexibility that can conduct to more realistic efficiency scores in relation to the Cobb-Douglas model" (Martins et al., 2012, p. 9). Finally, in all the industries except the retail/wholesale industry, markups estimated using the production function approach (translog and Cobb-Douglas) are higher than the markup estimates from the flexible cost-share method, and this difference can be attributed to the two methods underlying assumptions highlighted in section 4.

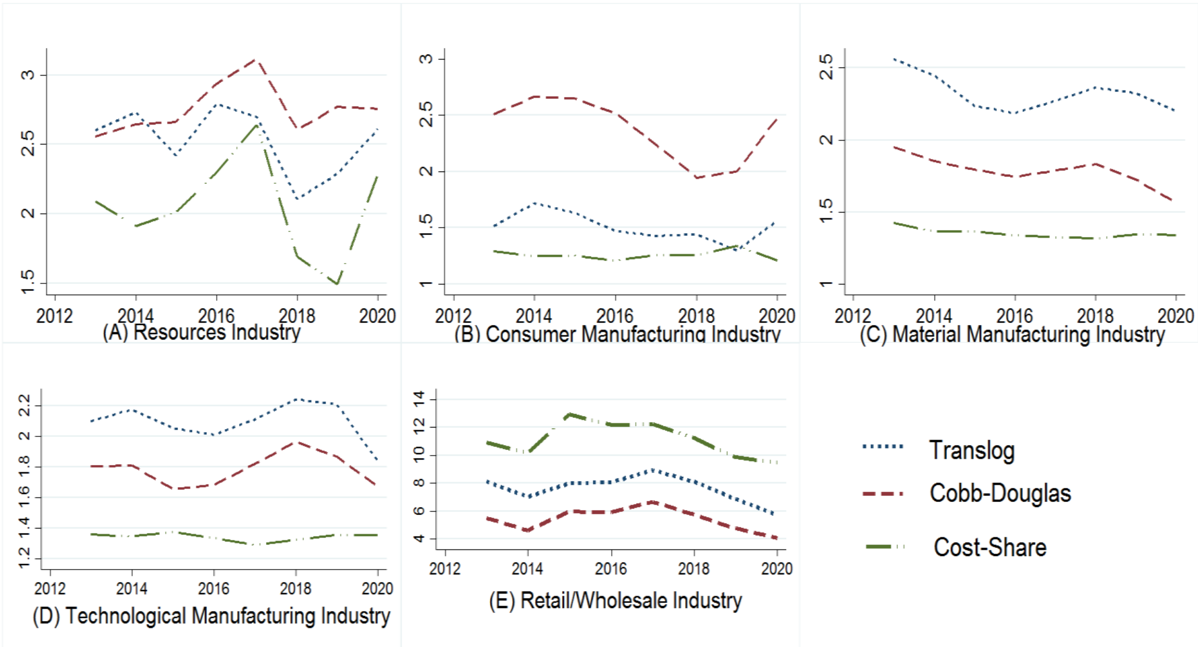

Figure 3. Aggregate Median Markups using Output Elasticity of Labour Input.

Source: Author's Calculations using Estonia's firm-level data from the EKOMAR survey.

On the other hand, *Figure 4* shows the trend of aggregate median markup estimates using output elasticity of material input in the production function approach (only Cobb-Douglas PF) and the flexible cost-share approach. Like *Figure 3*, aggregate median markup estimates are different in both approaches despite using the same output elasticity of input. Also, from *Figure 4*, there is a visible similarity in the trends of median markup estimates by the production function approach (Cobb-Douglas PF) and the flexible cost-share approach in the resource, consumer manufacturing and retail/wholesale industries, with slight differences in trend in material manufacturing and technological manufacturing industries.

Figure C 1 and figure *Figure C 2* in Appendix C show that there is a marginal difference in the values of markups computed using the output elasticity of material input and output elasticity of labour input across all five industries in both the production function approach (Cobb-Douglas specification) and flexible cost-share approach of markup estimation. However, the markups estimated using the flexible cost-share approach with the two variable inputs (labour and material) show similar trends across time and industries. Theoretically, these values are supposed to be the same, but in practice, they are different because of the variation in labour-augmenting productivity across plants (Raval, 2023).

Figure 4. Aggregate Median Markups using Output Elasticity of Material Input.
Source: Author's Calculations using Estonia's firm-level data from the EKOMAR survey.

5.3. The Trend of Markups: Means and Other Moments of the Distribution

The trend of average markups and other moments weighted by the value-added share of the firm is analysed in *Figure 5*. We used markups computed with the output elasticity of labour input in the flexible cost-share approach.

Overall, markups have been relatively stable in the lower half of markup distribution across all five industries, but the upper half of the distribution is characterised by fluctuations. Similar to the United States (De Loecker et al., 2020) and across the European Union (IMF's World Economic Outlook, 2019), markups are higher in the nonmanufacturing industries compared to the manufacturing industry. This might signal high fixed costs or less competitiveness in the nonmanufacturing industries.

Also, while there is an overall smaller decline in markups in the manufacturing industries — 6.8 percentage points decrease in consumer manufacturing, 10.7 percentage points decrease in material manufacturing, and 4.8 percentage points decrease in technological manufacturing, the nonmanufacturing industries saw a more considerable decline in markups between 2013 and 2020 — 38.6 percentage points decline in the resource industry and 28.3 percentage points in the retail/wholesale industry. The overall decline in markups across all the industries is similar to the trend observed by Weche & Wambach (2021) in the entire aggregate economy of Estonia, Hungary, Sweden, Romania, and Slovenia. The common feature of these countries is that four are catching-up economies (Estonia, Hungary, Romania, and Slovenia). The policies aimed at increasing competition in Estonia might be playing a role in the decline of markups in Estonia — Estonia ranks 5th as the best country for startups, 2nd out of 50 European nations in terms of both labour force quality and cost of doing business, and 3rd in Europe with respect to the number of startups per capita according to Veskus (2019). This is evident in the results of the decomposition exercise highlighted in section 5.4 — the "Within effect" component of the decomposition has a downward effect on aggregate markup across all five industries, which indicates either a decrease in the pricing power of firms within the industries due to an increase in competition or a decrease in the production cost of firms due to advancement in technology and/or efficiency improvements.

Finally, the overall relative stability of markups in the manufacturing sector is not only peculiar to Estonia but also other emerging markets economies (mostly central and eastern European countries) — IMF's World Economic Outlook (2019) and even in the US – Jaumandreu (2022) for at least the past decade.

Figure 5. Trends of Markup: Means and Other Moments of the Distribution.

Source: Author's Calculations using Estonia's firm-level data from the EKOMAR survey.

5.4. Results of Markups Decomposition

To get a disaggregate understanding of markup and its implication on labour share of value-added, we plot a graph of aggregate markups estimated by the cost-share method[9] (weighted by value-added) for each industry together with three counterfactual experiments (allowing for changes in only one component of the decomposition equation while keeping the values of the other components at zero) — the "Within", "Reallocation", and "Net Entry" effects. The counterfactual approach of visualizing the effects of individual components of the markup decomposition results, as adopted by De Loecker et al. (2020) and Vlokhoven (2021), gives a much more explicit pictorial representation of the effects of each of the decomposition components. To construct the counterfactuals, we chose 2013 as the base year and added cumulatively the changes caused by each component of the decomposition equation to the 2013 aggregate markup in each industry. Using the counterfactual approach allows us to understand the effect of the individual component of the decomposition equation on the observed trend of aggregate markup in each industry and their possible implications on the labour share of value-added.

