Norwegian University
of Life Sciences

Master's Thesis 2019 30 ECTS
Norwegian University of Life Sciences
School of Economics and Business

The Evolution of Firms' Market Power in Norway

Johanne Lindheim Butenschøn
Master of Science in Economics

THE EVOLUTION OF FIRMS' MARKET POWER IN NORWAY

JOHANNE LINDHEIM BUTENSCHØN*

May 2019

Abstract

This thesis documents the evolution of market power in Norway from 1980 to 2017. Firm-level markups are estimated through a production approach, relying on income statements and balance sheets of all publicly listed Norwegian firms. Several interesting results emerge from this exercise. First, the aggregate markup has increased by about 24 percent since 1980. Second, the cross-sectional distribution of firm-level markups has become more dispersed, and the aggregate trend is mainly driven by firms in the upper tail of the distribution. Third, markups at the firm level are negatively correlated with firm size. Fourth, at the industry level, markups have grown substantially in industries such as financials, telecommunications and petroleum, while they have declined in consumer goods. Fifth, a detailed decomposition of firm-level markups reveals that the secular rise in Norway is due to growing markups within firms, rather than reallocation of market shares across firms. Finally, I also do a first attempt at shedding some light on the possible drivers of rising markups. In particular, I investigate whether declining global interest rates can explain some of the results described above. Using panel data techniques, I find that the secular decline in global interest rates might have benefited high productivity firms more than others, possibly allowing them to acquire market power at the expense of less productive competitors. These results have potentially important implications for monetary and fiscal policy.

**Disclaimer:* The findings, interpretations, and conclusions in this thesis are entirely those of the author and do not necessarily reflect those of her employer or affiliations. *Correspondence:* Johanne L. Butenschøn, johanne.butenschon@gmail.com. While writing this thesis, I have benefited from comments by Jan Eeckhout, Kalle Moene, as well as seminar participants in Norges Bank. I am also grateful for excellent discussions and guidance by my supervisors Drago Bergholt (Norges Bank) and Roberto Garcia (NMBU).

CONTENTS

1 INTRODUCTION

> "How markups move, in response to what, and why, is almost *terra incognita* for macro. (...) [W]e are a long way from having either a clear picture or convincing theories, and this is clearly an area where research is urgently needed."
>
> *Blanchard (2009, p. 220)*

The presence of market power distorts the mechanisms of an efficient economy. Weak competitive pressure increases market concentration and allows market leaders to charge higher prices. In recent decades, several secular trends have been observed across advanced economies, such as falling labor shares, rising inequality, less entry of new firms, and productivity slowdown. One of the leading explanations put forth for several of these trends is the rise in firms' market power. This has motivated researchers and policy-makers to redirect attention from sector-specific case-studies of local markets, to aggregate trends in market power, across sectors, across countries, and over time. A secular rise in corporate market power has been detected in the US and several other advanced economies. Since 1980, the average markup, i.e., the price-to-marginal cost ratio, has increased substantially for US publicly traded firms (De Loecker and Eeckhout, 2017). Similar trends have been identified across a broad range of European countries (Diez, Leigh, and Tambunlertchai, 2018; Weche and Wambach, 2018; Calligaris, Criscuolo, and Marcolin, 2018; De Loecker and Eeckhout, 2018). The evolution of markups has been found to be broad-based across regions and sectors, indicating a fundamental structural change in the macroeconomy.

The secular rise in global markups is important for two reasons. On the one hand, it has implications for market efficiency. Positive markups may imply that goods are priced too high relative to their fundamental values. The quantity of output produced will thus be at a sub-optimally low level, pricing marginal consumers out of the market. This may affect the aggregate economy through several mechanisms. A reduction in output will shift firms' demand for intermediate inputs and labor inward, dampen investment incentives, and perhaps even weaken technological growth due to e.g. lost learning by doing (Aghion, Bloom, Blundell, Griffith, and Howitt, 2005). Moreover, a decline in labor demand may hurt labor force participation and reduce aggregate income. The combination of higher prices and lower investment rates will ultimately pose a dilemma for central banks, through their dual policy rate objectives of inflation targeting and the stimulation of investment and economic growth. The rise in markups may also lead to inefficiency through the misallocation of resources across firms. Market power allows less efficient firms to survive and produce using unproductive processes. Incumbents may erect barriers to entry for new and more productive firms (Bloom and Van Reenen, 2010). The allocation of resources between efficient and inefficient firms will therefore not be optimal, in contrast to highly competitive markets which ensure that resources are allocated to the firms which at any time can produce to maximize the social welfare of the economy as a whole. Second, the evolution of markups is also important due to its impact on inequality. Across advanced economies, the distribution of income and wealth has become increasingly skewed (Alvaredo, Atkinson, Piketty, and Saez, 2013; Baker and Salop, 2015; Wolff, 2014). In the US, the top 1 percent of income-earners have seen their income rise by 90 percent from 1983 to 2013, while the average income of the bottom 60 percent declined by 4 percent (Wolff, 2014). Across OECD countries, the richest 10 percent now have an average income nine times that of the poorest 10 percent (OECD, 2011). Market power has been found to exacerbate these trends by redistributing income and wealth from wage earners to the owners of firms, through two mechanisms. First, higher prices reduce consumers' real wages and hamper their propensity to save. Second, the excess margins from higher markups are paid out as profits to company owners, inflating their income and wealth at the expense of workers who derive their income mainly from labor services. This effect is also stressed by Piketty (2014), who argues that as long as the return to capital exceeds the growth rate of wages, inequality will rise. These regressive effects of market power on inequality have been quantified by Ennis, Gonzaga, and Pike (2017). On average, excessive markups magnifies the wealth accruing to the top 10 percent by between 12-21 percent. For the poorest 20 percent, the rise in market power contributes to a 14-19 percent reduction in income.

To date, very little is known about the evolution of markups in Norway. Most international evidence on markups come from the US (de Loecker et al, 2017) and from broad cross-country comparisons in Europe (Calligaris et al., 2018; Weche and Wambach, 2018; Diez et al., 2018). This motivates a country-specific analysis, which permits a more detailed study of granular patterns and distinctive trends within sectors often masked by aggregate developments. Moreover, several characteristics distinct for Norway may suggest that the international tendencies of increased market power found in large and more closed economies may not translate automatically to the Norwegian context. As a small and open economy, domestic trends are highly driven by global factors and shocks, due to the interconnectedness through the exchange of goods and services with trading partners. In addition, being heavily dependent on natural resources, aggregate Norwegian markups may be driven by firms operating in or supplying the petroleum sector. Evidence on aggregate and cross-sectional markup trends in Norway will be of importance to both fiscal and monetary policy, as increased market power may act as a negative supply shock to the economy. Moreover, a systematic documentation of markups across firms and sectors may also be informing for competition authorities and help them formulate effective remedies in order to strengthen competition.

The objective of this thesis is to explore market power in Norway: how have Norwegian markups developed over time and across firms and industries? Is it a broad trend apparent across all firms and industries or is it rather driven by a few distinctive market leaders? Moreover, what is driving the evolution of markups in Norway? To this end I focus on global interest rates. Is their effect on markups stronger for highly productive firms, as proposed by Liu, Mian, and Sufi (2019)? This latter question is especially important given the observed global trends in declining interest rates, increasing market power and diverging productivity gaps across firms.

I address these questions as follows: first, a panel of firm-level markups for all publicly traded Norwegian companies is estimated from 1980 to 2017, using annual data. These firms had a market value of 72 percent of Norway's GDP in 2017 (The World Bank, 2017). The estimation technique follows the approach proposed by De Loecker and Eeckhout (2017), in which data on input and output from firms' balance sheets and income statements is used to construct markups through the specification of a production function. This approach contrasts with traditional measurement methods prevalent in the industrial organization (IO) literature, where market power conventionally has been proxied either by concentration indices or by markups estimated through a demand-side model, requiring a wide range of assumptions on consumer behavior and the nature of competition. By relying on production data instead, firm-level markups can be estimated as the margin between the variable input's revenue share, scaled by that input's output elasticity.

Second, markups are then explored both at the aggregate level and for the cross-section of firms. I find that the aggregate markup in Norway has increased by about 24 percent from 1980 to 2017. This result is robust to a variety of different specifications, including different production functions, data on profitability among firms, as well as the inclusion of firms which are not publicly listed. The rise of aggregate markups in Norway broadly mirrors international evidence both in growth rates and in levels, but masks substantial heterogeneity across firms. The distribution of markups has become wider and more rightly-skewed over time. Moreover, the aggregate growth is mainly driven by the top percentiles of firms, while the median has stayed mostly stable.

Third, the evolution of markups is analyzed across industries. To do so, the firms are categorized into 10 industries, following the FTSE/Dow Jones Industrial Classification Benchmark (ICB) available in the dataset. These industries include oil and gas, basic materials, industrials, consumer goods, health care, consumer services, telecommunications, utilities, financials and technology. Although I find markups to increase across the majority of industries, the largest growth was found in financials, telecommunications and oil and gas. The aggregate markup increase over time is then decomposed into three effects: a pure markup growth within firms, a reallocation of market shares between firms and a net entry of firms into the market. For the Norwegian sample, I find that it is the pure change in markups within firms that drive the aggregate increase over time.

The last part of this thesis investigates whether the secular decline in global interest rates can account for rising market power in Norway, consistent with the arguments put forward by Liu et al. (2019). Specifically, I explore the role of global interest rates as a transmission channel through which firms invest in productivity-enhancing technology and raise markups. I propose a hypothesis on how the decline in global interest rates is more strongly associated with an increase in markups among highly productive firms relative to low-productivity firms, due to unequal investment responses in a low interest rate environment. I test this relationship formally in an econometric model and find a significant negative relationship between natural rates of interest and markups in highly productive firms. The empirical results lend support to the argument that falling global interest rates is a unified explanation for the reduced market dynamism and the consolidation of corporate market power documented across countries in recent decades.

The rest of the paper is organized as follows. A literature review is presented in Section 2. Section 3 covers the methodological framework used in the estimation of markups, as well a description of the data. Section 4 presents the main results, with several robustness analyses offered in section 5. In section 6, the potential role of global interest rates in explaining markups is analyzed. Finally, section 7 discusses possible implications of the analysis and concludes.

2 LITERATURE REVIEW

2.1 THEORY OF MARKET POWER

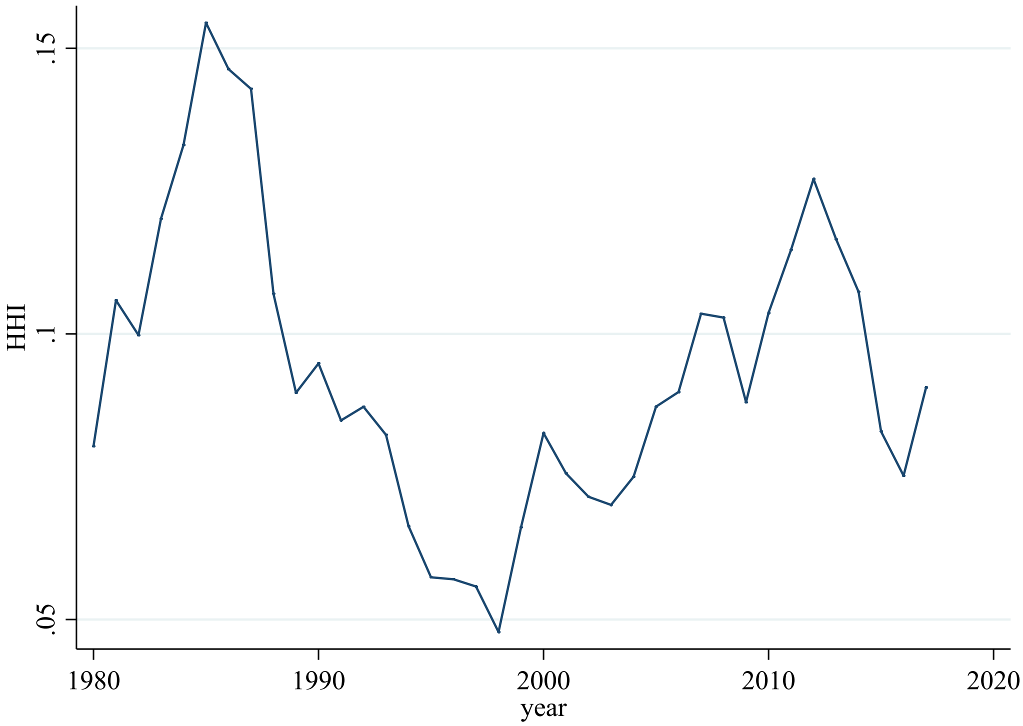
This thesis relates to several branches of literature. The overarching theoretical framework is the market theory central in industrial organization (IO): producers and consumers interact in a market characterized by perfect competition, where all agents are assumed to be price-takers. Production is expanded until the marginal cost of goods sold equals the market price (Tirole, 1988). In presence of market power, however, firms with monopolistic or oligopolistic power reduce output and raise prices, either through legal channels such as product differentiation and patent use, or through illegal means of cartels and predatory pricing (Calligaris et al., 2018). Market power can thus lead to an inefficient allocation of resources and production between firms, the creation of deadweight losses (Harberger, 1964) and to the redistribution of income from consumers and wage earners to business owners (De Loecker and Eeckhout, 2017).

Market power has conventionally been measured by the proxy of market concentration, either as the ratio of total sales accrued to the largest companies within an economy or industry, or by the Herfindahl-Hirschman Index (HHI Index) which is defined as the sum of firms' squared market shares (Hirschman, 1964). Using such indicators, several papers have found a growing concentration in product markets across many advanced economies in recent decades. Grullon, Larkin, and Michaely (2018) were among the first to document the rise in concentration across most industries in the US since 1980, coupled with a reduction in the number of publicly traded firms by half since 2000. Similar concentration trends have been found by former US President Obama's Council of Economic Advisers (2016), Autor, Dorn, Katz, Patterson, and Van Reenen (2017) and Philippon (2018). The rising market concentration in the US is consistent with evidence from Europe, documented across OECD countries since 2000 by Calligaris et al. (2018), Autor et al. (2017) and Haldane, Aquilante, and Chowla (2018).

