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Modelling economic policy issues

Modeling markups and its determinants: The case of Norwegian industries and regions[☆]

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ABSTRACT

In this paper we use an innovative and nonstandard approach to model and estimate markups and market power. The approach uses a regression framework with determinants as well as a random component. We use this innovative tool to investigate the level of market power in Norwegian industries and regions. Norway is an interesting case study because in Norway prices on most consumer goods and services are higher than in similar countries. Given that many studies show substantial and an increasing trend in markup, it is naturally interesting to investigate the market power in different industries and different regions in Norway. We use an unbalanced panel collected by The Norwegian Tax Administration for the period 2000–2018 to address this issue. We find low and non-increasing market power in Norway, which is different from other countries. Further, we find that market powers decrease with firm-size, increase with geographical industrial concentration and decrease with rural location.

1. Introduction

Economic theory tells us that an economy benefits from competition among firms. Lack of competition often leads to prices above marginal costs of providing the product, which in turn means that the consumers pay more than what is costs (on the margin) to produce. A society might want to minimize deadweight losses as much as possible. Perfect competition, even though it is not really feasible, where output prices equates the marginal costs (i.e. $P = MC$, where P being the output price and MC its marginal cost), works as a target for well functioning markets. In this context, it is interesting to investigate the level of competition, or lack of it among Norwegian industrial organizations (IO). Alternatively, the issue is to examine whether some producers are overcharging, i.e., there are markups – $P > MC$. Norway is known for being a high cost country and thus, have prices on most consumer goods and services which is higher than in other comparable countries. One might think that the high output prices mainly stems from high costs in production, like high wages. However, recent studies have indicated firms' price markups over marginal cost both in Europe (Weche and Wambach, 2021) and USA (De Loecker et al., 2020) have increased over the last decades. It is interesting to investigate if we can find the same development in Norway. If we find high markup values also in Norwegian industries, meaning that prices are

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well above marginal costs, it will mean that the high price level in Norway is not only caused by high input costs such as high wages.

While producers would benefit from less competition and seek to keep their products rare and costly to imitate, the opposite will usually benefit consumers. Over time, one would expect that, due to a competitive environment, markups within a specific industry would converge toward marginal costs so that the potential of exercising market power would decline. Although the notion of markup output price over its marginal cost, or the Lerner index (Lerner, 1934), is quite old, there is a recent resurgence of it (e.g., De Loecker et al., 2020; Weche and Wambach, 2021).[1] Historically, the importance of it rose from assessing the functioning of a market. Perfect competition is used as the benchmark. Any other market structures would lead to a deadweight loss. Since the objective of the society is to minimize deadweight loss, any change in the market structure towards perfect competition will be beneficial. Consequently, it is of interest to examine the nature of markups.

The literature includes different approaches to estimate markups, and there seems to be no strong consensus about what is the best way to do it. In the mid-1980s we got the structure-conduct-performance paradigm (SCPP), where typically economic performance where measured by profits of price-cost margin (e.g., Sheldon and Sperling, 2003; Garcia et al., 2022). The SCPP posits a one-way causal relationship from market structure to conduct to performance. Later it became more usual to use a structural model, or to estimate a total cost function (e.g., Hyde and Perloff, 1995; Wolfram, 1999; Størdal and Baardsen, 2002). In more recent times several studies have used the New Empirical Industrial Organization (NEIO) approach, which estimate markup without directly estimating marginal costs. The markup of price over marginal cost is estimated from a regression (frequently called a supply relation) that controls for the variables that determine marginal cost (Appelbaum, 1982; Bresnahan, 1982). Perekhozhuk et al. (2017) describes two commonly used methods for estimation of the NEIO approach — the Production-Theoretic Approach (PTA) and the General Identification Method (GIM). De Loecker (2011) and De Loecker and Warzynski (2012), building on the work of Hall (1988), introduced the Production Function Approach (PFA) to recovering markups. That approach is based on estimates of a production function, to recover markups from production data. In recent studies that approach has been frequently used (e.g., De Loecker et al., 2020; Weche and Wagner, 2021). Quite recently Kumbhakar et al. (2012) introduced a new innovative method for estimating market power, drawing on the stochastic frontier analysis (SFA) methodology from the efficiency literature.[2] With their method either a production function/distance function or a cost function framework can be used, and markups can be estimated with or without the constant returns to scale assumption.[3]