In *Figure 6*, we notice that if there were only a reallocation effect on aggregate markup, the

[9] See also, also graphs for the changes in the individual components of the decomposition equation in Appendix C *Figure C 3* to *Figure C 5*.

aggregate markup would have increased across all the industries except the retail/wholesale industry, which has seen a minimal decrease of about 1.9 percentage points between 2013 and 2020. The upward effect of reallocation of economic activities on aggregate markup across the industries is similar to De Loecker et al. (2020) and Vlokhoven (2021) findings in the case of the US. However, it contrasts with the IMF's World Economic Outlook (2019) findings on the aggregate markup of some 28 countries. This result means the reallocation of economic activities from firms with lower markups to firms with higher markups, which is a feature of an imperfect market and can potentially increase the concentration of the industries. We establish the existence of an imperfect market or market power of firms in section 5.5 by showing that firms do not charge higher prices to cover fixed costs or investments in intangible assets. The established inverse relationship between markup and labour share of value-added in Estonia (section 5.6) suggests a depressing effect of reallocation of economic activities on the labour share of value-added. In other words, as economic activities are reallocated to firms with higher markups, it could lead to a decline in the portion of value-added allocated to labour. Tiwari (2022) found a similar effect (reallocation of resources among automation-adopting firms) in Estonia, which increases the aggregate factor productivity of those firms. This effect is termed the "superstar effect" by Autor et al. (2020), where economic activities are reallocated to dominant firms with significant market power and relatively lower labour share on an individual basis. The observed phenomenon in Estonia suggests that while aggregate productivity may increase, value-added distribution may disproportionately favour capital over labour due to the reallocation dynamics and market imperfections.

On the other hand, the "Within effect" hurts aggregate markup across all the industries, as shown in *Figure 6* below. This is contrary to De Loecker et al. (2020) and Vlokhoven (2021) findings about the US as well as the IMF's World Economic Outlook(2019) findings on the aggregate markup of some 28 countries. While the negative effect of within-firm markup changes on aggregate markup is the greatest in the retail/wholesale industry (about 35.7 percentage points decline), it is only in the material manufacturing industry that the entire decline in the aggregate markup is caused by the "Within effect". The overall downward effect of the "Within effect" across all the industries indicates a decrease in markups of surviving firms across industries while these firms' market share or value-added share remains unchanged. This result is an indication of either an increase in competition among firms in the industries — a decrease in the pricing power of firms in the industries caused by a change in the market structure or a decrease in the cost of production of firms resulting from technological advancements and efficiency improvements (or both). This suggests that while there is a "superstar effect" (reallocation of economic activities from firms with lower markups and smaller market shares to firms with higher markups and larger market shares), the effect of an increase in competition, as evident by the negative net entry effect coupled with a decrease in the cost share of firms as highlighted in *Figure C 6* of Appendix C have caused a general decline in the markups of surviving firms. The overall effect is an increase in labour share of value-added in the affected industries.

Finally, while the "Net Entry" plot as shown in *Figure 6* has shown many fluctuations compared to the "Within" and "Reallocation" plots, contrary to the US (De Loecker et al., 2020; Vlokhoven, 2021), there would have been an overall decline in aggregate markup by 24.7 percentage points in the resource industry and 65.1 percentage points in the consumer manufacturing industry if the other effects were non-existing. The negative effect of net entry on aggregate markups suggests an increase in competition and changes in the market structure of the affected industries. However, the material manufacturing, technological manufacturing and the retail/wholesale industries would have recorded an overall increase in aggregate markup by about 7.9, 5.4 and 53.6 percentage points respectively, if markups were affected by only the changes in net entry effect of firms in those industries.

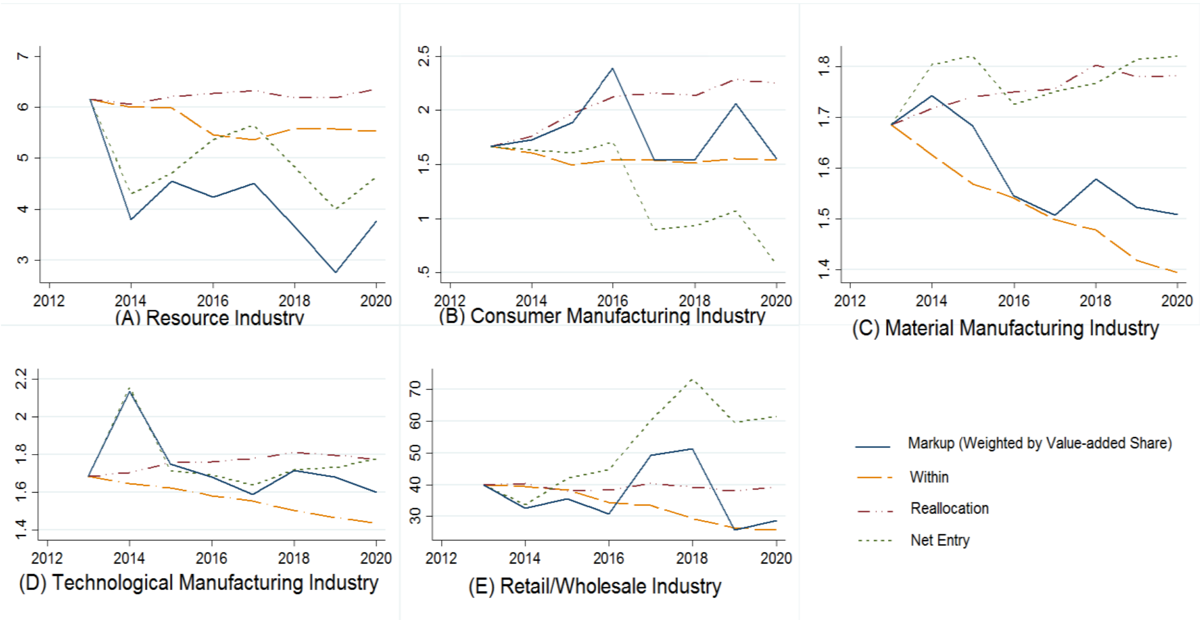

Figure 6. Decomposition of Aggregate Markup from the Cost-share Method using Output Elasticity of Labour Input.

Source: Author's Calculations using Estonia's firm-level data from the EKOMAR survey.

5.5. Market Power

As highlighted in section 4.4, firms might charge high markups to compensate for substantial investment in intangible assets like research and development. The panel regression (fixed effect model) results in Appendix C (*Table C 5 —Table C 8*) show that some coefficients of investment in intangible assets are insignificant for some industries, possibly because significantly fewer firms have recorded investments in intangible assets in those industries[10]. The retail/wholesale industry and the technological manufacturing industry are the areas where an impressive number of firms invested in intangible assets, hence the relative consistency and significance in the regression coefficients in those industries, as shown in *Table 1* below for the retail/wholesale industry.

Table 1: Regression of logarithm of markups on the logarithm of investment in intangible capital — Retail/Wholesale Industry

	(Translog) θ^L	(CD) θ^L	(CD) θ^M	(CS) θ^L	(CS) θ^M
ln(Inv_Int_Cap	-0.0362*** (0.0053)	-0.0335*** (0.0054)	-0.0306*** (0.0069)	-0.0018 (0.0070)	-0.0429*** (0.0110)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
R^2	0.354	0.344	0.369	0.141	0.247
Observations	9,505	9,505	9,505	9,505	9,505
Number of firms	6,259	6,259	6,259	6,259	6,259

Note: Robust standard errors in parenthesis
***p<0.01, **p<0.05, *p<0.1
θ^L: output elasticity of labour input, θ^M: output elasticity of material input, CD: Cobb-Douglas specification, CS: cost-share method
Source: Author's Calculations using Estonia's firm-level data from the EKOMAR survey.

While it is difficult to arrive at a conclusion for some industries based on the regression results, the retail/wholesale (*Table 1*) and the technological manufacturing industries (*Table C 8* of Appendix C) regression results show that markups respond negatively to increase in investment

[10] NB: Firms' investment in intangible capital in Estonia might be very small based on the evidence from this data, especially in the resource and consumer manufacturing industries. For instance, out of 4, 330 observations in the resources industry, only 353 (8.15%) observations recorded investment in intangible capital.

in intangible assets contrary De Loecker et al (2020) findings about the United States — increase in investment in intangible capital dwindle firms markup in Estonia which is a sign of changes in the market structure of those industries (increasing competition). The implication is that while industries in the US are becoming more concentrated (Autor et al., 2020) and firms' market power are increasing (De Loecker et al., 2020), industries in Estonia are becoming more competitive and firms market power is declining as suggested by the decomposition results in section 5.4 (the within and net entry effects). The regression coefficient of -0.0362, as shown in *Table 1*, indicates that as investment in intangible capital increases by 100 percentage points in the retail/wholesale industry, markup will decrease by 3.62 percentage points. The results indicate the existence of market power of firms (where markups translate into profit) because, in a perfectly competitive market where firms break even, the elasticity of markup to investment in intangible assets will be one or unitary to prevent losses and a possible shutdown of the business. Evidence of the existence of market power across the industries is further highlighted in *Figure 7*, where the graph of aggregate markup is plotted together with markup estimates under perfect competitive market assumptiom (zero-profit markup) following De Loecker et al. (2020) approach of zero-profit markup estimation[11].