However, the use of market concentration as a valid and robust measure of market power has recently been contested (Haldane et al., 2018; Shapiro, 2018; Diez et al., 2018; Syverson, 2019). First, the HHI is constructed merely from firms' revenues, and does not consider the margin between price and marginal cost. It thus fails to represent the power of firms in setting prices. Second, a clear definition of what constitutes a relevant market is needed, as well as a requirement of including the whole universe of firms of that market. Missing firms will therefore positively bias each firms' sales share. A third objection to its attractiveness as a market power measure is that it is an outcome of market competition, rather than a determinant of the competition structure in itself. It is not the concentration level that drives the degree of competitiveness, but the other way around.

The relationship between concentration and market power is therefore ambiguous. Highly concentrated industries may signal weak competition if the dominant firms use their market power to determine prices and erect barriers to entry. Norwegian examples include meat and dairy suppliers and fitness franchises. However, there could also be a negative correlation between concentration and market power. Highly competitive markets characterized by economies of scale and network effects may result in a concentrated market structure where ”the winner takes most”, such as in telecommunictions and software apps. Moreover, concentration is not positively associated with market power if a highly concentrated national industry exports

Figure 1: Herfindahl-Hirschman Index in Norway (1980-2017)



homogenous products to an international market where prices are determined globally. Firms with low market shares may also enjoy market power in the presence of brand loyalty, such as for high-end clothing and food products. Finally, although a firm captures a large market share at the national level, it may not dominate at local levels, for example in the restaurant and retail sectors.

The ambigious relationship between concentration and market power can be illustrated by constructing the HHI index for the Norwegian sample. The index can be expressed as the following:

$$HHI_t = \sum_{i=1}^{N} s_{i,t}^2,$$

where $s_{i,t} = \frac{Sales_{i,t}}{\sum_{i=1}^{N_t} Sales_{i,t}}$. The index is supposed to capture the degree of concentration in the economy. In a market of only one firm, the index takes the value 1. Conversely, if there are an infinite number of firms with equal market share, the index would approach zero. The HHI index for the aggregate Norwegian economy is plotted in Figure 1 based on the firms in the sample from 1980 to 2017.

The HHI index shows some cyclicality, but does not exhibit any clear trend. Thus, according to this index, there is no evidence of a secular rise in market power in Norway. It is, therefore, good reasons for not relying on the HHI as a measure of market power, and these shortcomings have motivated the macro market power literature to depart from such concentration indices in favor of more direct measures of firms' pricing power: firms' price-cost markups.

2.2 Literature on Markups and Markup Dynamics

Markups are defined as the wedge between unit prices and marginal costs (Diez et al., 2018). Larger markups imply greater market power. The theory is as follows: the marginal product of a variable input falls as its use is increased in production. In a perfectly competitive market, a firm takes the output price as given and will maximize profits by expanding the use of the variable input until its marginal product equals price. The revenue share of the input thus equals the output elasticity, i.e. the markup is unity (Calligaris et al., 2018). If, on the other hand, the output elasticity of the input is greater than its revenue share in production, then it means that the firm has not expanded the use of the input according to its marginal product. The firm chooses to produce a lower quantity, purchase fewer intermediate goods and rather set a higher price of its final good. Consequently, the unit price will be above marginal cost, which means that the markup is higher than unity and the firm exercises market power (Brandt, Biesebroeck, Wang, and Zhang, 2017).

Markups have been documented to be increasing significantly in the US and Europe since 1980. Studying all publicly traded US firms across all sectors from 1950-2014, De Loecker and Eeckhout (2017) find that while markups remained relatively stable between 1950 and 1980, the period from 1980 to 2014 saw a substantial rise in average markup, from 1.18 to 1.67, meaning that the average firm priced its good 67 percent above marginal cost in 2014. The increase was evident across almost all industries, but showed substantial heterogeneity across firms, as it was mainly driven by the top percentiles of companies, while the median and lower percentiles had flat or even declining markups. The markup rise was also more pronounced among smaller firms. Furthermore, when the aggregate markup growth was decomposed over time, it revealed that the increase was mainly due to a pure markup increase within firms, rather than a reallocation of market shares between firms. Finally, the authors extended the analysis to cover 70,000 publicly listed firms in 134 countries and confirmed that the secular increase in markups was evident across most advanced economies from 1980 to 2016 (De Loecker and Eeckhout, 2018).

Mirroring these results, Diez et al. (2018) estimated markups for publicly traded firms in 74 countries from 1980 to 2016 and found that the average markup increased by 39 percent in advanced economies during the time period considered. Again, the rise in markups was documented to be driven by high-markup firms in each sector, with an increasingly broad and right-skewed distribution. Although their findings were prevalent across all sectors, finance and health care saw the greatest increases. Similarly, Weche and Wambach (2018) tracked European companies during and after the economic recession of 2008-2009. The average markup in 28 countries reached a level of 3.61 in 2014, which is substantially higher than the estimate of De Loecker and Eeckhout (2017). The reason for this difference is suggested to be the inclusion of privately owned firms, whereas De Loecker and Eeckhout (2017) only considered publicly traded companies. Small private firms may operate in niche markets and also enjoy local monopoly power to a greater degree than larger publicly owned firms. The average markup was found to fall markedly during the crisis, with an increase in the aftermath of the crisis. The broad-based markup increase across European countries was also detected by Calligaris et al. (2018), in their study of 26 European countries during 2001-2014. Apart from confirming the distributional markup heterogenetiy among firms, they also found that digitally intense sectors saw a 2-3 percent larger markup increase than non-digitally intense sectors.

Two country-specific studies confirm the general findings of these cross-country comparisons. Haldane et al. (2018) relied on data from 3,500 UK-listed firms to show that markups increased from 1.2 in 1987 to 1.6 in 2017. While the trend was broad-based across most sectors, the largest increases were found in manufacturing, transport and the scientific and technical sector. Across firms, the distribution was strongly skewed, showing a fattening of the upper tail. While the lowest three quartiles barely saw any increase, the top quartile had markups rising by 50 percentage points on average. This pattern is also apparent in the difference between the mean and the median markup, which in 1987 amounted to 7 percentage points. By 2016, this wedge had increased to 44 percentage points. As the authors conclude, it establishes that the aggregate trends are driven by the top markup firms raising their markup further.

Likewise, De Loecker, Fuss, and Van Biesebroeck (2018) estimated markups for all non-financial private Belgian firms from 1980 to 2016. Their estimates show that markups increased from 1980 to 1995 by 15 percentage points, and that firms in the manufacturing sectors saw a continued increase until the early 2000s. Since then, the aggregate markup remained fairly stable. As for the decomposition of markup change over time, some distinct patterns emerged: when the aggregate markups rose from 1980 to 1995, it was mostly driven by the increase within each sector. From 1996 onwards, when aggregate markups stabilized, two conflicting trends were evident. The firms of the top markup-percentiles in each sector continued to raise their markups, but there was a significant reallocation of market shares from those sectors to sectors with lower markups. Markups were rising, but there was a negative correlation between markups and market shares, which made the two effects offset each other. The authors suggest the decreasing international competitiveness of Belgian firms as a potential explanation for this development.

Although no empirical investigations on markups in Norway exist to date, it is reasonable to expect that it will mirror the global secular trend. The earliest evidence in the macroeconomic markup literature came from US firms, which as a large and less trade-reliant economy does not serve as a natural comparison to Norway as a small and open country. Yet, as new research on smaller European countries such as UK and Belgium confirm a secular trend, it is evident that the markup increase is not exclusive to the US economy, but rather indicates an international tendency. However, several unique country-specific characteristics may suggest that Norwegian markups may display some distinct patterns. First, the relatively small size of the economy may limit the emergence of giant ”superstar firms” which can charge excessive markups. Second, as Norway is a highly specialized petroleum exporter, the markup of the offshore sector may be an important determinant for the aggregate markup, due to the sector’s share of GDP and the strong intersectoral linkages between offshore and mainland industries.

Following the emerging literature documenting a secular increase in markups globally, some researchers have expressed concern over the validity of markups as a proxy for market power. Ramey (2018) contends that markups may not mirror market power, but could rather indicate rising fixed costs when firms invest in technology to improve productivity. The firm would then recover these fixed costs by setting an output price above the variable input cost, without yielding higher profits. A high degree of innovation does not necessarily mean rising market power (Calligaris et al., 2018; Martins, Scarpetta, and Pilat, 1996). To test these alternative explanations, Diez et al. (2018) examined the relation between rising markups and firms' profitability. They found strong evidence for a positive association, where a 10 percentage point increase in markups is accompanied by a 19 and 13 percentage point increase in the ratio of dividends to sales in the U.S. and advanced economies, respectively. Another measure of profitability was also tested, namely firms' market capitalization to sales, with similar positive results. Likewise, De Loecker and Eeckhout (2018) documented a strong comovement between markups and profitability: both measures increased similarly during the 1980s and 1990s, stabilized during the 2000s, and rose again after 2010. They conclude that markups do not reflect increasing fixed costs but rather that rising markups represent a consolidation of corporate market power. The link between markups and market power has also been studied through markups' inverse relationship with the labor share of output, which has been declining since 1980 across a broad range of countries (Karabarbounis and Neiman, 2014; Autor et al., 2017; Barkai, 2018; Kehrig and Vincent, 2017). The fall in the labor share is consistent with a rise in markups, as firms reallocate production from labor-intensive to capital-intensive production methods and extract higher profits.

Although the association between markups, profitability and labor share is an understudied topic in the Norwegian context, there are several reasons to believe that higher markups imply greater market power for Norwegian firms. The labor share of income in Norway has decreased by approximately 2 percent every ten year from 1991 to 2014 (Dao, Das, Koczan, and Lian, 2017). Profitability, as measured by dividends received across all Norwegian holding sectors, increased by 78 percent from 2012 to 2017 (Statistics Norway, 2019). The strong association between market power and markups are thus hypothesized to hold in the Norwegian economy as well.

2.3 Potential Drivers of Markups

The documentation of a secular trend in markups has triggered a search for potential causal drivers. Acknowledging that the trend is broad-based across advanced economies, attention has been redirected from domestic anti-trust policy to the significance of global factors. Especially for small, open economies such as Norway, with a share of trade amounting to 70 percent of GDP, the role of international business cycle synchronization may have explanatory power in determining the evolution of domestic aggregate markups.

Small, open economies are highly sensitive to global economic fluctuations. Business cycles of aggregate activity have been found to show a significant co-movement across a broad range of countries (Kose, Otrok, and Whiteman, 2003). Global shocks to macroeconomic variables such as output, inflation and interest rates propagate across countries and strongly influence domestic volatility in open economies (Justiniano and Preston, 2010; Adolfson, Lasen, Lind, and Villani, 2005; Christiano, Trabandt, and Walentin, 2011). The global disturbances are assumed to be exogenous to these countries, and the influence of foreign shocks have been quantified to explain between 50-75 percent of fluctuations in domestic output, investment and consumption (Kose et al., 2003; Justiniano and Preston, 2010). The transmission of global shocks to the Norwegian economy has been found to be of similar magnitude as in other open economies (Aastveit, Bjørnland, and Thorsrud, 2016; Nygaard, 2013; Bergholt, 2015).

An emerging strand of literature relates the transmission of global business cycle shocks to firm-level performance. di Giovanni, Levchenko, and Mejean (2018) propose a model in which aggregate global shocks to output and productivity propagate to domestic production networks through intermediate input linkages. The aggregate shocks lead to heterogenous responses at the micro level, however, as the largest firms show greater response due to more foreign linkages.

Specifically, Liu et al. (2019) study the role of global natural interest rates and firm-level markups in a model where firms compete for market leadership. In their framework, the falling long-term interest rates observed internationally in recent decades trigger increasing markups, higher market concentration and a greater productivity gap between the market leader and the follower. According to their argument, lower interest rates have the traditional effect of increasing productivity-enhancing investment in firms in order to gain market shares from competitors. However, the incentive to respond to a lower interest rate is larger for the leader than for the follower. If the productivity gap between them is large, the follower is discouraged from improving its production processes as the probability of reaching the leader becomes too low. The leader is closer to the state where investment will pay off in profits and market shares. The investment incentives following an interest rate decline is thus higher for the leader, an effect that strengthens as the interest rate approaches zero. Lower global interest rates will therefore widen the productivity gap between the leader and follower, raise the leader's markup and reduce market dynamism. This mechanism is consistent with Akcigit and Ates (2019), who found that the widening productivity gap following from lower natural interest rates lead to higher markups, an effect reinforced by the reduction in knowledge diffusion between the market leader and the follower, through greater use of intellectual property protection and higher patent concentration. The role of interest rates on the rise of monopoly power is also studied by Eggertsson, Robbins, and Wold (2018).

This thesis contributes to the literature in several ways. First, it presents novel evidence on how markups have moved, both at the aggregate and cross-sectional level, in Norway since 1980. Apart from being the first of its kind on Norwegian data, it adds to the growing documentation of country-level markups across Europe in a literature dominated by evidence from the US. Moreover, as common global causal drivers of markup trends have been left relatively unexplored to date, the thesis represents a first step towards understanding the potential role of global interest rates on markups in Norway as a small, open economy.

3 Methodological Framework and Data

3.1 Methodological Framework

The estimation of markups follows the production approach proposed by De Loecker and Eeckhout (2017), a framework originally put forth by De Loecker and Warzynski (2012). In turn, they build on the seminal work by Olley and Pakes (1996). The measurement technique is based on firm-level cost data, and thus represents a deviation from demand-side methods prevalent in the IO literature (Bekes, Hornok, and Murakozy, 2016). By relying on data extracted directly from the firms' balance sheets and income statements, previously required assumptions on consumer behavior, the nature of competition and degree of product homogeneity, are circumvented. In so doing, the production approach overcomes limitations of traditional methods and allows for a more precise analysis of market power at the aggregate and cross-sectional level.

In the application of this cost-based method, two assumptions must be made. First, a production function must be specified. Second, it is assumed that firms are optimizing and that their factor adjustments are not hampered by adjustment frictions.