Partly based on the past findings, with high and increasing markup estimates around the world, there is an ongoing discussion about the reliability and usefulness of these studies. The NEIO approach has been criticized because of its underlying assumptions; see Sexton and Xia (2018), Perekhozhuk et al. (2017), Sheldon (2017), Mei and Sun (2008) and Corts (1999) for more on this. Basu (2019) raise a discussion about the evidence provided for rising price-cost markups in the United States. He argue that large markup estimates coming from analysis using firm micro data do not relate to macro economic observations. Further, macro data indicates low and stable markups, while investment rates indicates the opposite. Syverson (2019) and Berry et al. (2019) raise questions if the observed trends in different industries have other plausible explanations than the "market power hypothesis". The development in trends might be multi-causal, meaning that to much of the explanations has been focusing solely on market power in the existing literature. The studies by Raval (2022) and van Heuvelen et al. (2021) shows that, within the PFA framework, the choice of flexible input variable is important, because it highly influence the trend of the markup estimates. They conclude that different choice of flexible input in PFA markup studies may explain some of the discrepancies in the findings of the recent studies. Koppenberg and Hirsch (2022a) compare the SFA and the PFA methods, and their results suggest that the PFA leads to significantly larger markups and more than three times higher welfare losses compared with predictions by the SFA method. As these selected examples of studies and discussions shows, there is a large on-going debate about how to best estimate markups.

In our study we use the above mentioned model by Kumbhakar et al. (2012), but extended it to also account for firm heterogeneity of markups. In addition, to get a better understanding of the reasons for the markup estimates, we extended the model to include determinants of market power. Then it is possible to measure how different factors affects markups.

By including the determinants, we wanted to test in which direction and to what extent the following factors influence the level of markup: (1) firm size, (2) centrality, (3) geographical industrial concentration and (4) geographically location. The size of the firm is an interesting determinant to investigate because one might think that a bigger firm is likely to have higher market power than a smaller firm. A centrality index describing the firm's location, urban or rural, is interesting to measure in the context of market power. Firms that are operating in local markets are likely to have higher market power in rural areas because competition will be lower (fewer firms) compared with urban areas. However, firms that do not

[1] The last decade has yielded several empirical studies of market power in different countries and various industries around the world. From Europe we have, for example, Koppenberg and Hirsch (2022a), Koppenberg and Hirsch (2022b), Weche and Wambach (2021), Rudinskaya (2019), Perekhozhuk et al. (2017), Perekhozhuk et al. (2013), Sckokai et al. (2013), Vancauteren (2013), De Loecker and Warzynski (2012), van Heuvelen et al. (2021) and Kumbhakar et al. (2012). From US we have, e.g., De Loecker et al. (2020), Silva et al. (2019), Hall (2018), Lopez et al. (2018), Traina (2018) and Hovhannisyan and Gould (2012). And we also mention a few studies from the rest of the world (e.g. Akcigit et al., 2021; De Loecker et al., 2016). The overall findings for most of these studies are that they show increasing market power.

[2] Reviews of SFA models can be found in Kumbhakar et al. (2015), Sickles and Zelenyuk (2019) and Kumbhakar et al. (2022a,b).

[3] Orea and Steinbuks (2018) and Karakaplan and Kutlu (2019) used a SFA to estimate markups. However, they estimate a demand–supply system and used conduct parameter approach (and not a Lerner index approach as we do).

have a local market, for example, manufacturing firms with a national and/or international market, will not necessarily meet the same pattern in market power with regards to the level of centralization. Further, firms in urban areas may benefit from knowledge spillovers because these firms are members of networks connecting highly productive frontier suppliers or customers with access to more advanced knowledge. Geographical concentration of industries, often named agglomeration, is expected to influence markups. As more firms in related fields of business cluster together, their costs of production may decline. Also, when competing firms in the same sector cluster, there may be advantages because the cluster attracts more suppliers and customers than a single firm could achieve alone, and typically the cost level in this area will decrease. To further measure geography's effect on market power, we also included determinants for different regions. In Norway most people live in the south. Therefore, the activity is highest in this region. Further, the main industries differ between regions. For example, the coastline of Norway will, of course, include more firms connected to the maritime industry then those located inland, farther away from the coast.

To sum up, in this paper we make three main contributions. First, we investigate the level of market power in Norwegian industries and regions and compare our findings with studies of other countries. Second, we account for heterogeneity in the markup estimates, that is supposed to exist within industries and regions. Third, we include determinants of markups, to get a better understanding of the reasons for the markup estimates.

The remainder of the paper is organized as follows. Section 2 describes the modelling approaches used in this study. Section 3 gives a description of data. Section 4 presents the results and, finally, Section 5 provides concluding remarks.

2. Modelling markup

Our model is based on Kumbhakar et al. (2012) but extended to account for firm heterogeneity and inclusion of markup determinants. We specify the efficient production technology in terms of a standard production function, viz., $Y = f(X, T)$ or more generally the transformation function $F(Y, X, T) = 1$ where Y is output and X is the vector of inputs used. T is the production function shifter and is different from the inputs X. The usual practice is to proxy T by the time trend. According to the duality theory, all characteristics of the production technology, implied by the production function $Y = f(X, T)$, can be uniquely represented by a minimum total cost function $C(W, Y, T)$, where C is the minimum total cost and W is the vector of all input prices. Thus, one can extract all the features of the production function from the cost function. Alternatively, features of the cost function can be extracted by estimating the production function. Note that there are differences in terms of data requirements–the cost function requires information about input prices that are not needed in estimating a production function.