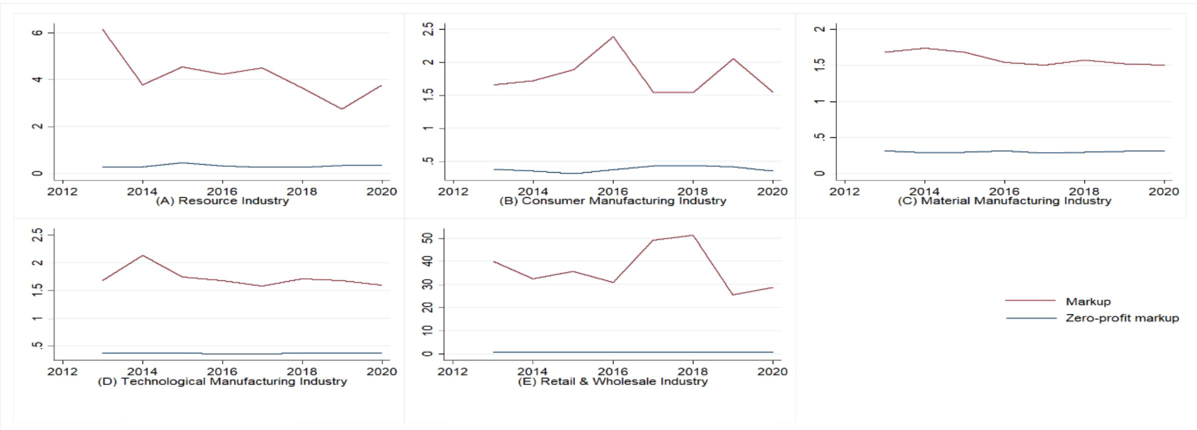

Figure 7. Aggregate Markups: Zero-profit markup and Actual Markups of Firms.
Source: Author's Calculations using Estonia's firm-level data from the EKOMAR survey.

[11] *Note*: See De Loecker et al. (2020, pp. 592–600) for details on the estimation of zero-profit markup. The equation for estimating zero-profit markup based on De Loecker et al. (2020) is as follow:

$$\mu_{it}^{Z} = \frac{\theta_{it}^{V}}{1 - \frac{r_t K_{it}}{R_{it}} - \frac{P_{it}^{X} X_{it}}{R_{it}}}$$

Where μ_{it}^{Z} is the zero-profit markup of a firm i at time t, $\theta_{it}^{V}$is the output elasticity of variable input, $r_t K_{it}$is the cost of capital, $P_{it}^{X} X_{it} = investment\ in\ intangible\ assets$ is the fixed cost and $R_{it}$is the sales revenue of the firm.

Note: The zero-profit markup is estimated under perfect market competition assumption (firms breakeven).

From *Figure 7*, the markup estimates under perfect competitive market assumptions (zero-profit markup) are much less than the actual markup over marginal cost charged by the firms across the industries. This indicates that the markups charged by the firms translate into profit (market power) but not necessarily to break even.

5.6.Markups and Labour Share of Value-added

To understand the effect of markups on the labour share of value-added, we run a panel regression (fixed effect model) of the logarithm of labour share on the logarithm of markup for each industry. The regression result for the material manufacturing industry is presented in *Table 2* below, while the other four industries are shown in *Table C 1* to *Table C 4* of Appendix C. Across all the industries, we get negative coefficients for all the markup estimates except for markups calculated with output elasticity of material input estimated from the Cobb-Douglas production function in some industries. The coefficients vary across industries depending on the method and the elasticity of variable input used in the markup estimation. For instance, the coefficients of markups estimated by the production function approach using output elasticity of labour input are -0.337, -0.331, -0.612, -0.568 and -0.648, respectively, for the resources, consumer manufacturing, material manufacturing, technological manufacturing, and the retail/wholesale industries. All these values are significant at one per cent level and similar to the results of -0.20 to -0.73 found in the US by De Loecker et al. (2020).

Table 2: Regression of logarithm of labour share of value-added on the logarithm of markups — Material manufacturing industry

	(Translog) θ^L	(CD) θ^L	(CD) θ^M	(CS) θ^L	(CS) θ^M
ln(markup)	-0.612*** (0.008)	-0.485*** (0.007)	0.282*** (0.013)	-1.107*** (0.008)	-0.468*** (0.009)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
R^2	0.123	0.108	0.042	0.509	0.207
Observations	18,149	18,149	18,149	18,149	18,149
Number of firms	4,680	4,680	4,680	4,680	4,680

Note: Robust standard errors in parenthesis
***p<0.01, **p<0.05, *p<0.1
θ^L: output elasticity of labour input, θ^M: output elasticity of material input, CD: Cobb-Douglas specification, CS: cost-share method
Source: Author's Calculations using Estonia's firm-level data from the EKOMAR survey.

The markup coefficient of -0.612 means that as markup increases by 100 percentage points in the material manufacturing industry, labour share will decline by 61.2 percentage points, and a similar interpretation is given to the rest of the coefficients. In essence, we have established an inverse relationship between firms' markup and labour share of value-added at the firm level in Estonia, consistent with the literature.

The consumer manufacturing and the resources industries exhibited both the "superstar" effect (reallocation of economic activities from less productive firms with below average markups and above average labour share to more productive firms with above average markup and below average labour share) and changes in the market structure of firms due to increased in competition. The established inverse relationship between markups and labour share signifies that while aggregate labour share of value-added in the consumer manufacturing and the resources industries are suppressed by the reallocation effect, the combined positive effect of the net entry and within-firm effects (change in market structure due to increase in competition) is higher — partly explaining the observed rise in labour share in these industries. Tiwari (2022) found similar reasons to be partly responsible for the rise in labour share of value-added among automation adopters and non-adopters in Estonia.

On the other hand, while the labour share of value-added in the material manufacturing and the technological manufacturing industries are positively influenced by the within-firm effect, the negative effect of the reallocation effect is reinforced by a negative net entry effect. However, the magnitude of the within-firm effect supersedes the combined effect of the reallocation and the net entry effect, contributing to the observed rise of labour share in the material manufacturing and the technological manufacturing industries. This means that while there is an increase in concentration in these industries, most of the surviving firms have witnessed a decrease in their pricing power resulting from competition from the "superstar" firms or new entrants.

The retail/wholesale industry is becoming much more competitive compared to the other industries since both the reallocation effect and the within-firm effects are having a positive effect on labour share of value-added. Despite evidence of relative competitiveness in the retail/wholesale industry, firms in the industry stile poses some market as evident in the negative effect of the net entry effect and the regression results shown *Table 1*.

6. CONCLUSION AND DISCUSSION

In this thesis, we studied the implication of market power on the labour share of value added across five major industries in Estonia — resource industry, consumer manufacturing, material manufacturing, technological manufacturing and the retail/wholesale industries using EKOMAR data from 2013 to 2020. While there is growing empirical work on the effect of market concentrations and markups on the labour share of value added due to the observable rise in concentration, particularly in the US, there is less attention on this topic, especially in catching-up economies. This work fills the research gap by providing evidence on the evolution of labour share and markups at the industry level and the implication of markups on labour share using micro-level data from Estonia.