Consider an economy with N firms, indexed by $i = 1, ..., N$. Each firm i produces output Q at time t given a production function of variable inputs, capital and technology, denoted by:

$$Q_{i,t} = Q_{i,t}(\Omega_{i,t}, V_{i,t}, K_{i,t-1}), \tag{1}$$

$Q_{i,t}$ represents units of output produced, $\Omega_{i,t}$ is the firm-specific technology level or total factor productivity, $V_{i,t}$ is a vector of variable inputs and $K_{i,t-1}$ is the capital stock, determined one period ahead. The firm's optimization problem can be formulated by the following Lagrangian function subject to the production function:

$$\mathcal{L}_{i,t} = P^V_{i,t} V_{i,t} + P^K_{i,t} K_{i,t-1} - \Lambda_{i,t}(Q_{i,t} - \bar{Q}_{i,t}), \tag{2}$$

$P^V_{i,t}$ refers to the price of the variable input, $P^K_{i,t}$ is the user cost of capital, $\bar{Q}_{i,t}$ is a constant and $\Lambda_{i,t}$ is the Lagrangian multiplier. This multiplier is directly representing the marginal cost, because it takes the value of the objective function when the output constraints are relaxed (De Loecker and Eeckhout, 2017). The Lagrangian multiplier will therefore be denoted by MC hereafter.

The optimization problem leads to the first order condition with respect to the variable input:

$$P^V_{i,t} = MC_{i,t} \frac{\partial Q_{i,t}}{\partial V_{i,t}} \tag{3}$$

The firm's markup is defined as its price over marginal cost:

$$\mathcal{M}_{i,t} = \frac{P_{i,t}}{MC_{i,t}}$$

The term $P_{i,t}$ is the price of output and depends on the firm's market power. Using the optimality condition, the following expression can be derived:

$$\mathcal{M}_{i,t} = \alpha^V_{i,t} \frac{P_{i,t}Q_{i,t}}{P^V_{i,t}V_{i,t}}. \tag{4}$$

The expressions $\alpha^V_{i,t} = \frac{\partial Q_{i,t}/Q_{i,t}}{\partial V_{i,t}/V_{i,t}}$ is the elasticity of output with respect to variable inputs.

Thus, the calculation of the markup consists of two parts. First, the cost share of the variable input, $\frac{P_{i,t}Q_{i,t}}{P^V_{i,t}V_{i,t}}$, is retrieved directly from the data, as total sales ($P_{i,t}Q_{i,t}$) divided by total variable cost of production ($P^V_{i,t}V_{i,t}$). Second, the output elasticity $\alpha^V_{i,t}$ needs to be estimated.

To do so, a production function must be assumed. Among the Hicks-neutral production functions, where the proportion of inputs are unchanged by changes in productivity, the Cobb-Douglas production function is generally preferred in the literature for markup estimation, as it is considered both simpler and more stable (Calligaris et al., 2018). In the baseline, I assume that all firms belonging to a specific industry share the same technology, but differ in their productivity levels and preferred mix of inputs. An output elasticity is thus estimated for each industry. In this way, the variation in firm-level markups within an industry is solely driven by the difference in total sales-to-expenditure shares.

Other specifications of the production function could be made, for example the translog production function, which yields firm-specific output elasticities. I will treat the translog specification as a robustness test in section 5.

I start out with the specification of a production function. In the baseline, a Cobb-Douglas specification is assumed:

$$q^o_{i,t} = \alpha_j v_{i,t} + \beta_j k_{i,t-1} + \omega_{i,t} + u_{i,t} \tag{5}$$

The logarithm of output in year t is denoted by $q^o_{i,t}$, variable factor inputs by $v_{i,t}$, and capital (which is assumed to be predetermined) by k_{t-1}. Each firm i belongs to an industry j. $\omega_{i,t}$ represents the level of technology while $u_{i,t}$ is a measurement error. This production function is particularly simple to work with because it implies that the parameter α_j represents the output elasticity of the variable input, which is the coefficient needed for the estimation of markups. This parameter is specific for each industry and does not vary with time.

A key challenge for the estimation of this production function is that the productivity term, $\omega_{i,t}$, is unobserved to the econometrician and will therefore be captured by the error term if standard OLS techniques are applied. $\omega_{i,t}$ can be anticipated by the firm's management (but is unobserved for the econometrician) and hence may influence the input demand, i.e. if a positive shock induces the firm's management to increase production and input demand. The unobserved productivity will lead to a potential simultaneity and endogeneity bias, if productivity shocks correlate with the firm's input decisions and hence the output.

This bias can be corrected for by using a so-called control function approach. The demand for the variable input is assumed to be a function of productivity and capital:

$$v_{i,t} = f(\omega_{i,t}, k_{i,t-1}). \tag{6}$$

Following Olley and Pakes (1996), the demand function in (6) can be inverted so that $\omega_{i,t}$ is expressed as a function of observable variables:

$$\omega_{i,t} = f^{-1}(v_{i,t}, k_{i,t-1}). \tag{7}$$

Note that this inversion does not imply anything regarding causality. It can be entered into the production function (5), giving:

$$\begin{aligned} q^o_{i,t} &= f^{-1}(v_{i,t}, k_{i,t-1}) + \alpha_j v_{i,t} + \beta_j k_{i,t-1} + u_{i,t} &(8)\\ &= \phi_{i,t} + u_{i,t} &(9) \end{aligned}$$

where the function $\phi_{i,t}$ is defined as output filtered for the measurement error:

$$\phi_{i,t} = \phi(v_{i,t}, k_{i,t-1}) = \alpha_j v_{i,t} + \beta_j k_{i,t-1} + f^{-1}(v_{i,t}, k_{i,t-1}) \tag{10}$$

In order to proceed, I need to specify how productivity evolves over time. Here I suppose that productivity at the firm level follows a random walk with a drift:

$$\omega_{i,t} = g + \omega_{i,t-1} + z_{i,t} \tag{11}$$

The long run productivity growth rate is denoted by g, while $z_{i,t}$ represents temporary deviations from trend growth. The latter is assumed to follow a first-order autoregressive process:

$$z_{i,t} = \rho z_{i,t-1} + \eta_{i,t} \tag{12}$$

I can combine the laws of motion for $z_{i,t}$ and $\omega_{i,t}$. Then it follows that also productivity growth $(\Delta\omega_{i,t} = \omega_{i,t} - \omega_{i,t-1})$ follows an autoregressive process:

$$\Delta\omega_{i,t} = (1-\rho)\, g + \rho\Delta\omega_{i,t-1} + \eta_{i,t}$$

Next, this expression is manipulated using $\omega_{i,t} = f^{-1}(v_{i,t}, k_{i,t-1})$ and equation (10):

$$\begin{aligned} \eta_{i,t} &= \Delta\omega_{i,t} - \rho\Delta\omega_{i,t-1} - (1-\rho)\, g \\ &= [\Delta\phi_{i,t} - \alpha_j\Delta v_{i,t} - \beta_j\Delta k_{i,t-1}] - \rho\,[\Delta\phi_{i,t-1} - \alpha_j\Delta v_{i,t-1} - \beta_j\Delta k_{i,t-2}] - (1-\rho)\, g \end{aligned}$$

By solving for $\Delta\phi_{i,t}$, I arrive at an equation that can be estimated in order to find the output elasticity used to compute markups:

$$\Delta\phi_{i,t} = (1-\rho)\, g + \rho\Delta\phi_{i,t-1} + \alpha_j\Delta v_{i,t} + \beta_j\Delta k_{i,t-1} - \rho\alpha_j\Delta v_{i,t-1} - \rho\beta_j\Delta k_{i,t-2} + \eta_{i,t} \tag{13}$$

By inspecting equation (13), I note that estimation is subject to a simultaneity issue which invalidates the use of OLS: $\Delta\phi_{i,t}$ and $\Delta v_{i,t}$ are likely to be jointly determined. The production function of (9) is thus estimated in two stages. First, equation (9) is estimated by a non-parametric procedure, yielding the estimates $\hat{\phi}(v_{i,t}, k_{i,t-1})$. This procedure is used to account for the simultaneity between inputs and output. Next, in the second stage, the endogeneity issue present in this dynamic panel data model is handled through a GMM approach, as $\eta_{i,t}$ may be correlated with $v_{i,t}$ (Baltagi, 2005). A GMM technique is suitable for this panel setup as the dependent variable, output, is dynamic and depends on its own past values as well as a set of regressors in which some are not strictly exogenous (Roodman, 2009). To consistently estimate the production function, Arellano and Bond (1991) proposed a method where the lagged values of the variable input and capital are used as instruments. The validity of these instruments is based on the following: $v_{i,t-1}$ and $k_{i,t-2}$ are relevant for $v_{i,t}$ and $k_{i,t-1}$, as previous use of inputs is correlated with current input use. However, the lagged values of intermediate inputs and capital do not affect the productivity shock $\eta_{i,t}$ in the subsequent period. The following moments restriction must thus hold:

$$\mathbb{E}\left(\eta_{i,t}\Delta v_{i,t-m}\right) = 0 \qquad \text{for} \qquad 1 \leq m \leq T \tag{14}$$

That is, the growth in variable factor inputs m periods ago, $\Delta v_{i,t-m}$, is uncorrelated with current technology shocks $\eta_{i,t}$. This restriction suggests that I can use $\Delta v_{i,t-m}$ as instruments for $\Delta v_{i,t}$, as long as the former is a relevant predictor of the latter. Unlike De Loecker and Eeckhout (2017), I allow for multiple instruments by exploiting many lags of variable factor inputs, as in Arellano and Bond (1991) and Blundell and Bond (2000).

The parameter of the variable input, α_j, is recovered for each sector and is mulitplied with the firm-specific sales-to-expenditure ratio, which together make up the firm-specific markup:

$$\mathcal{M}_{i,t} = \alpha_j \frac{P_{i,t}Q_{i,t}}{P^V_{i,t}V_{i,t}}.$$

This estimation generates a database of markups for every firm-year observation where data are available.

3.2 Data

For the estimation of markups in Norway, firm-level data for all publicly traded Norwegian firms are used, spanning the years 1980 to 2017. The panel dataset was obtained from the *Thomson Reuters Worldscope* (TRW) database, through an institutional access that was granted by Norges Bank. The database contains over 70,000 firms in 134 countries, including more than 2,000 Norwegian companies. The choice of this dataset is based on the ability to cover as long a time period as possible, across a broad range of economic activity in Norway. The panel characteristic of the dataset allows for tracking the same firms over the entire period.

I use data from the balance sheets and income statements of all Norwegian firms in TRW. The variable *Sales* is total ouput, i.e. quantity produced times its selling price. As a measure of variable inputs in production, the cost of goods sold (*COGS*) is used, which includes intermediate inputs, labor, raw materials and electricity. *Capital* is proxied by the firms' property, plant and equipment variable. These three variables are used in the estimation of markups and are the same as in De Loecker and Eeckhout

(2017). Additionally, two other variables were extracted. First, a measure of firms' market capitalization is used to attest whether the markup estimates correlate with firms' profitability over time. Second, the share of exports of firms' total sales is included as a firm characteristic when markups are related to global factors in the econometric model in section 6.

The dataset had to be cleaned carefully before use. The raw dataset was trimmed and cleaned, following standard procedures in the literature. Negative values were removed and duplicates deleted, as some firms were listed several times in different currencies. The dataset contains 76,456 observations spanning 38 years.

In the *Worldscope* database, firms are categorized according to the FTSE/Dow Jones Industrial Classification Benchmark (ICB). They are grouped into 10 industries, which are further broken down into 19 super-sectors and 115 sub-sectors. This sectoral decomposition allows for a more detailed analysis of the mechanisms and drivers behind the aggregate evolution of markups. The broadest classification of industries was chosen for the Norwegian data, due to the limited number of firms in certain sectors. The ten industries include oil and gas, basic materials, industrials, consumer goods, health care, consumer services, telecommunications, utilities, financials and technology. An overview of the sample summary statistics is provided in Table 1. The mean, median, variance and number of observations are reported for the three main variables used in the estimation of markups, across the ten industries.

As is evident from the table, the sample shows great heterogeneity both across industries and over time. Across all three variables, three industries stand out with relatively high mean values: oil and gas, basic materials and utilities. Considering Norway's status as a highly specialized petroleum and mineral exporter, the scope of the first two industries is not surprising. The size and importance of these industries are also reflected in the number of firm-year observations. For utilities, the small number of observations may indicate its nature of network economies which limits the number of profitable agents in the market. However, its high mean values may be driven by giants like Telenor, with a considerable global outreach. A more detailed analysis of the ten industries is provided in section 4.3.

A large heterogeneity is also noteable in all industries. This may be due to the inclusion of all publicly listed firms in the database, i.e. that no trimming in terms of firm size was done, in contrast to other studies relying on the same database. This is also seen in the considerable difference between the mean and median of the three variables, as big firms of each industry drive the mean value far above the median in the sample. It should also be noted that the sample size increases over time. The dataset is an unbalanced panel, with relatively limited coverage in the first decade and then increasing as more firms enter and report their balance sheets and income statements.