When output markets are competitive (which is assumed in deriving the cost function), output price equals marginal costs (MC) and the markup component is zero. Consequently, if the output price P exceeds MC, it is argued that there is markup. To calculate MC, one first estimates a cost function from which MC is calculated. Markup is then computed for each firm from $(P - MC)/MC$. A positive value of markup indicates the presence of non-competitive behaviour in the output market. This is used by De Loecker and Warzynski (2012) although De Loecker et al. (2020) argued against it because prices can be higher when there are high fixed costs. We note that markups can be explained by other factors as well, which will be missed if markups are computed from the P and MC relationship, instead of modelling it.

We suggest a procedure that will overcome these weaknesses. Starting from $P > MC = \partial C/\partial Y$, it follows that

$$PY/C > MC(Y/C) = (\partial C/\partial Y)(Y/C) = \partial \ln C/\partial \ln Y, \tag{1}$$

where PY/C is the revenue share in total cost. We can transform the above inequality to an equality by adding a non-negative one-sided term, u to (1) and write it as

$$PY/C = \partial \ln C/\partial \ln Y + u \Rightarrow RS = E_{cy} + u, u \geq 0, \tag{2}$$

where $RS = PY/C$ and E_{cy} is the cost elasticity of output. In (2) the non-negative term u captures markup. It cannot, however, be computed directly from the data since the cost elasticity term $\partial \ln C/\partial \ln Y$ has to be calculated from an estimated cost function. Further, the revenue share might be affected by other unobserved variables. We assume that this noise is captured by a symmetric two-sided noise term, v. With the v term added in (2), the equation looks like a stochastic frontier (SF) function. In other words, we draw on the SF methodology from the efficiency literature to estimate markup for each observation.

Estimation of the cost function relies on availability and variations in input prices. This can be avoided by using the input distance function (IDF) formulation that relies on input and output quantities.

For this, we start with the transformation function $F(Y, X, T) = 1$. Using the homogeneity (of degree 1 in X) property of the IDF, it can be written as $-\ln X_1 = \ln F(1, \hat{X}, Y, T) \Rightarrow \ln X_1 = \ln f(\hat{X}, Y, T)$, where $\hat{X}_k = X_k/X_1$. Further, because the IDF is dual to the cost function (Färe and Primont, 2012), $E_{cy} = \partial \ln X_1/\partial \ln Y$. That is, for a translog IDF

$$E_{cy} = \beta_y + \sum_{k=2}^{J} \beta_{jk} \ln \hat{X}_k + \gamma_{yy} \ln Y + \beta_{yt} T. \tag{3}$$

Using (3) in (2) we get

$$RS = E_{cy} + u = \beta_y + \sum_{k=2}^{J} \beta_{jk} \ln \hat{X}_k + \gamma_{yy} \ln Y + \beta_{yt} T + u. \tag{4}$$

Note, because of the duality and use of the IDF, the estimation of (4) does not require data on input prices.

2.1. Empirical model

Because we use panel data, the model in (4) is extended in several dimensions. Note that we are not computing u from (4) because u can be affected by random outcomes that are not markups. For this we add a noise term with firm-specific unobserved heterogeneity components, viz., $v_{it} + \mu_i$ in (4). We also add determinants of markups and make u_{it} a function of Z_{it} variables. Note that in estimating markups we control for measurement errors in the revenue shares as well as unobserved firm effects. Thus, the final estimating model is

$$RS_{it} = \beta_y + \sum_{k=2}^{J} \beta_{jk} \ln \hat{X}_{kit} + \gamma_{yy} \ln Y_{it} + \beta_{yt} T_{it} + \mu_i + v_{it} + u(Z_{it}), i = 1, \ldots, N; t = 1, \ldots, T. \tag{5}$$

Our main objective is to estimate (5). There are at least three ways to estimate it. First, we can use the stochastic frontier approach (Kumbhakar et al., 2012) and include the Z variables in u which is assumed to be half-normal, and v normal. This will give observation-specific estimates of $u(Z_{it}) \geq 0$ along with the other parameters. Second, is to assume $u(Z)$ to be deterministic and assume a functional form on it (exponential, logistic to make it non-negative) and use nonlinear least squares to estimate the model. This avoids making distributional assumptions on both u and v. Third, is to assume that $u(Z)$ is deterministic but is a nonparametric function of Z. This makes the model semi-parametric, one part being parametric and another part non-parametric. It is clearly more flexible than the other two but it cannot estimate the constant term in the nonparametric function $u(Z)$. In this case, one can focus on the marginal effects of Z which are not affected by the unidentified constant term in $u(Z)$. Here we follow the first approach, and will consider the two others in further research.