As part of the empirical part of our study, we used the production function approach of markup estimation to estimate markups in both translog and Cobb-Douglas function specifications. Acknowledging the shortfalls of the production function approach of markup estimation, we also adopt the somewhat restrictive "flexible cost share" approach of markup estimation as a control. We used markups estimated from both approaches in our analysis. From our study, we establish the following:

i) The labour share of value-added is relatively stable, with a small overall rise across all the industries between 2013 and 2020. The rise in labour share at the firm level in Estonia within this period is supported by the finding of Tiwari (2022) using census data of firms in Estonia. At the macro-level, we also highlighted a similar rise in labour share post the global financial crisis until 2020, when labour share began to decline due to the effect of the COVID-19 pandemic.

ii) Like in the United States (De Loecker et al. 2020) and across the European Union (IMF's World Economic Outlook 2019), markups are higher in the nonmanufacturing industries compared to the manufacturing industries. Also, while there is an overall decline of markup across the industries between 2013 and 2020, the decline in the manufacturing industries is smaller compared to the nonmanufacturing industries. Weche & Wambach (2021) observe a similar decline in the entire economy aggregate markup of Estonia and other catching-up economies like Hungary, Romania and Slovenia.

iii) The markup estimation is very sensitive to how the output elasticity of variable inputs is computed. Recent literature (Jaumandreu, 2022; Raval, 2023) shows that apart from controlling for Hicks-neutral productivity, which affects all production inputs, there is a need to control for labour-augmenting productivity. Despite the similarities in the trends, the markup estimates from the production function approach proposed by De Loecker et al. (2020), which does not control for labour-augmenting productivity, differ from Raval's (2023) "flexible cost share" approach of markup estimation, which control for labour-augmenting productivity. Controlling for labour-augmenting productivity, Jaumandreu (2022) also noticed that markups in the manufacturing industry have been remarkably stable for at least the past decade in the US, contrary to De Loecker et al. (2020) findings of a much more fluctuation in markup in the manufacturing industry in the US in the same period using a production function approach that does not control for labour-augmenting productivity.

iv) There has been a reallocation of economic activities from firms with low markups to firms with higher markups in Estonia, just like in the US (De Loecker et al., 2020; Vlokhoven, 2021). The reallocation effect has a depressing effect on aggregate labour share of value-added. The finding suggests the existence of a "superstar" effect across these industries. However, the "Within" effect of the decomposition was negative across the industries implying either an increase in competition among firms due to changes in the market structure or a decrease in the cost of production of firms. The "Within" effect has the greatest negative effect on the markup and hence, it plays a significant role in the upward trend of labour share in the industries. Furthermore, the negative effect of the decomposition term "net entry" on aggregate markup in the resources industry and the consumer manufacturing industry further suggests that the decline of markup in those industries is caused by an increase in competition within the industries. But in material manufacturing, technological manufacturing and the retail/wholesale industries, aggregate markups have been affected positively by the "net entry" effect. This result, together with the negative effect of "Within" effect on aggregate markups in those industries, suggests that the overall decline in markups across these industries is caused by a decrease in the cost of production resulting from technological advancements and/or efficiency improvements and consequently the rise in labour share.

v) To a large extent, we found that the observed high markups in the material manufacturing and the retail/wholesale industries are associated with market power.
vi) There is an inverse relationship between markup and labour share of value-added across all the industries, and the observable rise in labour share can partly be attributed to the fall in markups.

Based on the takeaways from our results, there is a need for policy reforms particularly aimed at the nonmanufacturing sector to reduce the substantially high markups observed in the industry. Increasing competition through policies that encourage start-ups and foreign direct investments in the area will help to reduce markups in the sector. The consequences of such policy actions would be a further increase in labour share of value-added because of the established inverse relationship between labour share and markups.

Finally, our results reveal the existence of market power at the industry level, and the reallocation of economic activities from lower markup firms to higher markups firms further suggest the concentration of these industries. However, we did not probe this further to find out if the concentration is a "good concentration" or "bad concentration". This is an important area that needs further study since it directly explains the welfare of the consumer in the existence of market power. This thesis also faces a constraint related to the time coverage of the data, which spans from 2013 to 2020. The limited timeframe may impede a comprehensive exploration of labour share trends at the firm level. A more extensive time coverage is essential for a nuanced and in-depth analysis, providing a more thorough understanding of the dynamics and patterns that unfold over an extended period. The current temporal scope may restrict the ability to capture long-term shifts, cyclical patterns, or significant events that influence labour share dynamics in the context of individual firms.

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APPENDIX A: Production Function Estimation

The production function estimation approach used in this work follows the control function approach of Ackerberg et al.(2015). Using this estimation method, we consider a production function that is Leontief in material input such that material input is proportional to output and consequently, value-added is proportional to output. Using Leontief translog PF specification, the value-added production function is given to us as follows:

$$q_{it} = \theta_{it}^{L} l_{it} + \theta_{it}^{K} k_{it} + \theta_{it}^{LL} l_{it}^{2} + \theta_{it}^{KK} k_{it}^{2} + \theta_{it}^{LK} l_{it} k_{it} + \omega_{iy} + \epsilon_{it} \qquad (A.1)$$

Where q_{it}, l_{it} , k_{it}, represent the natural logs of output, labour, and capital, respectively. The log of the total factor productivity (TFP) is ω_{iy} and the ϵ_{it} is the error term.

We follow the two-step estimation procedure as discussed in ACF. However, the estimation is realised under the following assumptions:

Assumption one: *(Scalar Unobservable) Firm's material input demand function is given by*

$$m_{it} = f_{t}(k_{it}, l_{it}, \omega_{it}) \qquad (A.2)$$

Where m_{it} is the log of the value of material input.

Assumption two: *(Strict Monotonicity)* $f_{t}(k_{it}, l_{it}, \omega_{it})$ *is strictly increasing in* ω_{it}.
Given the above assumptions $f_{t}(k_{it}, l_{it}, \omega_{it})$ is invertible in ω_{it}. i.e.

$$\omega_{it} = f_{t}^{-1}(k_{it}, l_{it}, m_{it}) \qquad (A.3)$$

Assumption three: *(information Set) The firm's information set at t, i.e.* I_{it}, *includes current and past productivity shocks* $\{\omega_{i\tau}\}_{\tau=0}^{t}$ *but does not include future productivity shocks* $\{\omega_{i\tau}\}_{\tau=t+1}^{\infty}$. *The transitory shocks* ϵ_{it} *satisfy* $E[\epsilon_{it}|I_{it}] = 0$.

Assumption four: *(First Order Markov) Productivity shocks* (ω_{it}) *follow the distribution.*

$$p(\omega_{it}|I_{it-1}) = p(\omega_{it}|\omega_{it-1}) \qquad (A.4)$$

This distribution is known to firms and stochastically increasing in ω_{it}.

Assumption five*: (Timing of Input Choices) Firm's investment* i_{it-1}, *which is chosen in period* $t-1$ *is not productive until period* t. *i.e.*

$$k_{it} = (1-\delta)k_{it-1} + i_{it-1} \qquad (A.5)$$

Labour input l_{it} has potential dynamic implications and is chosen at period t, period $t-1$ or period $t-b$ $(with\ 0 < b < 1)$

From assumptions, we solve $\omega_{it} = f_t^{-1}(k_{it}, l_{it}, m_{it})$ into the production function to get:

$$q_{it} = \theta_{it}^{L} l_{it} + \theta_{it}^{K} k_{it} + \theta_{it}^{LL} l_{it}^{2} + \theta_{it}^{KK} k_{it}^{2} + \theta_{it}^{LK} l_{it} k_{it} + f_t^{-1}(k_{it}, l_{it}, m_{it}) + \epsilon_{it} \qquad (A.6)$$

This gives the following expression.

$$q_{it} = \Phi_t(k_{it}, l_{it}, m_{it}) + \epsilon_{it} \qquad (A.6)$$

Where $\Phi_t(k_{it}, l_{it}, m_{it}) = \theta_{it}^{L} l_{it} + \theta_{it}^{K} k_{it} + \theta_{it}^{LL} l_{it}^{2} + \theta_{it}^{KK} k_{it}^{2} + \theta_{it}^{LK} l_{it} k_{it} + f_t^{-1}(k_{it}, l_{it}, m_{it})$. This results in the first stage moment condition.

$$E[\epsilon_{it} | I_{it}] = E[q_{it} - \Phi_t(k_{it}, l_{it}, m_{it}) | I_{it}] = 0 \qquad (A.7)$$

This stage produces the estimate of $\Phi_t(k_{it}, l_{it}, m_{it})$ as $\widehat{\Phi_t}(k_{it}, l_{it}, m_{it})$.