A limitation of the dataset is that it only covers publicly traded firms. This may question the representativeness of the findings, in that the results may not be generalizable to the whole economy. Publicly traded firms tend to be larger than private firms, and their behavior may be different, which can yield different markup trends than for privately held companies. Several studies have performed robustness checks to detect such differences. De Loecker and Eeckhout (2017) compared their markup estimates from a dataset of publicly traded US firms with other datasets covering all US companies and found similar markup tendencies across most firms and sectors. I will therefore do a similar robustness

Table 1: Summary statistics (1980-2017)

	Sales				COGS				Capital			
Industry	Mean	Median	St.dev	No. of obs.	Mean	Median	St.dev	No. of obs.	Mean	Median	St.dev	No. of obs.
Oil and gas	11,273,102	901,392	54,428,101	1,472	6,749,987	512,593	30,109,999	1,393	20,834,984	2,297,777	107,739,814	1,290
Basic materials	14,822,211	3,351,400	28,766,777	456	11,188,800	2,568,429	21,199,908	437	20,957,943	5,636,000	38,604,174	394
Industrials	2,331,876	846,353	5,221,566	1,893	1,771,371	597,036	4,599,674	1,726	2,842,293	940,700	6,623,562	1,611
Consumer goods	4,657,094	1,857,000	8,614,300	640	3,378,746	1,281,142	6,014,987	599	3,291,517	905,199	7,092,710	521
Health care	209,913	49,760	837,078	199	92,439	24,997	253,232	182	175,207	7,819	748,859	155
Consumer serv.	2,416,910	1,093,319	3,727,259	451	1,560,415	599,350	2,289,102	392	1,867,728	628,965	3,248,317	342
Telecom	36,861,698	15,950,668	41,748,648	51	16,028,698	6,656,495	14,903,805	46	62,304,463	23,371,604	59,246,606	45
Utilities	6,531,396	2,568,300	10,346,445	96	3,266,279	2,019,476	3,730,215	90	10,718,097	3,752,179	13,947,728	77
Financials	5,752,895	873,968	14,721,883	1,367	2,137,824	80,153	9,177,704	316	5,340,606	638,100	11,181,430	293
Technology	1,561,663	311,119	4,149,193	743	1,342,102	207,853	4,004,780	640	260,682	63,004	549,473	572
All industries 1980	2,169,417	1,638,044	1,860,273	42	1,835,353	1,375,342	1,628,141	35	3,029,128	1,455,300	4,338,716	23
All industries 2017	9,201,902	1,228,435	36,577,002	232	5,034,951	559,655	19,865,679	190	24,438,095	2,638,257	132,279,471	143
All industries 1980-2017	5,891,829	862,622	27,135,326	7,368	3,876,960	529,127	16,711,788	5,821	8,950,414	954,513	55,589,369	5,300

Note: in NOK.

test, in order to verify whether the markup trend observed among publicly listed firms hold for the whole population of firms in Norway. To do so, I was granted institutional access to a dataset recently made available from the Brønnøysund Register Center (governmental business registry), which includes the balance sheets and income statements of all Norwegian firms from 1999 to 2018. Although the time period is regrettably shorter, it contains 3,795,835 firm-year observations, and will hence serve as an important point of comparison to the publicly listed firms.

Indeed, although the number of publicly traded firms are few in relation to the whole population of Norwegian companies, they represent a fair share of economic activity due to their firm size. In 2017, Norway's listed companies had a market value of 72 percent of Norway's GDP (The World Bank, 2017). This share is consistent with the countries studied in other papers measuring markups using data for listed companies, as the average GDP share of publicly listed firms in the advanced economies studied by Diez et al. (2018) is 75 percent. The findings from the Norwegian dataset thus elucidate some general macroeconomic trends and developments in Norway.

4 RESULTS

This section presents the main evidence of how markups have evolved across firms and over time in Norway. First, the aggregate markup is constructed as a share-weighted average of firm-level markups, and its time-series movement from 1980 to 2017 is documented. To explore whether the aggregate trend holds across most firms, the markup distribution is further disaggregated into densities and percentiles. Next, a sectoral decomposition of the economy sheds light on how markups have developed across industries. Finally, an analysis of the dynamics behind the markup growth is presented, by a disaggregation of the overall markup change into a pure markup growth effect, a reallocation effect of shifting market shares between firms and a net entry of firms into the market.

4.1 THE EVOLUTION OF AGGREGATE MARKUPS

The aggregate markup for the whole economy in a given year can be defined in the following way:

$$\mathcal{M}_t = \sum_{i=1}^{N_t} s_{i,t}\mathcal{M}_{i,t},$$

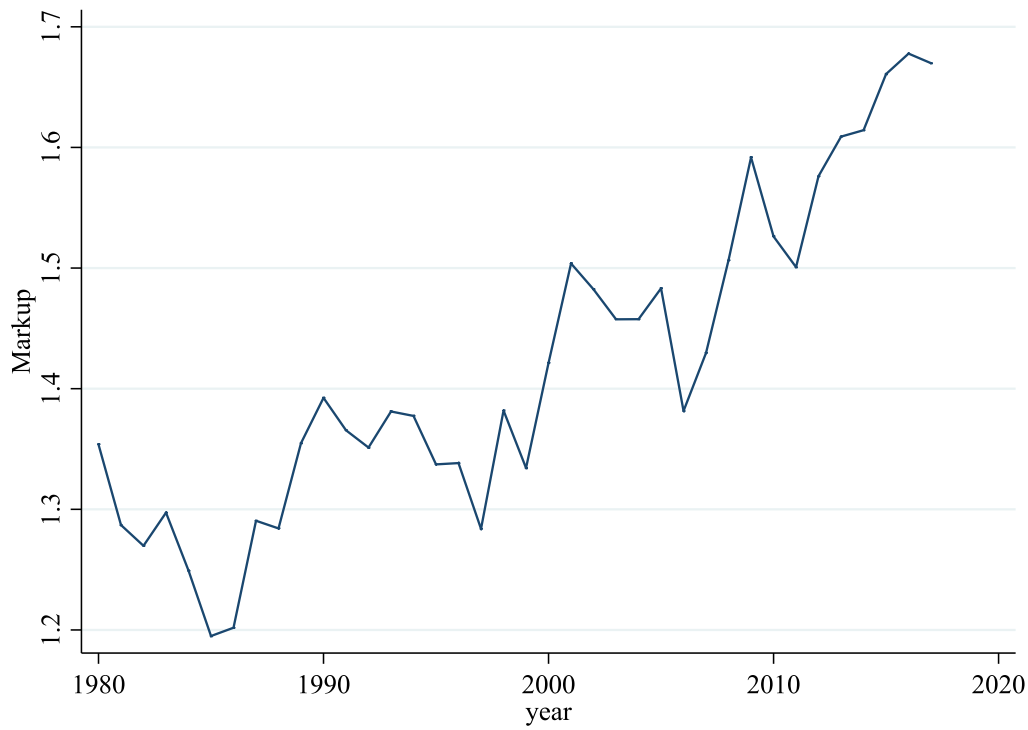
where $s_{i,t} = \frac{P_{i,t}Q_{i,t}}{\sum_{i=1}^{N_t} P_t Q_t}$ (the share of each firm's sales of total sales) and $\mathcal{M}_{i,t} = \frac{P_{i,t}}{MC_{i,t}}$ (the firm-level markup).

The evolution of aggregate markups in Norway is reported in Figure 2. The aggregate markup, weighted by each firm's sales, has increased markedly from 1980 to 2017. Starting at 1.35 in 1980, the markup decreased slightly to 1.19 in 1985. It then took off, showing a clear growing trend, reaching a level of 1.67 in 2017. The whole time period represents a markup growth of about 24 percent. This trend broadly mirrors international evidence, both in terms of growth rates and the absolute level of markups, as De Loecker and Eeckhout (2017) and Diez et al. (2018) identified markups at 1.60 and 1.67 in 2016 for advanced economies and the US, respectively. It is clear from the aggregate markup growth that rising market power in the Norwegian economy matches the secular trend documented globally. The substantial rise in markups in Norway may also suggest that corporate market power may have implications for market inefficiency and rising income inequality.

4.2 DISTRIBUTION OF MARKUPS

DENSITY OF MARKUPS: The first step to explore the dynamics behind the aggregate growth of markups is to compare the densities of the markup distribution over time. As the kernel density plot in Figure 3 reports, the dispersion of unweighted markups has changed markedly between 1980 and 2017. First, the variance is greater, indicated by the fatter tails in the 2010-2017 distribution. Moreover, the distribution has become increasingly skewed to the right, as the upper tail for 2010-2017 is both longer and much fatter. This reflects that high-markup firms have seen the largest increase in markups over time, which drives the aggregate trend. The finding is highly consistent with trends in global markup

Figure 2: The Evolution of Aggregate Markups in Norway (1980-2017)



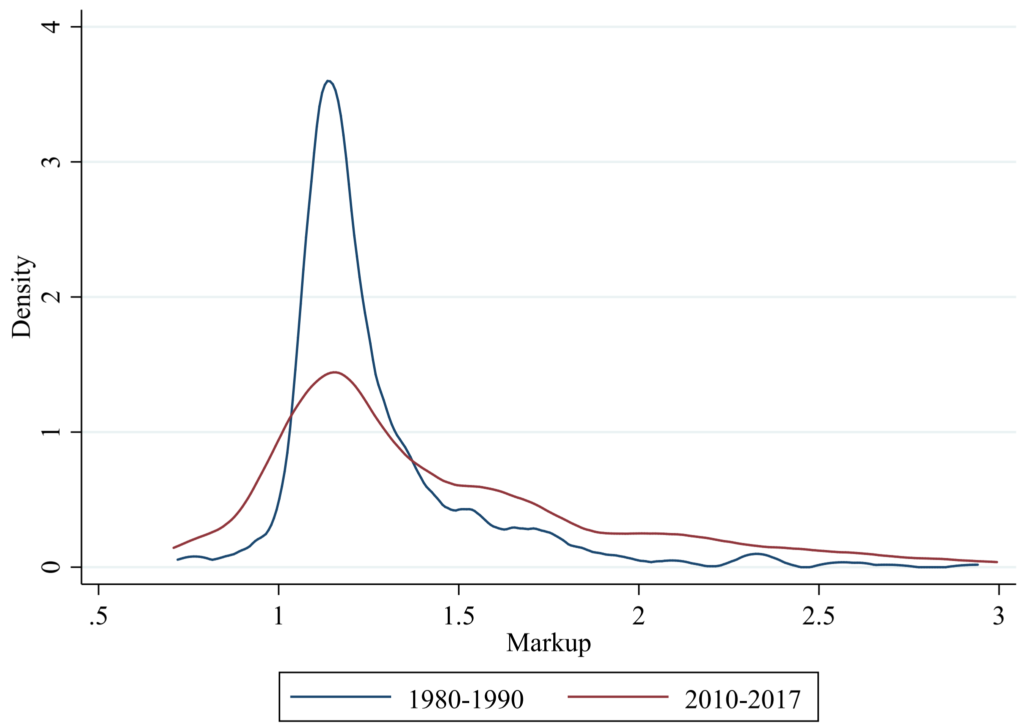
Note: the aggregate is an average of firm-level markups weighted by their market share of total sales in the sample in a given year.

distributions, where greater variance and a fattening of the upper tail has been firmly documented.

PERCENTILES: Another way to slice the data is to consider the different percentiles of the markup distribution. This is done by ranking the firms according to their markup. As is evident from Figure 4, the lower percentiles of the distribution did not experience any notable markup growth over the time period. The median firm in the sample had its markup grow from 1.2 to 1.4. The markup for the bottom 25th percentile decreased slightly, from 1.15 in 1980 to 1.1 in 2017. In contrast, as is evident from the figure, it is the top percentiles of the distribution that drive the aggregate markup growth. The 75th percentile of the firms saw a significant increase during the time span, from 1.4 in 1980 to 2.25 in 2015, before decreasing slightly to 1.8 in 2017. This pattern is again evidence of the aggregate markup growth being driven by a few firms in the upper part of the distribution, with exceptionally high markups. The shape of the green curve also follows the aggregate pattern of Figure 2. This finding is consistent with markup distributions found in other countries, which reveal considerable heterogeneity at the cross-sectional level (Calligaris et al., 2018; Weche and Wambach, 2018; Haldane et al., 2018).

The aggregate markup trend in Norway is thus not representative for the majority of firms. The markup growth has not been broad-based across most firms, but is rather a reflection of how high-markup firms have progressively been raising their markups over time. This illustrates the significant amount of heterogeneity among Norwegian firms, as

Figure 3: The Distribution of Markups, 1980-1990 and 2010-2017



well as the limitations embedded in analyses on aggregate data only. The finding may also indicate a growing productivity gap between firms, where market leaders positioned in the frontier have increasingly adopted productivity-enhancing technologies and thereby increased the distance to their followers, with higher markups as a result.

Firm Size and Markups: The aggregate markup for the whole economy is weighted by the sales share of each firm. Alternatively, the aggregate markup can be estimated as an unweighted average across the economy, which yields an aggregation irrespective of each firm's size. In Appendix A, I show that the weighted aggregate markup can be decomposed as:

$$\mathcal{M}_t = \bar{\mathcal{M}}_t + \sum_{i=1}^{N_t} (s_{i,t} - \bar{s}_t)(\mathcal{M}_{i,t} - \bar{\mathcal{M}}_t),$$

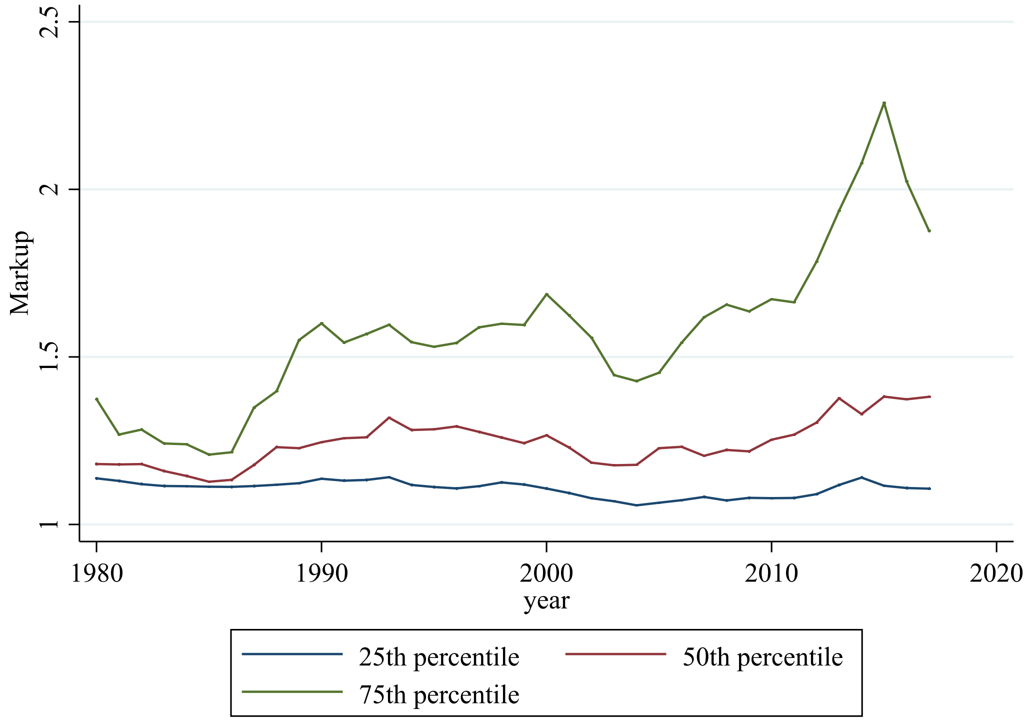
where $\bar{\mathcal{M}}_t$ denotes the unweighted average markup, $\bar{\mathcal{M}}_t = \frac{1}{N_t}\sum_{i=1}^{N_t} \mathcal{M}_{i,t}$.