3. Data

We used firm-level economic accounting data from The Norwegian Register of Company Accounts merged with the Business Register collected by Statistics Norway. These data include a wide range of accounting variables (e.g., sales revenues, operating costs, operating results, assets and equity) as well as firm-specific and location (municipalities and degree of urban centrality) characteristics, and NACE-classification,[4] for the years 2000 to 2018.

We investigated the service and manufacturing sectors, and included four sub-sectors in our analyses, namely, knowledge intensive business services, other services, high-tech manufacturing and low-tech manufacturing (Table 1). The classification in the four sub-sectors were identified based on the NACE codes. Knowledge Intensive Business Services (commonly known as KIBS) are services and business operations heavily reliant on professional knowledge. Service industries not categorized as KIBS were categorized as "other services". We grouped the manufacturing sector into high-technology (High-tech) and low-technology (Low-tech) sectors, based on the OECD classification (Hatzichronoglou, 1997). This classification divides manufacturing into groups that are characterized by the basic nature of their technology and innovation patterns. Table 1 shows the industries classified to the four sub-sectors. For each of the four sub-sectors, we then obtained unbalanced panel data sets. We excluded observations with negative values. We further identified and dropped multiple outliers, using the "Bacon" algorithm proposed by Billor et al. (2000). The number of firms included and total number of observations for each of the four sub-sectors are also shown in Table 1.

3.1. Variable description

Of the variables included in the empirical estimation of Eq. (5), we specified revenue share (RS_{it}) by dividing operating revenue (as is output quantity multiplied by output price) on total cost, at the firm level. Output (Y) was specified as sales revenue. The three inputs were specified as: labour (X_1), measured as labour costs; equity (X_2), measured as the capital owners have invested in the firm; and total debt (X_3), measured as short-term and long-term debt. The time trend (T) was captured by year of observation. Labour (X_1) was used as the numeraire in the model specification to impose the linear homogeneity property. All monetary values were measured in Norwegian kroner (NOK). We deflated the monetary variables to their 2018 values using the consumer price index (CPI) for the output (sales revenue), the wage price index (WPI) (collected by Statistics Norway) for labour and the goods price index (GPI) (collected by Statistics Norway) for capital.

[4] The acronym for Nomenclature of Economic Activities, named NACE codes, are a standard classification system of similar European industries in function to Standard Industry Classification (SIC) and North American Industry Classification System (NAICS) for classifying business activities.

Table 1
Description of sub-sectors and industries investigated.

(Sub)sector	Short-name	Description
Services		
Knowledge intensive business services	KIBS	This group consists of the following industries: computer programming; consultancy and related activities (NACE = 62); information service activities (NACE = 63); financial and insurance activities (NACE = K); professional, scientific and technical activities (NACE = M); and administrative and support service activities (NACE = N). The group includes 238 876 observations from 38 425 firms.
Other services	Other services	This group consists of the following industries: accommodation and food service activities (NACE = I), information and communication (NACE = J, except NACE = 62 and NACE = 63) and real estate activities (NACE = l). The group includes 126 841 observations from 24 112 firms.
Manufacturing		
High-tech manufacturing	High-tech	This group consists of the following industries: Manufacture of chemicals, chemical products, pharmaceutical products, pharmaceutical preparations, computer, electronics, optical products, electrical equipment, machinery and equipment, motor vehicles, trailers and semi-trailers, and other transport equipment (NACE = 20,21,26,27,28,29,30). The group includes 25 919 observations from 3668 firms.
Low-tech manufacturing	Low-tech	This group consists of the following industries: Manufacturing of food products, beverages, tobacco products, textiles, wearing apparel, leather and related products, products of wood and cork, paper and paper products, coke and refined petroleum products (NACE = 10–19). Further, manufacture of rubber and plastic products, non-metallic mineral products, basic metals, fabricated metal products (NACE = 22–25). The group includes 68 891 observations from 8677 firms.

Table 2
Descriptive statistics.