The production function parameters are estimated in the second stage, as in ACF.
Considering assumptions four and five, we can estimate the output elasticity by considering the productivity process given by $\omega_{it} = h(\omega_{it-1}) + \xi_{it}$. This gives the following moment conditions.

$$E\left[\xi_{it}(\theta_{it}) \begin{pmatrix} l_{it-1} \\ k_{it} \\ l_{it-1}^{2} \\ k_{it}^{2} \\ l_{it-1} k_{it} \end{pmatrix}\right] = 0 \qquad (A.9)$$

APPENDIX B: Markup Estimation Using the Cost-share Method.

The flexible cost-share approach of markup estimation adopted from Raval (2023) is motivated by the fact that productivity might not be Hicks neutral and that productivity differences across firms tend to augment labour. Assume a production function with constant elasticity of substitution (CES) α, neutral productivity A_{it}, labour-augmenting productivity Ω_{it} and the distribution parameters β_l and β_m:

$$Q_{it} = A_{it}\left((1-\beta_l-\beta_m)K_{it}^{\frac{\alpha-1}{\alpha}} + \beta_l(\Omega_{it}L_{it})^{\frac{\alpha-1}{\alpha}} + \beta_m M_{it}^{\frac{\alpha-1}{\alpha}}\right)^{\frac{\alpha}{\alpha-1}} \qquad (B.1)$$

Input shares of revenue give the following result:

$$\frac{w_{it}L_{it}}{P_{it}Q_{it}} = \frac{1}{\mu_{it}}\left(\frac{w_{it}}{\lambda_{it}A_{it}}\right)^{1-\alpha}(\beta_l)^{\alpha}(\Omega_{it})^{\alpha-1} \qquad (B.2)$$

$$\frac{P_{it}^{m}M_{it}}{P_{it}Q_{it}} = \frac{1}{\mu_{it}}\left(\frac{P_{it}^{m}}{\lambda_{it}A_{it}}\right)^{1-\alpha}(\beta_m)^{\alpha} \qquad (B.3)$$

Where, μ_{it} is the markup, λ_{it} is the marginal cost, P_{it}^{m} is the price of material input and P_{it} is the price of output.

From the equations, the implication is that changes in the neutral productivity A_{it} is compensated by an equal change in marginal cost λ_{it}—has no effect on the revenue share of inputs. However, changes in labour-augmenting productivity Ω_{it} affect revenue share of inputs, and if the value of α is less than one, plants with higher Ω_{it} will have a lower labour share of revenue, a higher material share of revenue, and a lower labour-material cost ratio. Hence, in a competitive inputs market, the expression for markup is obtained as:

$$\mu_{it} = \frac{\theta_{it}^{X}}{S_{it}^{X}} \qquad (B.4)$$

Where θ_{it}^{X} is the output elasticity of variable input X, and S_{it}^{X} is the revenue share of input X The approach, therefore, relies on the following assumptions for markup estimation.

Assumption one: (Cost Minimisation) *On average, the first-order condition for cost minimisation conditions holds for all inputs:*

$$\theta^{V} = \frac{E(p_{it}^{V}V_{it})}{E(\lambda_{it}Q_{it})} \qquad (B.5)$$

Where, $p_{it}^{V}V_{it}$ is the cost of variable input V_{it}, λ_{it} is the marginal cost, Q_{it} is output and θ^{V} is the output elasticity of the variable input.

Assumption two: (Returns to Scale) *There are constant returns to scale.*

The implication of this assumption is that the average cost of production is equal to the marginal cost. This assumption makes it much easier to compute $\lambda_{it}Q_{it}$ from our data since $\lambda_{it}Q_{it}$ becomes the total input cost of production. Therefore, output elasticity of labour input can be estimated as:

$$\theta^L = \frac{E(w_{it}L_{it})}{E(w_{it}L_{it} + r_{it}K_{it} + p_{it}^m M_{it})} \qquad (B.6)$$

Using this method of estimating the output elasticity of labour, we can observe all the variables from our data except $r_{it}K_{it}$, which requires an estimation of the rental cost of capital r_{it}. We estimated the rental cost of capital using consumption data of Estonia by adopting the approach of Glover & Short (2020).

To account for the possible difference in labour-augmenting productivity in the estimation of output elasticities, we sorted firms into five quantiles for each industry based on the labour-to-material cost-share ratio. We then estimated the output elasticities as the input cost-share of total cost within each industry group. After computing the output elasticities of inputs — labour and capital, directly from our data, we estimated the revenue share of inputs. Hence, labour share is computed by simply taking the ratio of the output elasticity of input to their revenue share.

APPENDIX C: Figures and Tables

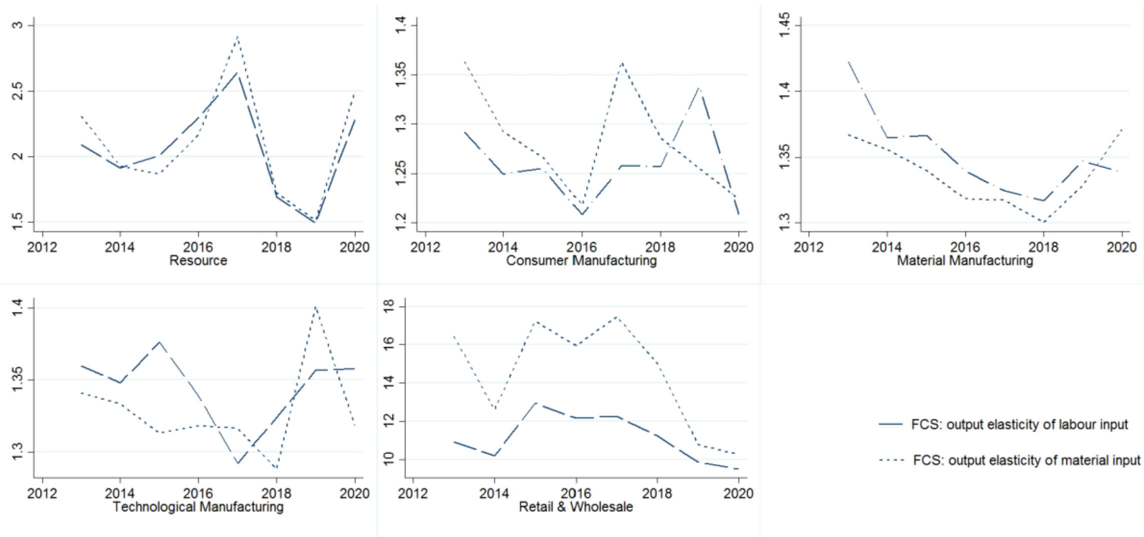

Figure C 1: Trend of median markups using output elasticity of labour /material input estimates from Cobb-Douglas PF– weighted.

Source: Author's Calculations using Estonia's firm-level data from the EKOMAR survey.