The second term at the right hand side is proportional to the sample covariance between a firm's market share and its markup. Thus, if the sales-weighted markup is greater than the unweighted, then there is a positive correlation between firm size and markup. In contrast, if the unweighted average markup is larger than the sales-weighted markup, then smaller firms are associated with higher markups and vice versa.

The sales-weighted baseline markup $\mathcal{M}_t$ and the unweighted average markup $\bar{\mathcal{M}}_t$ are plotted in Figure 5.

The unweighted markup lies above the weighted markup most of the time and also

Figure 4: The Dispersion of Markups (1980-2017)



Note: the percentiles are weighted by market share of total sales in the sample in a given year.

shows a sharper rise from the mid-1980s to mid-1990s, and from 2003. While the weighted baseline markup grows from 1.35 in 1980 to 1.67 in 2017, the unweighted average increases from 1.35 in 1980 to 2.0 in 2014, before it decreases to 1.87 in 2017. The total change over the entire time period for the unweighted markup is 39 percent, compared to 24 percent for the weighted markup.

As the unweighted aggregate markup is higher than the aggregate markup weighted by sales, it follows that the covariance term between firm size and markup is negative, i.e. $\text{cov}(s_{i,t}, \mu_{i,t}) < 0$. This implies that smaller firms tend to have higher markups. Larger firms are thus depressing the aggregate markup when they are assigned more weight in the estimation, an insight compatible with the results in De Loecker and Eeckhout (2017). This finding indicates that the top percentiles of firms which have been found to drive the aggregate markup in Norway are not necessarily the largest firms of the economy.

FIRM SIZE AND PRODUCTIVITY: The same decomposition can be done for productivity, which in the markup estimation is captured by ω_{it} from equation 5. The estimation yields a firm-level productivity level for each year, and the sales-weighted average productivity can thus be expressed as follows:

$$\Omega_t = \bar{\Omega}_t + \sum_{i=1}^{N_t} (s_{i,t} - \bar{s}_t)(\Omega_{i,t} - \bar{\Omega}_t),$$

Figure 5: The Evolution of Unweighted Average Markups versus Sales-Weighted Average Markups (1980-2017)

where Ω_t denotes the sales-weighted productivity and $\bar{\Omega}_t$ is the unweighted average productivity. Again, the covariance term at the right hand side represents how firm size is related to the level of productivity. The weighted and unweighted measures are plotted in figure 6.

In contrast to figure 5 above, it is clear from figure 6 that sales-weighted productivity lies consistently above the unweighted productivity, and grows more rapidly. This implies that larger firms are inherently more productive than smaller firms. Firm size is thus positively correlated with productivity, but negatively correlated with markups. These relationships will be formally tested in an econometric model in section 6.

4.3 Industries

The ICB classification system separates the publicly listed firms into ten main industries, which is a standard categorization of the global firms covered by the *Thomson Reuters* database.

An outlook of the industry composition of the sample is presented in Figure 7. The share of each industry is calculated as the share of total sales per year. The size of each industry is thus shown as the width of each band, totalling to 100 percent. From the figure, it is evident that oil and gas is the largest industry, expanding its share over time, to above 50 percent of the total stock exchange in 2013. This industry includes oil and gas producers, equipment and service providers, as well as alternative energy producers.

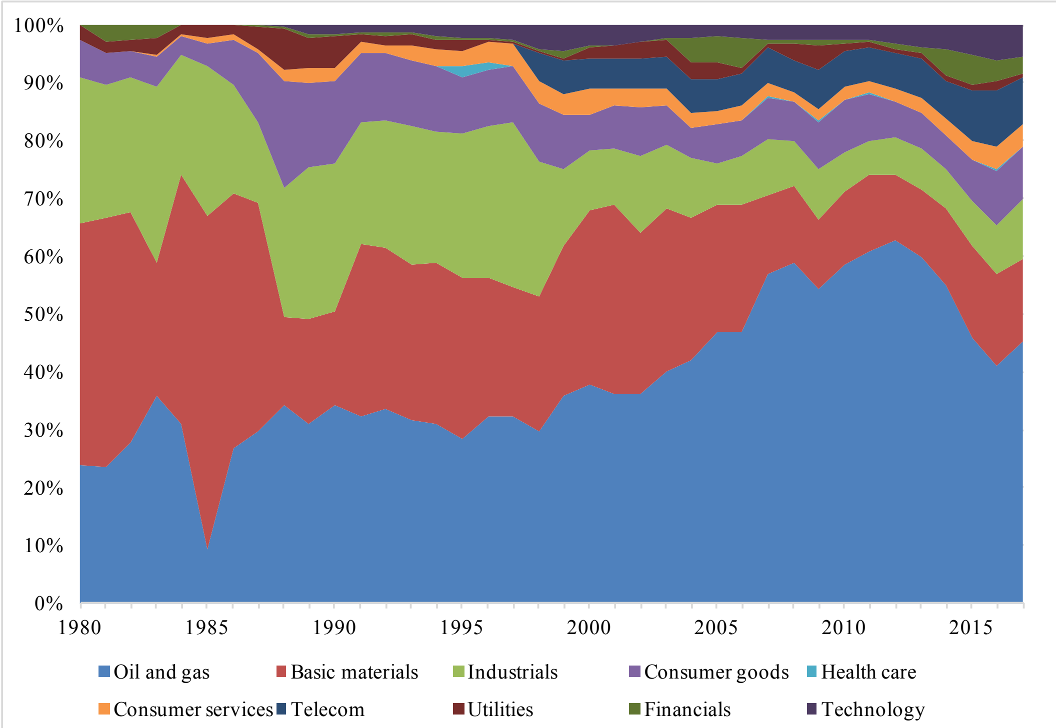
Figure 6: The Evolution of Unweighted Average Productivity versus Weighted Average Productivity (1980-2017)

Next comes basic materials, consisting of firms active in the production of chemicals, forestry and paper, industrial metals and mining. The third largest industry is industrials, which includes construction, electrical equipment, industrial engineering and industrial transportation. These three industries amount to 70-90 percent of total sales over the time period considered. This is indeed a reflection of Norway being a specialized petroleum exporter, in addition to having a substantial production of minerals, hydropower and forestry products. It also mirrors the resource-heavy composition of firms listed at the Oslo stock exchange.

Then comes consumer goods (automobiles, food and beverages, personal and household goods), telecommunications, technology, financials (banks, insurance, real estate, financial services) and consumer services (retail, media, travel and leisure). The smallest industries are health care and utilities. The pattern is indeed a reflection of firms that are listed, and not of the whole population of firms in Norway. Although publicly listed firms tend to be large and thus represent a sizable share of total sales, the shares in terms of number of firms per industry would potentially be different if privately held firms were included, which possibly would increase the share of firms belonging to the consumer goods and consumer services industries.

Markups have so far been estimated at the aggregate level and for the cross-section of

Figure 7: The Evolution of Industry Composition (1980-2017)



Note: the composition is calculated as each sector's share of total sales in a given year. The industry classification follows the FTSE/Dow Jones Industrial Classification Benchmark (ICB) available in the dataset.

firms. Now, sectoral markups can be constructed for each industry j, expressed as:

$$\mathcal{M}_{j,t} = \sum_{i=1}^{N_{j,t}} s_{i,t}^{j} \mathcal{M}_{i,t}$$

where $\sum_{i=1}^{N_{j,t}} s_{i,t}^{j} = 1$. $\mathcal{M}_{j,t}$ is the markup per industry and N_j is the number of firms within each industry. The markups are reported in Table 2, with the markup level in 2017, the total change in markups from 1980 to 2017 and the number of observations for each industry.

The highest markup in 2017 was in telecom with 2.91, which includes the leading market agent Telenor. Oil and gas comes in second with 1.74, somewhat not surprising due to petroleum giants such as Equinor (formerly Statoil) and Aker Solutions, which have seen substantial profitability due to high oil prices and increasing global demand. The lowest markups are found among technology (0.89) and health care (1.04). The low markup observations among technology firms mirror the findings of Haldane et al. (2018), who found the ICT sector to experience both the smallest markups among all sectors and the largest drop over time. However, it contrasts the results of Calligaris et al. (2018), in which the digitally intense sectors saw the highest markup growth. Bearing in mind that the Norwegian sample only includes publicly listed firms, which tend to be inherently large, it may be that it is smaller firms and especially start-ups which occupy

Table 2: Markups per Industry (1980-2017)

Industry	Markup 2017	ΔMarkup 1980*-2017	No. of observations
Oil and gas	1.74	0.36	1,280
Basic materials	1.20	-0.09	394
Industrials	1.35	0.17	1,574
Consumer goods	1.16	-1.37	519
Health care	1.04	-0.66	153
Consumer serv.	1.68	0.53	341
Telecom	2.91	1.31	45
Utilities	1.22	0.06	77
Financials	1.53	0.27	235
Technology	0.89	-0.27	568
Total	1.67	0.32	5,186

* or by earliest year available

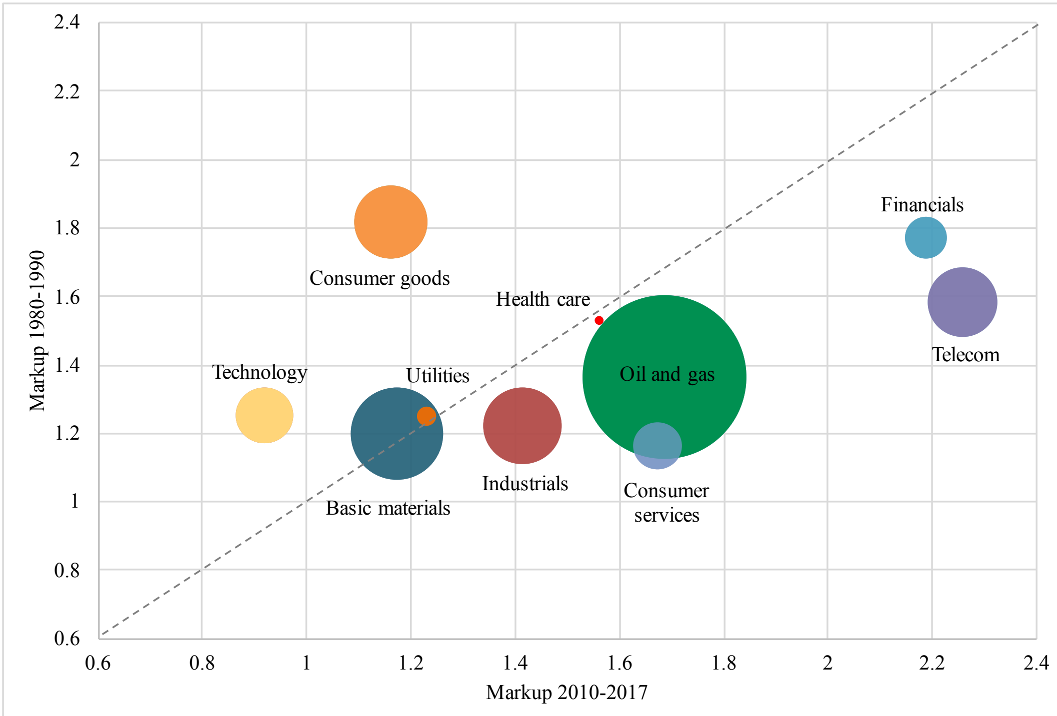
the technological frontier and are able to extract the high markups found in Calligaris et al. (2018).

In terms of markup change, telecom and consumer services have experienced the largest growth over time, of 1.31 and 0.53 points, respectively. Four industries had decreasing markups from 1980 to 2017: consumer goods, health care, technology and basic materials, although the last one of only 0.09 points. It is also worth noting the number of firm-year markup observations varies considerably across industries. The markup for industrials draws on 1,574 observations, while telecom only has 45. This is partly because I only consider publicly listed firms. Also, telecom is an industry with a considerable role for network economies, which limits the number of firms which can profitably exist in a relatively small country. Moreover, another implication of the great variance in number of observations across the industries is that some industries lack observations for the first years in the sample. Health care is only observed from the year 1995, consumer services from 1983, telecom from 1996, financials from 1981 and technology from 1988. The remaining industries include observations for the whole time period considered, from 1980 to 2017.

A graphical representation of the temporal change in markups per industry is presented in the bubble plot in Figure 8. The y-axis represents the average markup level from 1980-1990 and the x-axis the average level from 2010-2017. The 45 degree line illustrates the situation if the markup levels in the two time periods are equal. Industries above the line have seen a markup decrease, while industries below have had growing markups. The size of each bubble is scaled by the industries' total sales in 2017.

The majority of the industries are below the 45-degree line, indicating that their markups have increased over time. Telecom and financials have seen the largest increases from 1980-1990 to 2010-2017. The telecom sector was liberalized during the 1990s, after which companies such as Telenor has been expanding its global outreach considerably. The strong markup growth for telecom and financials matches the results found in Diez et al. (2018). Consumer goods, in contrast, experienced a larger decline in markups, also consistent with Diez et al. (2018). This may be a reflection of increasing competition from international brands and stores, as well as the growing importance of online retail

Figure 8: The Change in Markups per Industry: 1980*-1990 versus 2010-2017



Note: *or year of earliest observation. The industry classification follows the FTSE/Dow Jones Industrial Classification Benchmark (ICB) available in the dataset. The 45-degree line indicates the level at which markups are the same in the two time periods. The size of the bubbles represent each industry's share of sales in 2017.

dominated by giants such as Amazon and Ebay.