Variable	*Services*				*Manufacturing*			
	KIBS		Other services		High-tech		Low-tech	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Revenue share, output and inputs								
Revenue share ($RS = \frac{PY}{C}$)	1.18	0.36	1.14	0.38	1.07	0.17	1.06	0.14
Sales income (Y) (1000 NOK)	3711	4596	4494	5447	14 361	20 220	12 974	17 125
Labour(X_1) (1000 NOK)	1688	1878	1579	1854	5268	6326	3255	3249
Equity (X_2) (1000 NOK)	765	1083	1122	1767	2184	3456	1879	2759
Total debt (X_3) (1000 NOK)	1287	1594	2223	2929	3976	5472	3515	4548
Time/year (T)	2010	5.13	2009	5.48	2007	5.15	2008	5.36
Determinants of markups								
Firm size (Z_1) (no. employees)	4.28	6.30	6.93	9.68	12.28	17.13	10.80	12.77
Index for concentration (Z_2)	0.10	0.08	0.10	0.09	0.07	0.04	0.06	0.02
Centrality (Z_3) (dummy, 1 = rural)	0.20	0.40	0.29	0.45	0.40	0.49	0.40	0.49
Region (R): Oslo (Z_4) (share)	0.22	0.41	0.21	0.40	0.09	0.28	0.09	0.29
R: Eastern Norway (base) (share)	0.35	0.48	0.33	0.47	0.37	0.48	0.37	0.48
R: Southern Norway (Z_5) (share)	0.05	0.22	0.05	0.23	0.07	0.25	0.07	0.25
R: Western Norway (Z_6) (share)	0.25	0.42	0.23	0.42	0.29	0.45	0.29	0.45
R: Central Norway (Z_7) (share)	0.07	0.25	0.08	0.27	0.09	0.28	0.09	0.28
R: Northern Norway (Z_8) (share)	0.07	0.26	0.10	0.30	0.10	0.30	0.10	0.30

As determinants of markups, we included: firm size (Z_1), approximated by the firm's number of employees; the index of concentration (Z_2), is approximated by a Herfindahl–Hirschman index, which is used to measure geographical industrial concentration (Rhoades, 1993; Nakamura and Paul, 2011); centrality (Z_3), which is a code with a value for each municipality, which provides a measure of the municipality's centrality (Høydahl, 2017). For our analysis, we defined the centrality measure as a dummy, given the value 0 if urban location and 1 if rural location of the firm; to control for geographic effects we include five different region dummies ($Z_4 - Z_8$), represented by Oslo (the Capital of Norway), Eastern Norway, Southern Norway, Western Norway, Central Norway (Trøndelag) and Northern Norway.

Table 2 includes the descriptive statistics. Note that firms in the service sector, on average, have a larger revenue share than manufacturing firms. Further, firms in the service sector are smaller, with both lower inputs and outputs, and fewer employees. The highest geographical industrial concentration is in services, while manufacturing to a larger extend is rurally located.

Table 3
Markup and returns to scale (*RTS*) estimates.

Industry (group)	Estimates of markup					Returns to scale				
	Mean	Std.dev	1. quart.	Median	3. quart.	Mean	Std.dev	1. quart.	Median	3. quart.
Services										
KIBS	0.039	0.105	0.022	0.031	0.042	1.069	0.115	0.985	1.061	1.135
Other services	0.035	0.079	0.020	0.028	0.039	1.145	0.189	1.034	1.107	1.206
Manufacturing										
High-tech	0.038	0.090	0.022	0.029	0.039	1.093	0.132	0.999	1.075	1.166
Low-tech	0.031	0.076	0.019	0.024	0.032	1.047	0.085	0.985	1.036	1.097

4. Results

We expected that there would be a large degree of heterogeneity between firms within each of the four subgroups. Table 5 in the Appendix shows the markups and RTS estimates based on the pooled SF estimator. These estimates diverge from the results based on the "true" random effect SF model (specified in Eq. (5)), reported in Table 3 below. Especially the markup estimates seem to be overestimated using the pooled SF estimator. This is as expected, because when assuming homogeneous firms, as the pooled SF estimator do, the firm-specific estimate (u in Eqs. (4) and (5)) is accounted as markup. This is in contrast to the "true" random effect SF model, where the firm-specific component is divided into firm effect (μ) and markup (u) (see Eq. (5)). We tested the pooled SF model against the "true" random effect SF model, with likelihood-ratio tests. For all 4 subgroups the tests rejected the null-hypothesis of no firm heterogeneity. Therefore, in the following, the results are based on the "true" random effect SF model.[5]

4.1. Markups estimates and time-trends

Table 3 presents the markup and returns to scale estimates for each of the four sub-sectors. All sub-sectors show, on average, low markup, and no clear differences in markups between services and manufacturing. The markups estimated range from 3.1% in the low-tech manufacturing sector to 3.9% in the KIBS sector. Comparing these findings with studies in other countries, we observe that the study of 28 EU countries by Weche and Wambach (2021) found an average markup at 131%, while the study of the US by De Loecker et al. (2020) found the average markup charged was 61% over marginal cost in 2016. While these large differences in level of markup between Norway and the US and Europe may have been influenced by estimation methods (Koppenberg and Hirsch, 2022a), several studies of other countries than Norway using the same SFA estimation method as ours shows higher markup estimates. For example, in the study of the dairy processing industry, Koppenberg and Hirsch (2022b) found an average markup at 19.5% in Spain, 12.5% in Italy and 7.3% in France for the period 2008 to 2017. Studies of US food industries between 1990 and 2010, by Lopez et al. (2018) found an average markup of 21%. In a study of the banking industry for a large group of countries, by Coccorese (2014), Senegal had the lowest average markup at 2.2%, while Zambia had the highest at 32.7%. For the Netherlands, van Heuvelen et al. (2021) estimated markups to be higher in the service sector than in the manufacturing sector. This is consistent with our findings, but the estimated differences between these sectors are small for Norway.