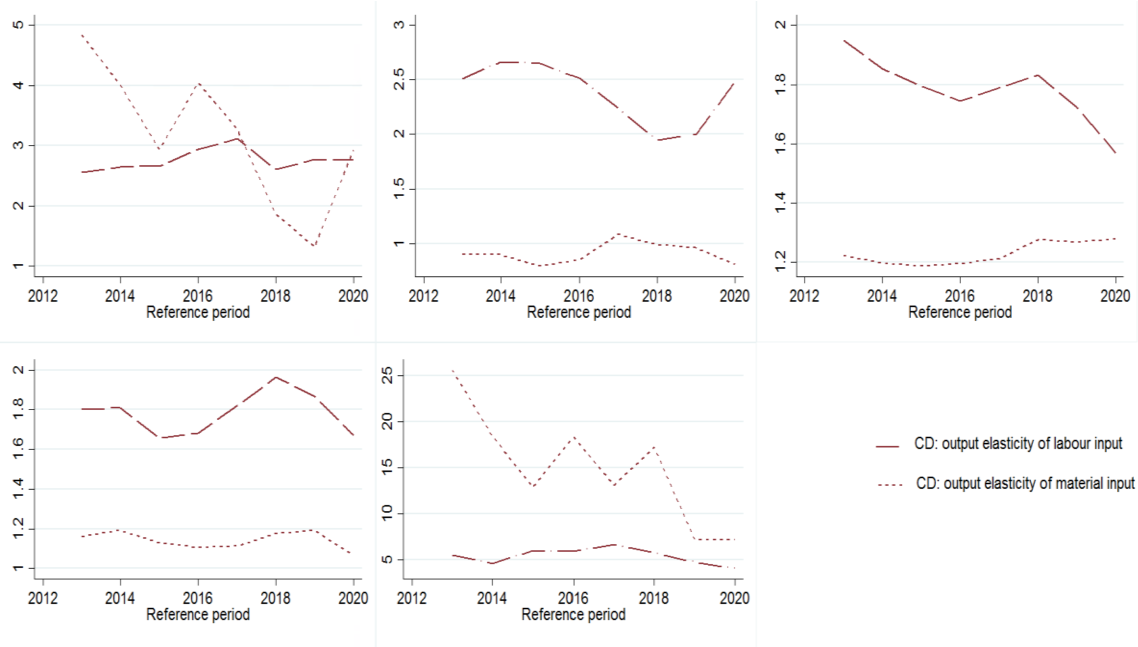

Figure C 2: Trend of weighted median markups using output elasticity of labour and material inputs estimated from flexible cost share approache.

Source: Author's Calculations using Estonia's firm-level data from the EKOMAR survey.

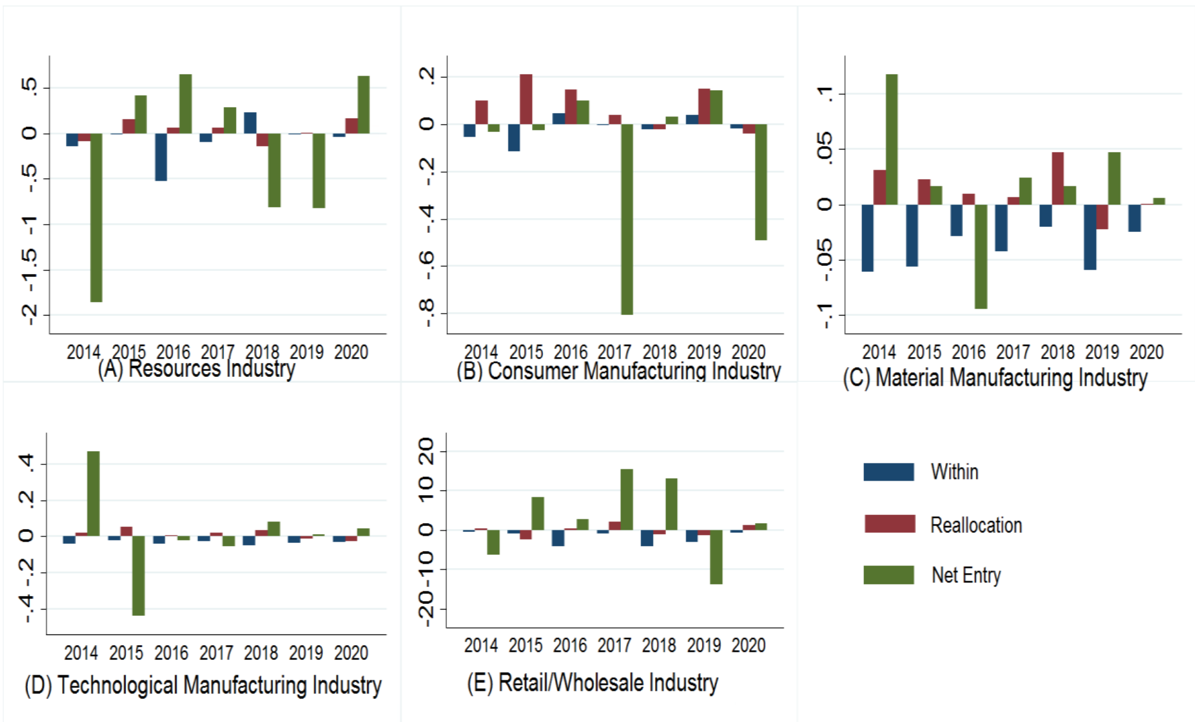

Figure C 3: Yearly change of markup decomposition components — Markup estimates from cost-share method.

Source: Author's Calculations using Estonia's firm-level data from the EKOMAR survey.

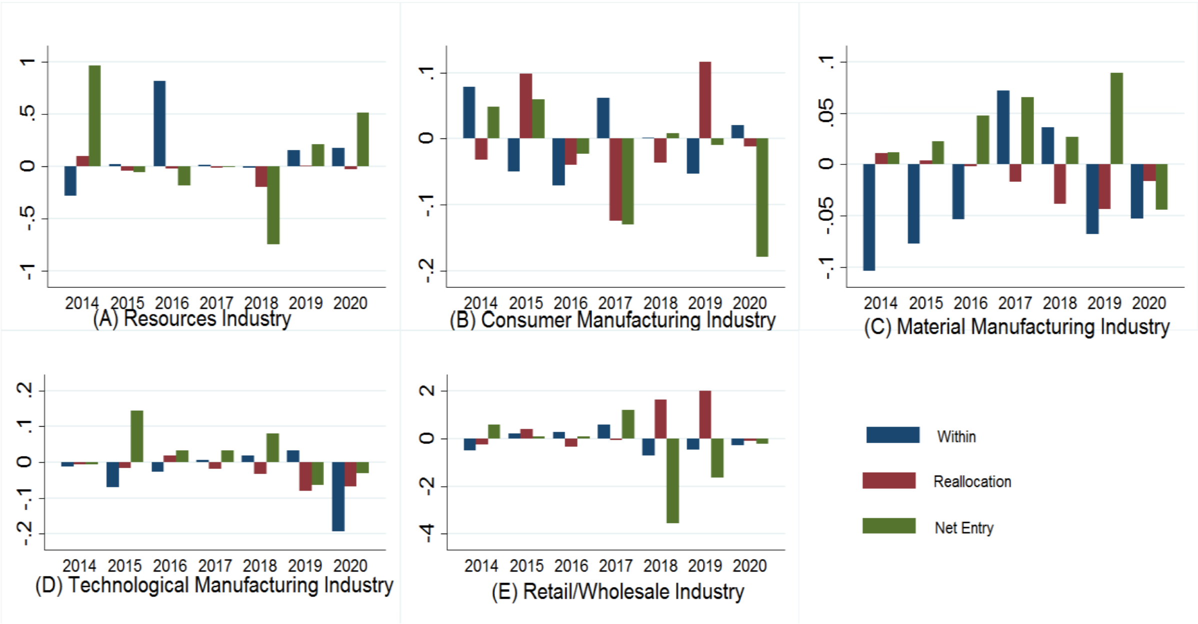

Figure C 4: Yearly change of markup decomposition components – Markup estimates from production function method using translog specification.

Source: Author's Calculations using Estonia's firm-level data from the EKOMAR survey.