The relative importance of each sector for the aggregate measure of markups is also evident by looking at the size of the bubbles. Oil and gas is by far the largest industry, and as its markup has increased during the period, it drives much of the aggregate markup growth in Norway.

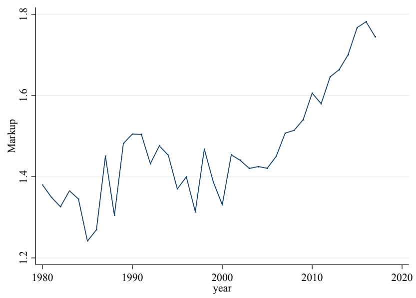
Detailed plots of the evolution of markups for each industry are presented in Figure 9. The plots exhibit great heterogeneity across the industries, both in terms of trend, scale and volatility. Moreover, they reveal the year-to-year development of sectoral markups, which is masked by the absolute change shown for each industry in the bubble plot of figure 8.

A couple of noteworthy insights can be drawn from the detailed plots. For the oil and gas industry, the markup deviated around 1.4 during the 1980s and 1990s, before it took off from 2000, reaching a peak in 2017. The take-off is consistent with the rise in oil prices starting in the early 2000s. Oil prices are highly volatile, probably much more than marginal costs in the oil industry. Therefore, it is likely that the oil price is strongly correlated with markups in oil firms. Moreover, the markup drop evident in the plots for oil and gas and industrials in the last two years of the time period may be responsible for the kink experienced for the 75th percentile in the markup distribution displayed in figure 4, especially due to the relative size of these two sectors.

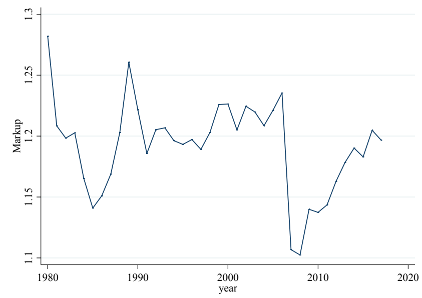
For consumer goods, figure 8 showed that it had seen the largest decline in markups among the industries. As is evident from figure 9d, the entire drop happened in the first decade, after which it remained fairly stable. Similarly, although health care has a lower markup in 2017 compared to the first annual observation, the time period shows a rapid increase in the 2000s, followed by sharp drop after the financial crisis. Moreover, markups in utilities and financials had markup observations at more or less the same level in 2017 as in 1980, but the time period masks substantial volatility.

It is clear that the markups in the ten industries display heterogeneous growth trajectories, although the majority has been rising from 1980 to 2017. This increase is in accordance with international evidence, where markups have been found to increase in most sectors. Different for the Norwegian economy is the large share of the oil and gas industry of the total economy, which clearly accounts for a considerable share of the aggregate markup growth.

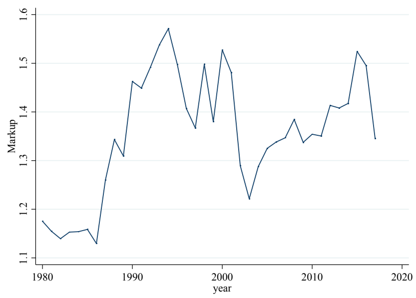
Figure 9: Aggregate Markups per Industry (1980-2017)



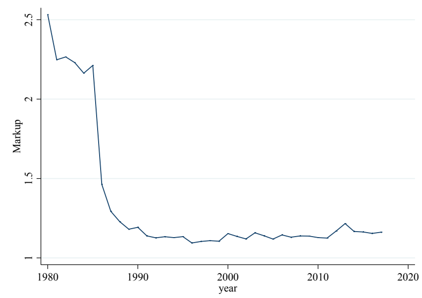
(a) Oil and gas



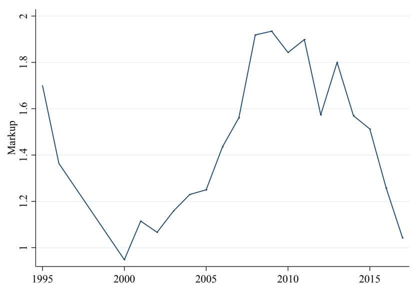
(b) Basic materials



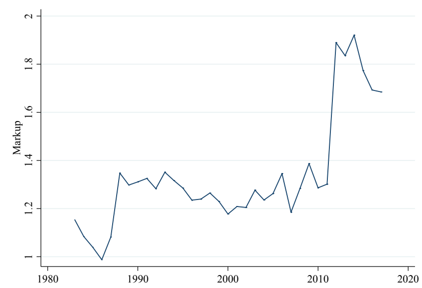
(c) Industrials



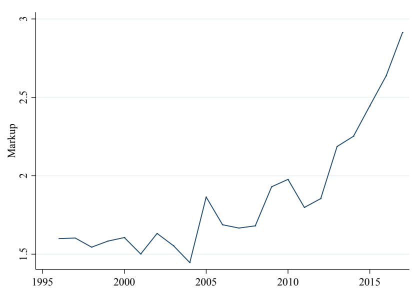
(d) Consumer goods



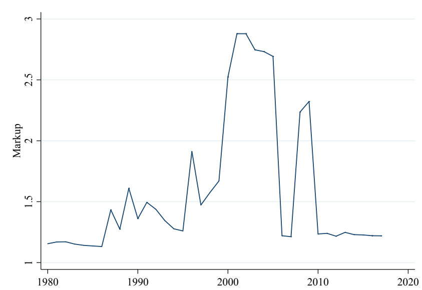
(e) Health care



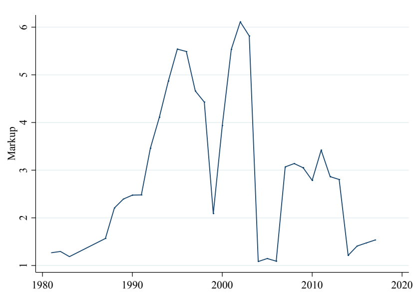
(f) Consumer services



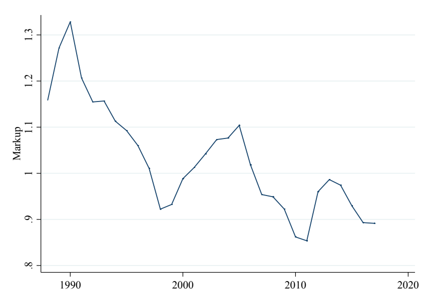
(g) Telecom



(h) Utilities



(i) Financials



(j) Technology

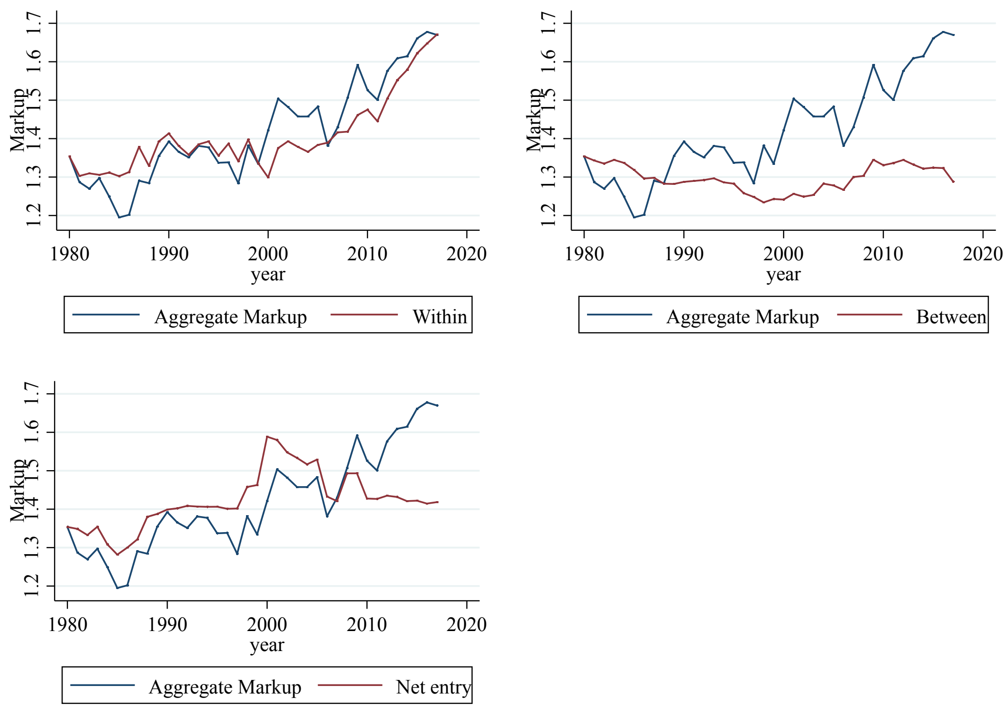
4.4 DECOMPOSITION: SOURCES OF AGGREGATE MARKUP GROWTH

So far, the aggregate growth in markups has been analyzed across firms and sectors. The growth has been found to be driven by the upper percentiles of the distribution, as well as being more prominent in smaller firms. At the sectoral level, several industries have seen rising markups, with the oil and gas sector accounting for a fair share of the aggregate growth due to its size and markup level. Next, I ask which underlying sources are driving the aggregate markup trend over time. For this purpose, the time-series of aggregate markups is decomposed into three effects: a pure markup growth within each firm, a structural shift in relative market shares between firms over time and a net entry of firms in the market.

DECOMPOSITION AT THE FIRM LEVEL: The break-down of the aggregate change into three main components follows the decomposition of plant productivity put forth by Haltiwanger (1997). First, a *within* component represents how much of the aggregate change in markup is explained by a pure growth in markups, within a single firm, had the sales share remained constant. If this effect is found to be positive, it may suggest that firms enjoy less competitive pressure and/or that technological innovation enables firms to charge higher prices for their goods. This would be consistent with the fattening of the upper tail identified in figure 3. Second, a *between* component captures the effect on markups purely from a shift in market shares between firms. It consists of two parts: a *reallocation* term and a *cross* term. The first represents the change in firms' market share, keeping the markup constant. The second is the joint significance of a change in markup and a change in market share. If the *between* component is positive, it implies that high-markup firms have captured a greater share of the market over time, thereby causing higher aggregate markups even if markups at the firm level are unchanged. Third, as the data span 38 years, several firms have entered and exited the market over time, implying that net entry will likely affect the aggregate markup. Therefore, I include a *net entry* component, which consists of the entry of new firms and an exit of firms leaving the market. If the effect is positive, it may suggest that low-markup firms tend to leave the market or that high-markup firms tend to enter. The aggregate markup will increase as a result. Based on Haltiwanger (1997), I derive the following decomposition of aggregate markup growth (see Appendix B for details):

$$\begin{aligned}
\Delta\mathcal{M}_t = & \sum_{i=1}^{N_1} s_{i,t-1}\Delta\mathcal{M}_{i,t} && \text{(within)}\\
& + \sum_{i=1}^{N_1} \Delta s_{i,t}\left(\mathcal{M}_{i,t-1} - \mathcal{M}_{t-1}\right) && \text{(reallocation)}\\
& + \sum_{i=1}^{N_1} \Delta s_{i,t}\Delta\mathcal{M}_{i,t} && \text{(cross)}\\
& + \sum_{i=1}^{N_2} s_{i,t}\left(\mathcal{M}_{i,t} - \mathcal{M}_{t-1}\right) && \text{(entry)}\\
& - \sum_{i=1}^{N_3} s_{i,t-1}\left(\mathcal{M}_{i,t-1} - \mathcal{M}_{t-1}\right) && \text{(exit)}
\end{aligned}$$

Figure 10: Sources of Markup Change: Within, Between and Net Entry



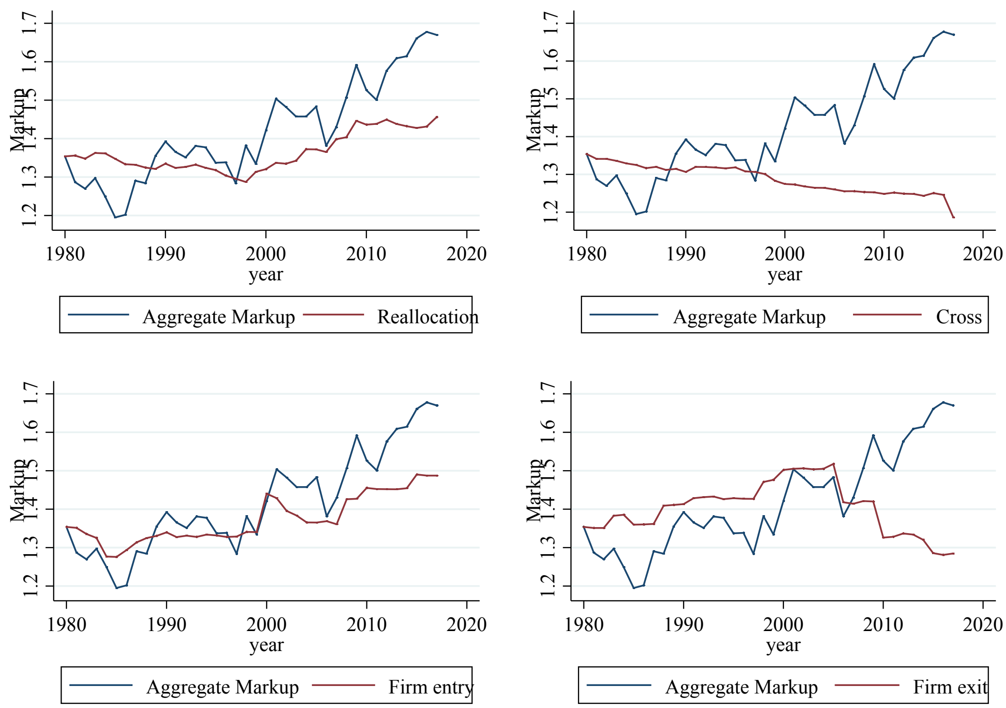
where $\Delta\mathcal{M}_t$ is the change in aggregate markup in period t in levels, $\mathcal{M}_{i,t}$ is the markup of firm i in period t and s_{it} is each firm's share of sales at time t. The *reallocation* and *cross* terms make up the *between* component, while the combination of *entry* and *exit* terms is the *net entry* component.