Consider the markup estimates by year (Fig. 1), our results show more or less no trend in markup for Norway over the last 20 years. Only the KIBS sub-sector shows a slight rise in markup over the investigated period. We do not observe any increasing variation in the markup estimates over the years. These findings are in contrast to many other recent studies. For example, in the study of the US, De Loecker et al. (2020) found an increasing trend in markup, from 21% in 1980 to 61% in 2016. The results of the study of European countries, by Weche and Wambach (2021), show a drop in markups (as does the US study) during the financial crisis in 2008, followed by a post-crisis increase. While the post-crisis markup estimates were increasing, it was slower than in the US. Using data from 82 countries, Akcigit et al. (2021) found that the "global" markup increased more than 30% since 1980. Both Lopez et al. (2018) in their study of US food industries, Koppenberg and Hirsch (2022b) studying European dairy processing industries, Weche and Wagner (2021) in their study of German manufacturing, and van Heuvelen et al. (2021) estimating markups in the Netherlands, found results more like our findings, without any clear time trend.

[5] Although we specify a random-effect model, a fixed-effect model could have been used. However, for several reasons we did not used a fixed-effect model in this study: (1) For the 2 largest data samples (KIBS and Other Services) we never got convergence; (2) The estimates (not reported here) show reasonably low correlation between firm effects and the regressors (less than approximately 0.5) and we used an unbalanced panel in which 25% of the sample has four or fewer observations per firm (i.e., panel data with a large share of short time period/time series). In cases like this, based on Clark and Linzer (2015), a fixed-effect model exacerbates measurement error bias and the random-effect model is preferable; (3) Use of the fixed effects estimator often give counter-intuitive results in empirical work, because the fixed effects capture a large share of the variation in the data, especially when the covariates do not change much across cross-sectional units (i). That is, most of the variations in such a case is captured by the fixed effects and nothing (or very little) is left for the covariates to explain. As a result, the coefficients tend to get imprecisely estimated (large standard errors, wrong signs, etc.).

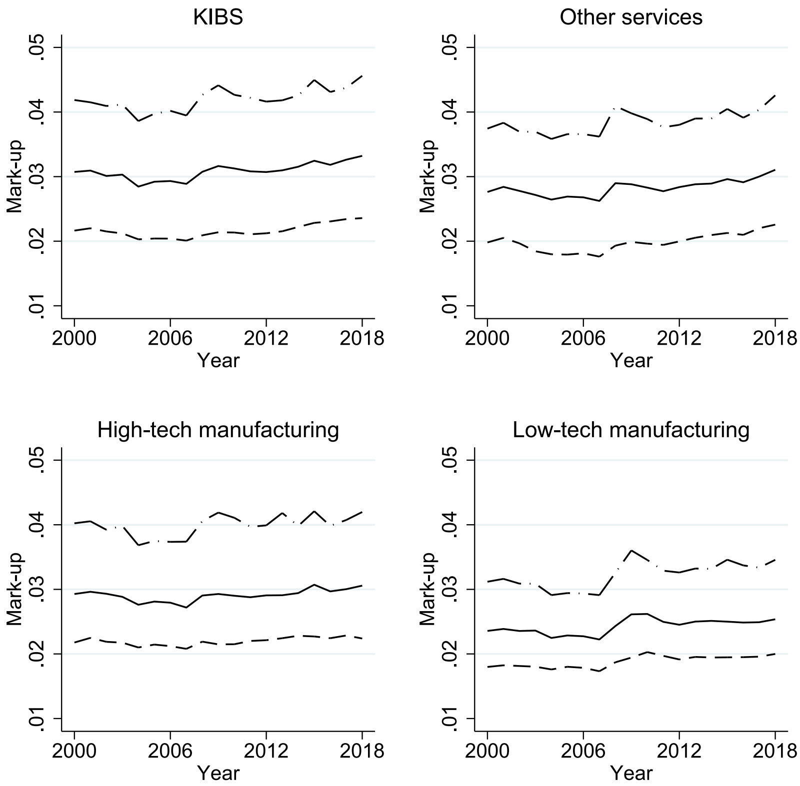

Fig. 1. Time-series plot of markup. Upper line is the 75th percentile, middle line is the 50th percentile and lower line is the 25th percentile.