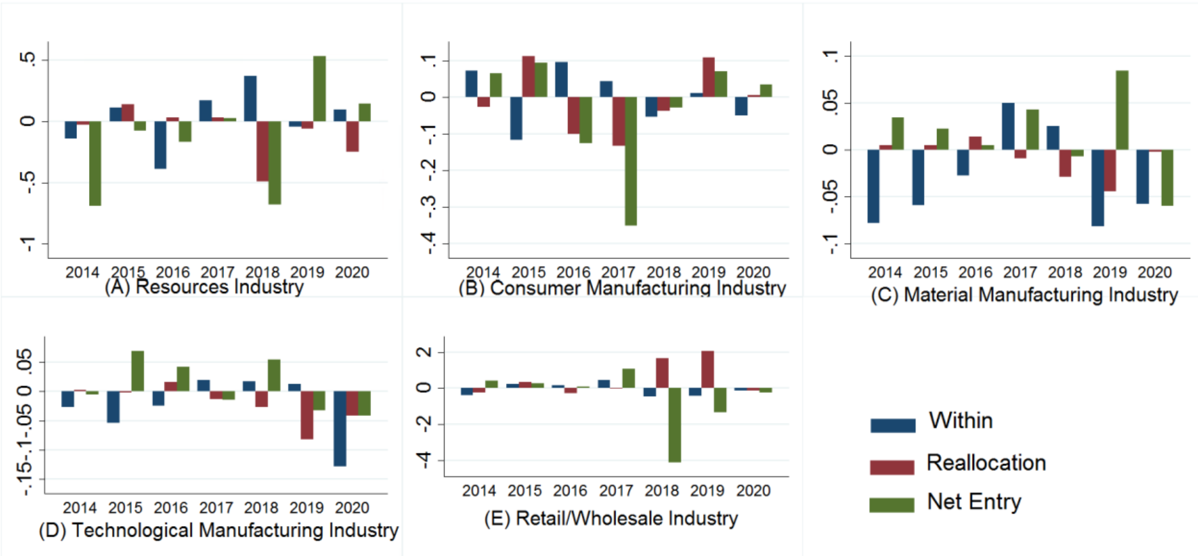

Figure C 5: Yearly change of markup decomposition components – Markup estimates from production function method using Cobb-Douglas specification.

Source: Author's Calculations using Estonia's firm-level data from the EKOMAR survey.

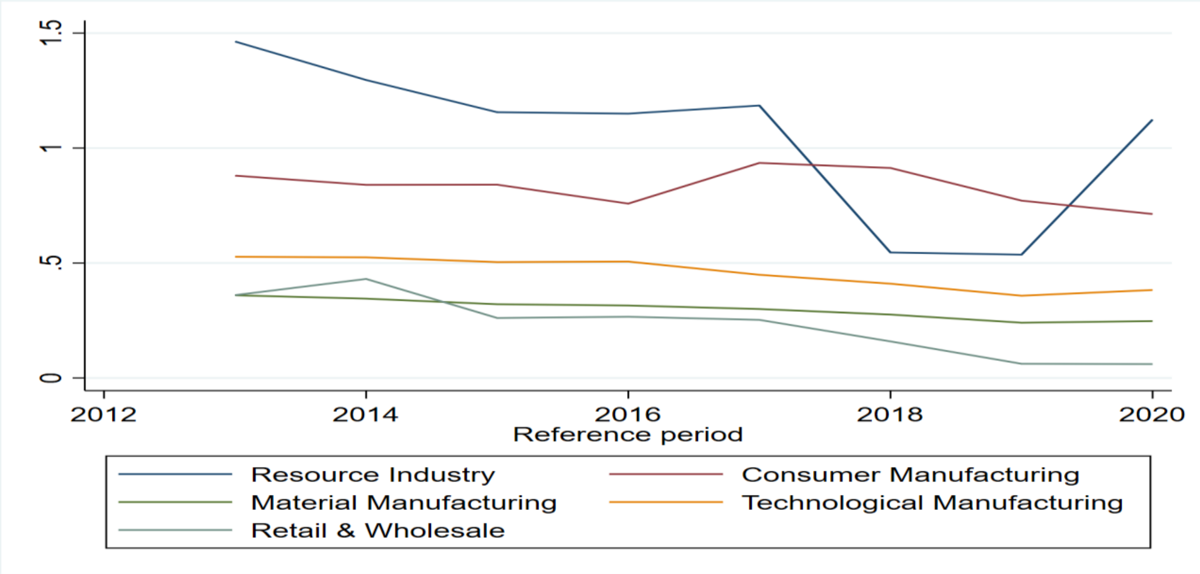

Figure C 6: Average Cost Share of Firms Across the Industries.

Source: Author's Calculations using Estonia's firm-level data from the EKOMAR survey.

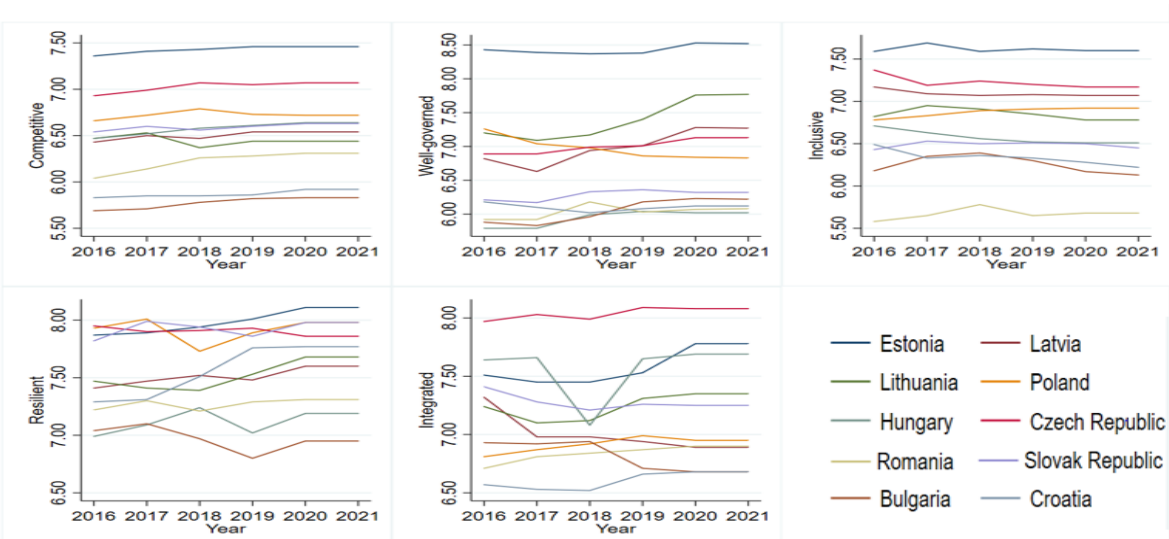

Figure C 7: Transition Quality Assessment Indicators.
Source: European Bank for Reconstruction and Development (EBRD) data.

Table C 1: Regression of logarithm of labour share of value-added on the logarithm of markups — Resources industry

	(Translog) θ^L	(CD) θ^L	(CD) θ^M	(CS) θ^L	(CS) θ^M
ln(markup)	-0.337*** (0.023)	-0.331*** (0.037)	-0.034*** (0.012)	-0.910*** (0.011)	-0.481*** (0.003)
Year fixed effects	Yes	Yes	Yes	Yes	Yes

Firm fixed effects	Yes	Yes	Yes	Yes	Yes
R^2	0.080	0.099	0.010	0.712	0.353
Observations	4,314	4,330	4,330	4,330	4,330
Number of firms	1,493	1,493	1,493	1,493	1,493

Note: Robust standard errors in parenthesis
***p<0.01, **p<0.05, *p<0.1
θ^L: output elasticity of labour input, θ^M: output elasticity of material input, CD: Cobb-Douglas specification, CS: cost-share method
Source: Author's Calculations using Estonia's firm-level data from the EKOMAR survey.

Table C 2: Regression of logarithm of labour share of value-added on the logarithm of markups — Consumer manufacturing industry

	(Translog) θ^L	(CD) θ^L	(CD) θ^M	(CS) θ^L	(CS) θ^M
ln(markup)	-0.331*** (0.015)	-0.255*** (0.013)	0.061*** (0.013)	-0.919*** (0.014)	-0.373*** (0.012)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
R^2	0.123	0.108	0.042	0.509	0.207
Observations	6,783	6,783	6,783	6,783	6,783
Number of firms	1,978	1,978	1,978	1,978	1,978

Note: Robust standard errors in parenthesis
***p<0.01, **p<0.05, *p<0.1
θ^L: output elasticity of labour input, θ^M: output elasticity of material input, CD: Cobb-Douglas specification, CS: cost-share method
Source: Author's Calculations using Estonia's firm-level data from the EKOMAR survey.