Note that the firm-level markup in the *reallocation*, *entry* and *exit* terms are constructed as deviations from the average aggregate markup. This demeaning is done to correctly account for each contribution, as shown in the appendix. It implies that a firm which has increased its sales share only contributes positively to the aggregate markup change if its markup is higher than the average aggregate level. If the markup is lower, the contribution is negative. Similarly, an entering firm represents a positive increase only if its markup is higher than the aggregate, while an exiting firm affects the aggregate markup positively if its markup is lower than the average aggregate.

The contributions of the three effects at the firm-level are shown graphically in Figure 10. The three effects are plotted individually against the aggregate markup in blue. Each of the red effects show the counterfactual pattern of markup change had the other effects been kept constant.

From the figure, it is evident that the *within* component closely tracks the aggregate markup, pushing it upwards. Both the aggregate and the *within* component increased by about 0.32 points from 1980 to 2017. They display similar volatility from late 1980s to 2000, after which both took off. The net effect of the *within* component can be interpreted as the counterfactual growth path of the markup had the sales shares remained constant over time. It reveals that the main source of aggregate markup growth is the pure markup

Figure 11: Sources of Markup Change: Detailed Components



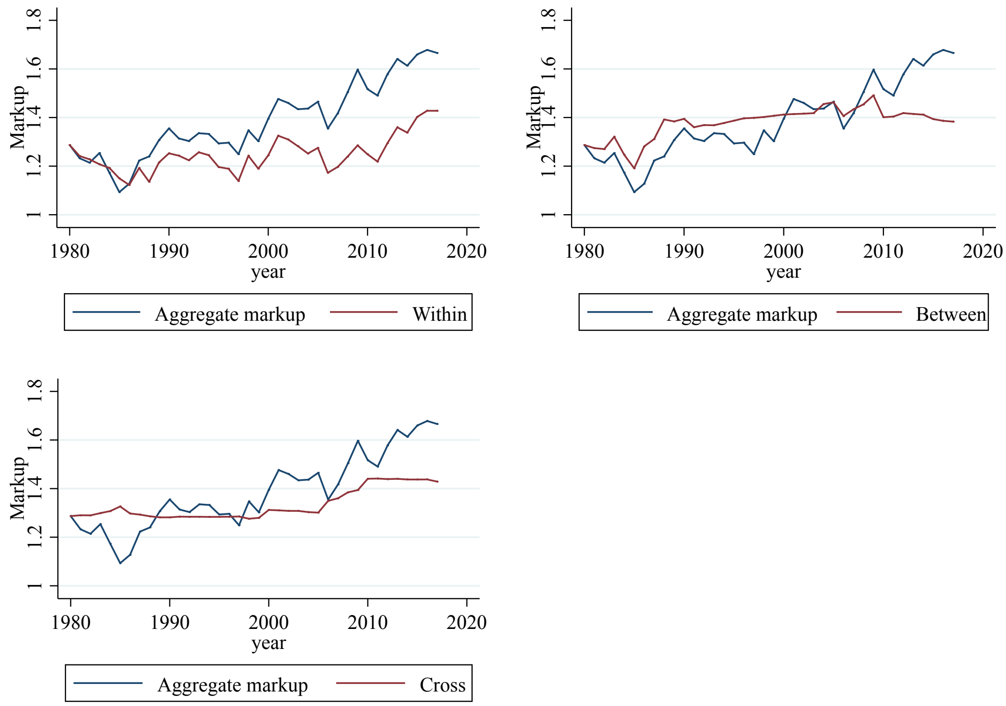
change within each firm. This finding is highly consistent with the fattening of the upper tail of the markup distribution, documented in figure 3.

The *between* component shows a slightly declining trend over time, i.e. the reallocation of market shares between firms was a negative contributing factor to the aggregate markup change. The interpretation is that market shares have been redistributed from high-markup firms to low-markup firms, depressing the aggregate markup, albeit by a small amount. This may intuitively be a surprising finding, but is consistent with the pattern detected in section 4.2 of a negative covariance between markups and firm size. It suggests that pricing power is not determined by relative firm size, but is rather a trait of firms which profit from other advantages such as productivity-enhancing technology or brand loyalty. It is also consistent with the negative covariance between firm size and markups detected in section 4.2.

Lastly, the *net entry* component has increased somewhat over time, suggesting that high-markup firms entered the market while low-markup firms exited, totalling to a positive net effect on the aggregate markup. The component seems to have some explanatory power for the aggregate markup especially in the fluctuations in the late 1990s and 2000s. This effect would also capture mergers and acquisitions (M&A), where the two firms merging will exit the market, while the newly consolidated company will enter the market. If M&As are conducted for efficiency reasons, the entering firm will potentially be more productive, contributing to higher aggregate markups.

Combined, the decomposition shows that while the negative effect from a reallocation of market shares between firms and the positive net effect of firms entering and exiting

Figure 12: Sources of Markup Change: Industry level



mostly offset each other, it is the pure markup growth within firms that seems to have been the driving force behind the aggregate markup change over time. The same patterns were found in Haldane et al. (2018) among UK firms, but differ from De Loecker et al. (2018) who for US firms found that the reallocation of market shares between firms accounted for about two-thirds of the aggregate markup change, while the remaining one-third was explained by a pure markup change within firms.

From the expression of the decomposition above, it was shown that the *reallocation* component is made up of a *between* term and a *cross* term. Similarly, the *net entry* component consists of an *entry* term and an *exit* term. The contributions from these particular terms are shown in Figure 11.

Interestingly, the disaggregation of the *between* component shows that the *reallocation* term exhibits a slightly positive trend, increasing by 0.10 points from 1980 to 2017, driving the aggregate markup upwards. The overall negative effect of the *between* component is evidently rather explained by the negative *cross* term, which decreases over time, depressing the aggregate markup. This implies that a positive change in markups is associated with a fall in market share, which is consistent with the negative covariance between markups and firm size. For the *net entry* component, it seems that the entry of high-markup firms had a positive impact on the aggregate change over the whole time period, while the exit of low-markup firms contributed positively only up to the mid-2000s. After that, the exodus of firms had a negative impact on markups, possibly due to mergers and acquisitions, i.e. that highly productive firms were bought by other firms.

Decomposition at the Sector Level: The decomposition of the aggregate markup change over time can also be performed at the sector level. As the number of industries are constant over time, the decomposition differs from the firm-level formula in that there is no entry or exit of industries. It can be expressed as follows:

$$\Delta\mathcal{M}_t = \underbrace{\sum_{j=1}^{N} s_{j,t-1}\Delta\mathcal{M}_{j,t}}_{\text{within}} + \underbrace{\sum_{j=1}^{N} \Delta s_{j,t}\mathcal{M}_{j,t-1}}_{\text{between}} + \underbrace{\sum_{j=1}^{N} \Delta s_{j,t}\Delta\mathcal{M}_{j,t}}_{\text{cross}}$$

where $\Delta\mathcal{M}_t$ is the change in aggregate markup in period t in levels, $\mathcal{M}_{j,t}$ is the markup of sector j in period t and $s_{j,t}$ is each sector's share of sales at time t. The *within* component represents how the markup has changed within an industry, keeping the sales share of the industry constant. If this effect is positive, it signals that the markup has increased in most sectors, driving the aggregate markup up. The *between* component accounts for the reallocation of sales shares between industries, keeping the markup level constant. If there has been a compositional shift where high-markup industries have captured a larger slice of the economy over time at the expense of low-markup industries, this component will be positive. Finally, the *cross* component represents the joint effect of the pure markup change within sectors and the compositional shift between sectors. The three effects are plotted against the aggregate markup in figure 12.

The decomposition shows that the aggregate markup change at the industry level is explained both by a pure markup change within each sector and a reallocation of shares between sectors. The *within* component can clearly explain the volatility of the aggregate markup, as the movements over time closely track the aggregate markup path. It confirms that markups have risen in most industries. The *between* component seems to have some explanatory power at least up until 2010, as it is steadily growing. The contributions of these two effects are captured by joint effect, the *cross* term, which shows that a pure markup growth within industries is associated with a positive compositional shift between the industries. The decomposition confirms that while markups have increased across sectors, there has also been a compositional shift between sectors, as the industries with the highest markup growth over time (oil and gas, financials and telecom), also have seen their share of the economy expand over time, as seen in figure 7.

The results in this subsection show that a decomposition of the aggregate markup trend into different effects provide valuable insights to the understanding of what determines the growth and variation in aggregate markups over time. At the firm level, the decomposition shows that the evolution of aggregate markups in Norway is highly driven by markups growing within firms, and less by a reallocation of shares from low-markup to high-markup firms. At the industry level, the aggregate change seems to be driven by both the pure markup change within sectors and a compositional shift of shares between sectors.

5 Robustness Analyses

In this section, I do a battery of robustness tests to investigate how sensitive my results are to different specifications, including different production functions, data on profitability among firms, as well as the inclusion of firms which are not publicly listed.

5.1 Alternative Specification: Aggregate Elasticity

The main results of the baseline markup is estimated using sector-specific output elasticities. This is motivated by the assumption that goods are produced using different production technologies across sectors, rather than all sectors sharing the same technology. An alternative specification of the markup estimation is to restrict the output elasticity from varying across industries. The markup can then be expressed as:

$$\mu_{i,t} = \alpha \frac{P_{i,t} Q_{i,t}}{P^V_{i,t} V_{i,t}}.$$

where α is now identical across industries, in contrast to α_j in the baseline calculation. The markups from the aggregate elasticity estimation is plotted together with the baseline markup in Figure 13.

The two markup specifications display an almost identical trend, although the assumption of an aggregate elasticity implies a lower level. This is due to the aggregate elasticity being lower than if the elasticity is allowed to adjust across sectors.

5.2 Alternative Specification: Translog Production Function

The baseline markup is calculated using a Cobb-Douglas production function with time-invariant output elasticities. This is the dominant specification found in the markup literature. Another production function commonly used is the so-called translog function, which permits the output elasticity to vary over time. Such time variation might be realistic, considering that the sample spans almost 40 years.

I specify the following translog production function:

$$q^o_{i,t} = \alpha_{1,j,t} v_{i,t} + \beta_j k_{i,t-1} + \alpha_{2,j,t} v^2_{i,t} + \beta_{2,j,t} k^2_{i,t-1} + \omega_{i,t} + \varepsilon_{i,t} \tag{15}$$

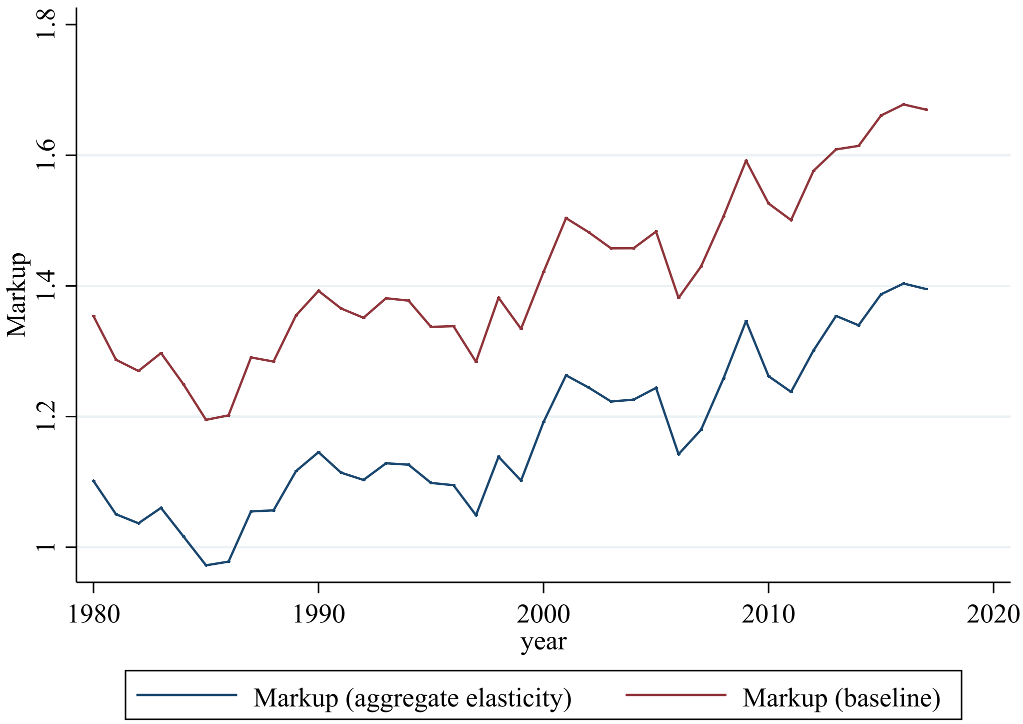
$q^o_{i,t}$ is the observed value of total sales, while $v_{i,t}$ and $k_{i,t-1}$ represent variable inputs and the capital stock, respectively. $\omega_{i,t}$ and $\varepsilon_{i,t}$ is the productivity term and idiosyncratic error term, respectively, as before. In contrast to eq. (5), this specification also includes $v^2_{i,t}$ and $k^2_{i,t-1}$, the squared terms of variable input and capital.

This implies that the output elasticity is time-varying and a function of variable inputs:

$$\theta^v_{i,t} = \alpha_{1,j,t} + 2\alpha_{2,j,t} v_{i,t}$$

Following the literature, the interaction term between variable input and capital is exempted. This is done in order to minimize the adverse effects of possible measurement

Figure 13: The Evolution of Markups (1980-2017): Aggregate Elasticity versus Sector-Specific Elasticity



errors in the capital variable, which would impact the output elasticity $\theta^v_{i,t}$, which is the coefficient of main interest.