If we rule out estimation methods as the whole explanation for our finding much lower markups and markup trends in Norway compared with studies from comparable countries, we must look at some other reason for these results. First, according to The World Bank, Norway is among the countries with the highest wages, or cost per man-hour, in Europe.[6] Norway is a small, open economy and is dependent on international trade. In this context, it is crucial for a small country that prices are not set too high, to be able to compete with other countries on the world market. In Norway, the wage bargaining system might play a role. The bargaining system in Norway is that the traded sector bargains its wages first (Holden, 1990). This is decided to make sure that the non-traded sector in the Norwegian economy does not drive wages up and thus, prices in the economy, making the traded sector in Norway less competitive. Further, the Norwegian Competition Act, enforced by an independent body, the Norwegian Competition Authority, could also play a role.[7] The legislation on competition in Norway, mainly corresponds to European Union legislation. However, the legislation might be more strictly enforced in Norway because of small narrow markets in Norway compared with other countries, making it even more important to prevent unwanted and damaging mergers (Lægreid and Stenby, 2010).

4.2. Determinants of markups

Table 4 presents the estimates for the relationships between the four determinants of markups: firm size, geographical industrial concentration, centrality and geographical location.

The coefficients for firm size are negative and statistically significant for all industries. It implies that markups decrease with firm size. This may be the opposite of what we expected. It is often assumed that large (possibly international) firms are expected to exercise high market power and hence high markups (e.g., Edmond et al., 2018; Autor et al., 2020; De Loecker et al., 2020). It can also be the case that larger firms are those that engage in competition most intensively and are then less able to exploit market power. Barla (2000) found a U-shaped relationship between market power and firm size in the US airline industries. Some studies also show that firms operating in small and/or niche markets have the opportunity to obtain a higher margin (e.g., Shaw et al., 1999; Bonnet and Bouamra-Mechemache, 2016; Richards et al., 2017). Our findings are consistent with the findings of Koppenberg and Hirsch (2022b) in the dairy processing industry in Europe.

6 https://data.worldbank.org/indicator/SL.EMP.WORK.MA.ZS.

7 https://konkurransetilsynet.no/norwegian-competition-authority/?lang=en.

Table 4
Estimates of the determinants of markups. Eastern Norway is the base region.

Determinants	*Services*		*Manufacturing*	
	KIBS	Other services	High-tech	Low-tech
Firm size (no. employees)	−1.463***	−1.427***	−1.015***	−1.161***
Index for concentration (HHI)	4.728***	3.600***	2.264*	1.536*
Centrality (dummy, 1 = rural)	−0.370***	−0.322***	−0.172***	−0.088**
Region Oslo	−0.745**	−0.773***	0.314***	0.172***
Region South	0.315***	0.075*	0.210*	0.093
Region West	0.259***	0.069***	0.088	0.121**
Region Central	0.056*	−0.200***	0.334***	−0.050
Region North	−0.111***	0.017	0.080	0.163**

*The symbol denote significance at 5% level.
**The symbol denote significance at 1% level.
***The symbol denote significance at 0.1% level.

The Herfindahl–Hirschman index of geographical industrial concentration is significantly positive for all sub-sectors, indicating that a higher concentration ratio results in higher markups. In other words, the more concentrated the marketplace, the higher the markups. As mentioned in the Introduction, when more firms in related or the same fields of business cluster together, it usually leads to decreased costs. If these same firms do not reduce their prices with their costs, the markup will rise. Another explanation could be that increasing industrial concentration may lessen competition in that area and may result in higher markups. Our finding here is consistent with what Lopez et al. (2018) found in their study of the US food processing industries. Both Weche and Wagner (2021), in their studies of industry-specific evidence about markups and industrial concentration in German manufacturing industries, and Davis and Orhangazi (2021), in their study of the US non-financial corporate sector, found a positive relationship between markups and industrial concentration in many but not all industries.

The coefficients for centrality are negative and statistically significant for all sub-sectors. That implies that markups are lower for firms located in rural areas (compared with firms in urban areas). One reason may be that most rural located firms compete in a national and/or international market and, thus, are less able to utilize market power. Criscuolo and Timmis (2018) evaluated the relationships between centrality (related to global value chains) and firm productivity. They found that as firms become increasingly central, they do not tend to show faster productivity growth, and that these findings are also robust when accounting for competition/markups. Then, their findings are consistent with ours, firms with central location did not have higher markups.

The determinants for the different regions show that the service sector had lower while manufacturing sector had higher markups in the Oslo and Northern regions, compared with Eastern Norway (the base region). Regions South and West had, on average, higher markups than Eastern Norway, while for Central Norway our results were mixed. Anderson et al. (2018) also found large regional dispersion in markups in the study of the American and Canadian retail sectors.

4.3. RTS estimates and time trends

On average, returns to scale (*RTS*) were 1.07 for KIBS, 1.15 for Other services, 1.09 for High-tech manufacturing, and 1.05 for Low-tech manufacturing (Table 3). These estimates were statistically different from unity, as indicated by the presence of increasing *RTS* at the mean of the data. Fig. 2 indicates a slightly increasing trend in *RTS* over the last 20 years in all sub-sectors. These results indicate that there is a (small) potential to reduce the cost by increasing the firm size, which can potentially result in lower markups.