Table C 3: Regression of logarithm of labour share of value-added on the logarithm of markups — Technological manufacturing industry

	(Translog) θ^L	(CD) θ^L	(CD) θ^M	(CS) θ^L	(CS) θ^M
ln(markup)	-0.568*** (0.011)	-0.438*** (0.009)	0.172*** (0.013)	-1.066*** (0.009)	-0.467*** (0.010)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes

R^2	0.270	0.226	0.043	0.612	0.221
Observations	11,350	11,350	11,350	11,350	11,350
Number of firms	3,099	3,099	3,099	3,099	3,099

Note: Robust standard errors in parenthesis
***p<0.01, **p<0.05, *p<0.1
θ^L: output elasticity of labour input, θ^M: output elasticity of material input, CD: Cobb-Douglas specification, CS: cost-share method
Source: Author's Calculations using Estonia's firm-level data from the EKOMAR survey.

Table C 4: Regression of logarithm of labour share of value-added on the logarithm of markups — Retail/Wholesale industry

	(Translog) θ^L	(CD) θ^L	(CD) θ^M	(CS) θ^L	(CS) θ^M
ln(markup)	-0.648*** (0.008)	-0.618*** (0.007)	0.074*** (0.006)	-0.988*** (0.004)	-0.593*** (0.005)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
R^2	0.296	0.304	0.055	0.782	0.460
Observations	36,064	36,064	36,064	36,064	36,064
Number of firms	16,292	16,292	16,292	16,292	16,292

Note: Robust standard errors in parenthesis
***p<0.01, **p<0.05, *p<0.1
θ^L: output elasticity of labour input, θ^M: output elasticity of material input, CD: Cobb-Douglas specification, CS: cost-share method
Source: Author's Calculations using Estonia's firm-level data from the EKOMAR survey.

Table C 5: Regression of logarithm of markups on the logarithm of investment in intangible capital — Resources Industry

	(Translog) θ^L	(CD) θ^L	(CD) θ^M	(CS) θ^L	(CS) θ^M
ln(Inv_Int_Cap	-0.0314* (0.0174)	-0.0745** (0.0290)	0.0441 (0.0296)	0.0700*** (0.0203)	0.0228 (0.0179)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
R^2	0.160	0.230	0.194	0.223	0.191

Observations	353	353	353	353	353
Number of firms	221	221	221	221	221

Note: Robust standard errors in parenthesis
***p<0.01, **p<0.05, *p<0.1
θ^L: output elasticity of labour input, θ^M: output elasticity of material input, CD: Cobb-Douglas specification, CS: cost-share method
Source: Author's Calculations using Estonia's firm-level data from the EKOMAR survey.

Table C 6: Regression of logarithm of markups on the logarithm of investment in intangible capital — Consumer manufacturing Industry

	(Translog) θ^L	(CD) θ^L	(CD) θ^M	(CS) θ^L	(CS) θ^M
ln(Inv_Int_Cap	0.0118*	0.0142**	-0.0065	-0.0104	-0.0046
	(0.0065)	(0.0069)	(0.0063)	(0.0071)	(0.0077)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
R^2	0.216	0.163	0.259	0.227	0.083
Observations	1,442	1,442	1,442	1,442	1,442
Number of firms	771	771	771	771	771

Note: Robust standard errors in parenthesis
***p<0.01, **p<0.05, *p<0.1
θ^L: output elasticity of labour input, θ^M: output elasticity of material input, CD: Cobb-Douglas specification, CS: cost-share method
Source: Author's Calculations using Estonia's firm-level data from the EKOMAR survey.

Table C 7: Regression of logarithm of markups on the logarithm of investment in intangible capital — material manufacturing Industry

	(Translog) θ^L	(CD) θ^L	(CD) θ^M	(CS) θ^L	(CS) θ^M
ln(Inv_Int_Cap	0.0117**	0.0114*	0.0010	0.0009	-0.0071
	(0.0052)	(0.0063)	(0.0037)	(0.0060)	(0.0056)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
R^2	0.202	0.149	0.032	0.058	0.012
Observations	3,538	3,538	3,538	3,538	3,538

Number of firms	1,834	1,834	1,834	1,834	1,834

Note: Robust standard errors in parenthesis
***p<0.01, **p<0.05, *p<0.1
θ^L: output elasticity of labour input, θ^M: output elasticity of material input, CD: Cobb-Douglas specification, CS: cost-share method
Source: Author's Calculations using Estonia's firm-level data from the EKOMAR survey.

Table C 8: Regression of logarithm of markups on the logarithm of investment in intangible capital — Technological manufacturing Industry

	(Translog) θ^L	(CD) θ^L	(CD) θ^M	(CS) θ^L	(CS) θ^M
ln(Inv_Int_Cap	-0.0234*** (0.0048)	-0.0184*** (0.0055)	-0.0146 (0.0107)	-0.0185*** (0.0057)	-0.0043 (0.0110)
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
R^2	0.219	0.092	0.057	0.113	0.027
Observations	2,462	2,462	2,462	2,462	2,462
Number of firms	1,271	1,271	1,271	1,271	1,271

Note: Robust standard errors in parenthesis
***p<0.01, **p<0.05, *p<0.1
θ^L: output elasticity of labour input, θ^M: output elasticity of material input, CD: Cobb-Douglas specification, CS: cost-share method
Source: Author's Calculations using Estonia Firm-level Data – EKOMAR Data.

Resümee

TITLE IN ESTONIAN

Faisal Mohammed

Vastupidiselt pikka aega pikaajalise majanduskasvu kohta kehtinud stiliseeritud faktile stabiilsest tööjõu osakaalust loodud lisandväärtuses on hiljutised empiirilised tõendid näidanud tööjõu osakaalu vähenemist ja ettevõtete turuvõimu suurenemist, mis on tingitud majandustegevuse ümberpaigutamisest suurettevõtete suunas. See nähtus võib olla osaliselt vastutav paljudes arenenyd riikides täheldatud ebavõrdsuse suurenemise eest. Hinnalisandid ettevõtte turuvõimu lähendina võivad varieeruda tugevalt üle erinevate majandusharude ning mõistmaks nende mõju tööjõu osakaalule lisandväärtuses on tarvis uurida hinnalisandit madalamal agregeerituse tasandil. Käesolevas magistritöös uuritakse turuvõimu mõju tööjõu osakaalule lisandväärtuses ettevõtte tasandil erinevates Eesti majandusharudes aastatel 2013-2020. Meie tulemused näitavad, et kui tööjõu osakaal lisandväärtuses on Eestis aja jooksul veidi tõusnud, on samal ajal täheldatav hinnalisandite üldine langus kõigis viies uuritavas harus – loodusressursside kasutamisele põhinevas harus, tarbekaupade tootmises, materjalitööstuses, tehnoloogiatööstuses ning jae- ja hulgimüügiettevõtetes. Analüüsides kapitalikulude ja üldkulude osakaalu kogukuludest koos kasumimarginaalidega ilmnes, et kapitali- ja üldkulude osakaal kogukuludest on üldiselt vähenenud, mis näitab, et osa hinnalisandi vähenemisest võib olla tingitud tootmiskulude vähenemisest. Üldkulude hinnalisandi regressioonianalüüsi tulemused näitasid, et tootmise piirkulu ületavad kõrgemad hinnalisandid võivad olla seotud turuvõimust tuleneva suurema kasumiga. Töö viimases osas uurides hinnalisandi mõju tööjõu osakaalule lisandväärtuses leiame kooskõlas kirjandusega vastupidise seose hinnalisandi ja tööjõu osakaalu vahel lisandväärtuses. Eesti erinevates majandusharudes täheldatud suhteliselt stabiilne ja minimaalse langusega kasumimarginaal võib tuleneda ka sellest, et tärkava majandusega ettevõtete toodang on väiksem ja nende tootmissisendid pärinevad madalama konkurentsitasemega turgudelt. Meie tulemuste põhjal on vaja reforme eelkõige mittetööstussektorile suunatud poliitikates vähendamaks täheldatud märkimisväärselt kõrgeid hinnalisasid. Samuti aitaksid hinnalisandeid vähedada konkurentsi suurendamine uute ettevõtete asutamist ja välismaiseid otseinvesteeringuid soodustavate poliitikate abil. Selliste poliitikameetmete tagajärjeks oleks tööjõu osakaalu edasine suurenemine lisandväärtuses, kuivõrd tööjõu osakaalu ja kasumimarginaalide vahel on kindlaks tehtud vastassuunaline seos.

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