5. Concluding remarks

Our findings show rather low markups in Norway, ranging from a mean of 3.1% in the low-tech manufacturing sector to a mean of 3.9% in the KIBS sector. Compared with other studies of countries in Europe and studies of the USA, markups in Norway have been low over the last two decades. Further, we found more or less no trend in the markup estimates for Norway in the last 20 years. This is different from many earlier studies of markups in Europe and the USA, which show a clear rising trend in markups, especially after the financial crises in 2008. In Norway, as in many other countries, in recent decades, there has been a large restructuring of the industry and service sectors, but it seems then that this restructuring has been followed by improved cost efficiency, unlike most of the comparable countries. Possible reasons for low and non-increasing markups in Norway may be Norway's strong competition legislation, which reduces opportunities for overpricing and mergers that reduce healthy competition, and a centralized wage bargaining system securing wage development that corresponds with the development of the economy.

Determinants of markups show that for both manufacturing and service sectors (and sub-sectors), markups decrease with firm size, increase with increasing geographical industrial concentration and decrease with rural location. Our results also show differences in markups between different regions of Norway. These results show there exists further potential

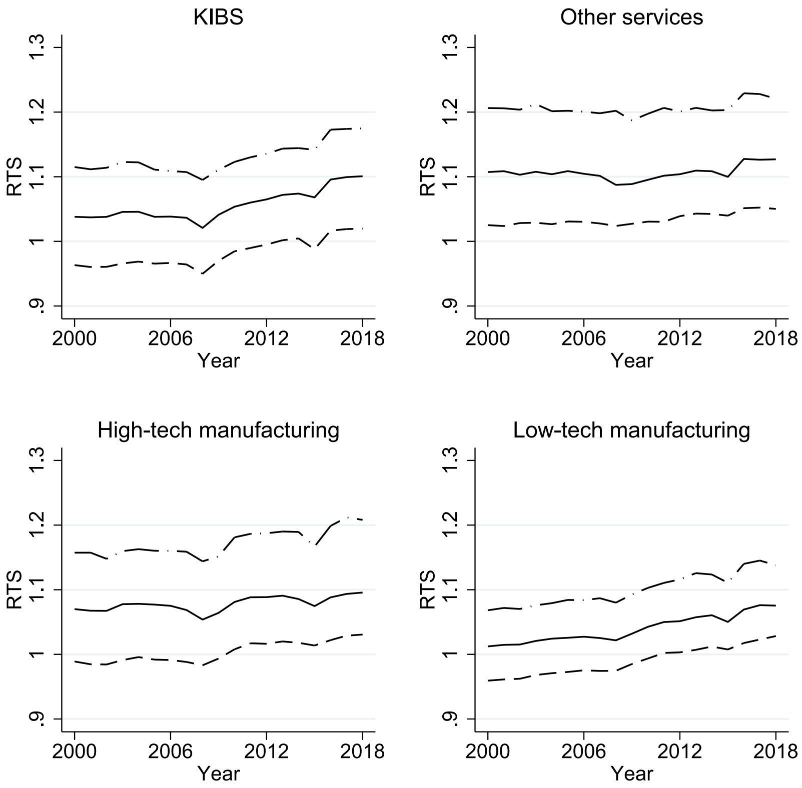

Fig. 2. Time-series plot of RTS. Upper line is the 75th percentile, middle line is the 50th percentile and lower line is the 25th percentile.

Table 5
Markup and returns to scale (*RTS*) estimates, based on the pooled SFA model.

Industry (group)	Estimates of markup					Returns to scale				
	Mean	Std.dev	1. quart.	Median	3. quart.	Mean	Std.dev	1. quart.	Median	3. quart.
Services										
KIBS	0.288	0.379	0.091	0.152	0.301	1.087	0.090	1.020	1.082	1.139
Other services	0.312	0.492	0.079	0.138	0.293	1.145	0.169	1.041	1.109	1.204
Manufacturing										
High-tech	0.103	0.129	0.044	0.070	0.112	1.036	0.059	0.993	1.030	1.071
Low-tech	0.089	0.102	0.040	0.059	0.093	1.026	0.044	0.995	1.022	1.052

for more "fair" pricing in some areas and sectors of Norway, and this information should be taken into account by policy makers.

We have found that firms in each of the four sectors (KIBS, other services and high-tech and low-tech manufacturing) we studied are quite heterogeneous. This implies that further research should, as in this study, account for firm heterogeneity. In this study, the service and manufacturing sectors were divided into four sub-sectors. In future research, more sector-specific studies might give more robust empirical markup results, as also highlighted by Syverson (2019). More detail may give insights into and reasons behind the development of markups within each of these industries.

Appendix

See Table 5.

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