For the two-step estimation of the markup, the translog specification implies the following moment conditions:

$$\mathbb{E}\begin{pmatrix} \eta_{i,t}, \Delta v_{i,t-m} \\ \eta_{i,t}, \Delta v^2_{i,t-m} \end{pmatrix} = 0 \qquad \text{for} \qquad 1 \leq m \leq T$$

The aggregate markup from the translog specification is plotted against the baseline markup in Figure 14. The growing trend of the translog specification is remarkably similar to the baseline markup. Both fall slightly in the beginning of the 1980s, before increasing from 1985. After stabilizing in the 1990s, both markups grow rapidly from 2000. The minimal difference between the two production function specifications is consistent with Calligaris et al. (2018) and De Loecker and Eeckhout (2017). Moreover, the similarity between the two production specifications imply that the output elasticity has not changed noteably over time. Thus, assuming a translog production function instead of a Cobb-Douglas does not alter the main result in this thesis: markups in Norway have grown over time.

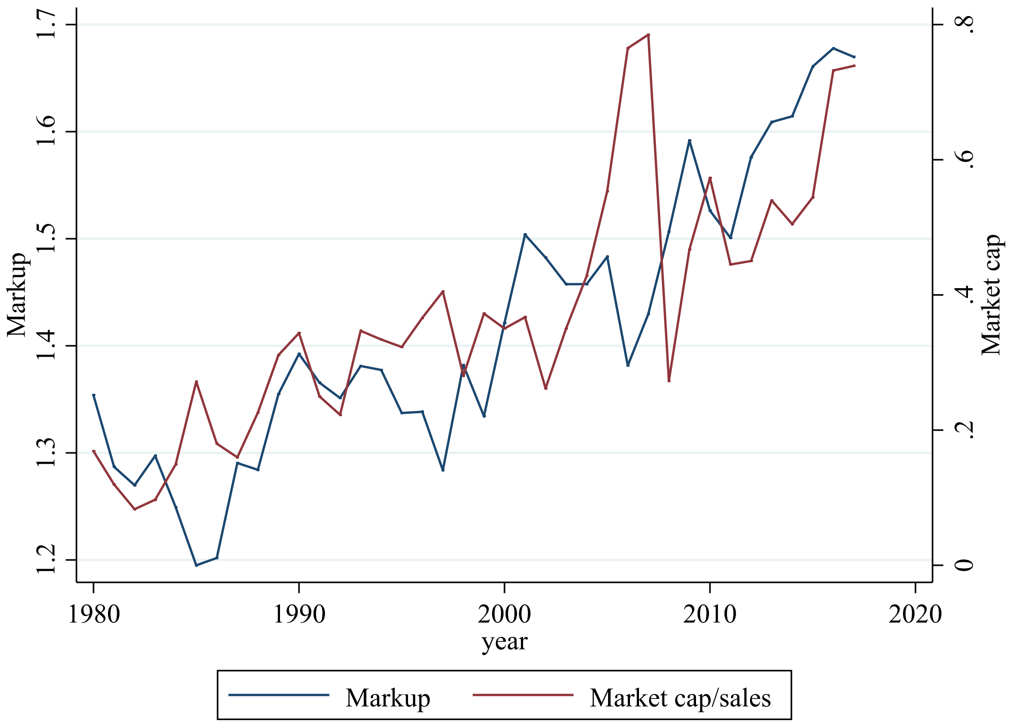
Figure 14: The Evolution of Aggregate Markups (1980-2017): Translog Specification versus Baseline Cobb-Douglas Specification

5.3 Markups and Firms' Profitability

Markups in Norway have been documented to increase by about 24 percent since 1980. Higher firm-level markups indicate that the margin between output price and variable costs of production has increased. Firms charge a higher price for their goods than what is needed to cover the variable costs of producing those goods. However, increasing markups may not represent improved profitability, if fixed costs have grown proportionally. In the case of rising fixed costs, firms would need to charge a high price to recoup these, irrespective of the relatively low variable costs. Fixed costs could increase if the firm invested in expensive technology that would enhance productivity in the long term. New technology would require a one-time investment which would increase fixed costs, while possibly reducing variable costs as the production becomes more efficient. An example is the production of software, which incurs high costs upfront, but which can be produced relatively inexpensive thereafter (De Loecker and Eeckhout, 2017). In the face of rising fixed costs, markups will be high without firms necessarily extracting high profits or exerting welfare-inhibiting market power. Although markups is the most direct measure of market power, the relationship can be further confirmed by examining how markups have developed compared to firms' profitability over time. Higher firm-level profits would signal that rising markups enable firm owners to extract higher profits, and not to recoup higher fixed costs.

The dataset contains a variable on profits, but as it is measured from the cost of goods

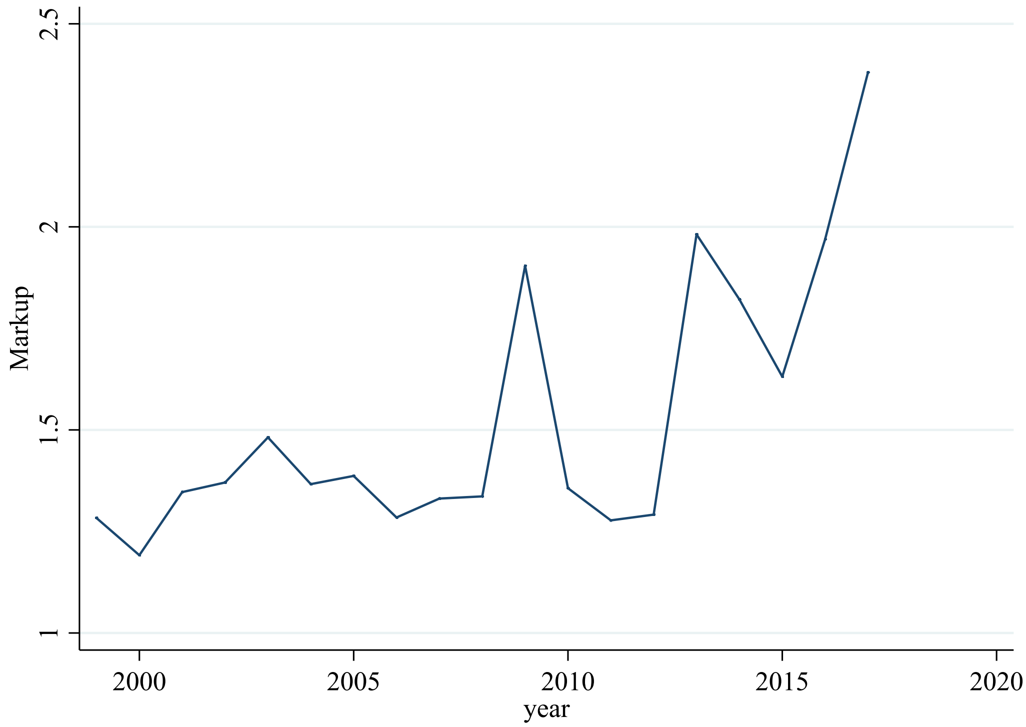
Figure 15: The Evolution of Aggregate Markups and Market Capitalization as a Share of Sales (1980-2017)



sold, it is of little help in a comparison with markups. Rather, following Diez et al. (2018) and De Loecker and Eeckhout (2017), another variable may be used as a measure of firms' profitability: firms' market capitalization as a share of sales. This variable reflects the firm's profitability as it is the opportunity value of the dividends received by the shareholder if he did not sell his shares. It can therefore be thought of as the discounted sum of all future dividend payments. Although this measure may capture expectations about future firm performance, it is considered a valid estimation of profitability in a large sample of firms over time (De Loecker and Eeckhout, 2017). If market capitalization increases together with markups, it serves as a confirmation of rising market power. The firms' markups and market capitalization as a share of sales are reported in Figure 15.

The graph shows that both markups and market capitalization rates have increased over the time period. Market capitalization as a share of sales show a clear rising trend over time, from 0.19 in 1980 to 0.73 in 2017, which is almost a fourfold increase. It fell drastically in 2008, probably due to the financial crisis, but resurged from 2009. The close association between the profitability of firms and markups evident from the graph confirms that the rise in aggregate markups reflects increased firm profitability and rising market power. The close association between profitability and markups is highly consistent with the macro market power literature (Barkai, 2018; Diez et al., 2018; De Loecker and Eeckhout, 2017). The growing trend of markups and firms' profitability over time may also be indicative of the redistributional implications of market power. Profits are paid out to business owners, which tend to occupy the upper percentiles of the

Figure 16: The Evolution of Aggregate Markups (1999-2018): Brønnøysund Dataset



income distribution. Coupled with a declining labor share, growing markups may have a regressive impact on income and wealth inequality (Ennis et al., 2017). Reconciling the evidence of growing profit shares and declining capital and labor shares observed across advanced economies in recent decades may suggest market power to be the causal driver.

5.4 Alternative Dataset

Although publicly traded Norwegian firms have seen a rising markup trend in recent decades, it may not represent the experience of the population of firms in Norway, which includes mostly privately held firms. In order to test the robustness of my results, I rely on a newly available dataset from the Brønnøysund Register Center, which includes 3,795,835 firm-year observations from 1999 to 2018. The markup trend observed for this alternative dataset may be different for two reasons. On the one hand, the majority of firms are relatively small compared to the sample of publicly listed firms, which according to the literature and my own findings may indicate that markup levels may be higher, as the covariance between firm size and markups has been found to be negative. On the other hand, the sample of publicly listed firms may suffer from a selection bias, in that firms listed at the Oslo stock exchange are ”survivors” and may thereby be inherently profitable and productive.

Firm-level markups were estimated for the Brønnøysund population following normal procedure. The aggregate share-weighted markup is plotted from 1999 to 2018 in figure 16.

Over the course of 19 years, the markup has increased by about 88 percent, compared to about 24 percent for the publicly listed firms over 38 years. The finding is consistent with the literature in that the level of markups is higher for privately firms than publicly listed firms (Weche and Wambach, 2018). However, whereas De Loecker and Eeckhout (2017) found the markup growth rate among private firms to be lower than for publicly traded firms, the opposite is found in my comparison of datasets.

It can also be noted that the Brønnøysund aggregate markup shows some clear spikes compared to the benchmark markup. The first spike evident in the graph may be explained by the lead-up and aftermath of the financial crisis. Moreover, the fall in 2013-2014 may be due the drop in oil prices.

Testing whether the markup trend found among publicly listed firms is robust and holds for the whole population of Norwegian firms clearly shows that the growing markup pattern is highly consistent in both samples. This robustness test indicates that corporate market power has been rising among all firms in Norway.

6 MARKUPS, TECHNOLOGY, AND THE NATURAL RATE OF INTEREST

The growing trend in aggregate markups identified in Norway matches similar patterns documented across a wide range of advanced economies since the 1980s. A natural next step would be to identify and explore potential causes for this evolution. As the first systematic documentation of rising markups came from the US, it initially led scholars to look for domestic and US-specific explanations, such as lax antritrust policy and market regulations. However, as similar trends are increasingly being identified internationally, attention is being redirected towards global driving forces.

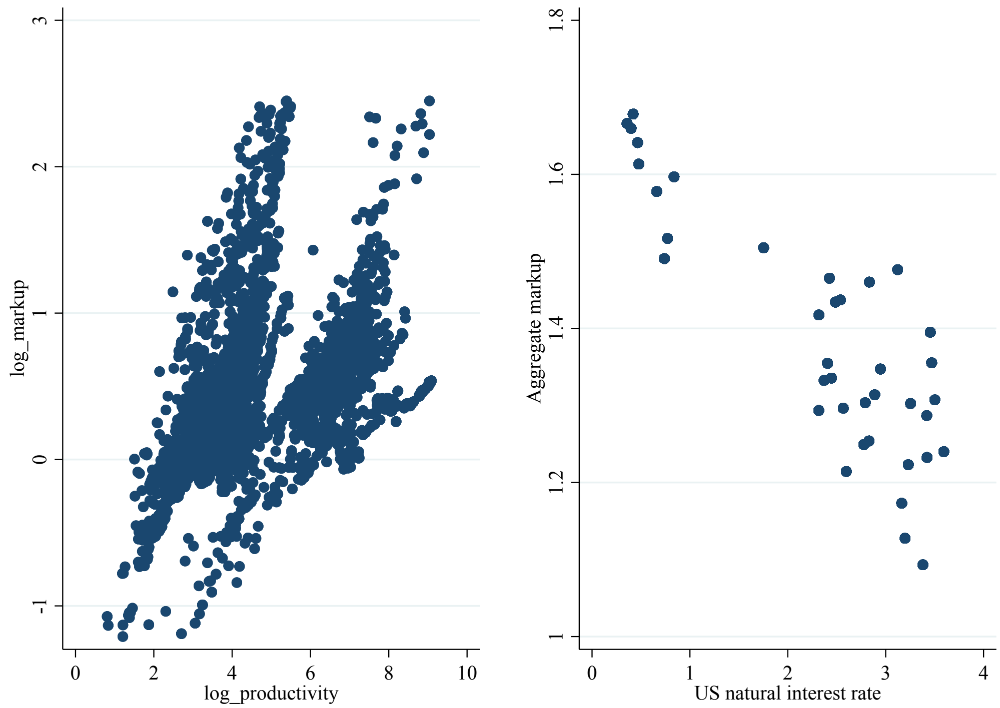
Several potential explanations have been put forth. These include a larger productivity dispersion across firms (Akcigit and Ates, 2019), the role of digitilization (Bessen, 2017; Calligaris et al., 2018), as well as increased scale economies and global network effects (Autor et al., 2017; Bessen, 2017). A specific transmission channel through which the aforementioned drivers may affect the rise of market power is the decline in long-term interest rates, which has been observed across countries since 1980. This is exactly what I am going to investigate in this section.

In a framework proposed by Liu et al. (2019), interest rates are suggested to be the common global factor which has contributed to larger productivity gaps across firms, a reduction in business dynamism and increasing markups. In their model, firms engage in a strategic competition game to gain the market leader position. Faced with lower interest rates, both the market leader and the follower firm respond by increasing investment in productivity-enhancing technology to improve their positions relative to each other. This investment response is the traditional effect of lower interest rates. However, as interest rates approach zero, the market leader has a stronger incentive to invest compared to the follower. The mechanism is as follows: forward-looking firms are motivated to invest due to the future flow of profits. Lower interest rates imply lower discounted future cash flows, which raise the market value of all firms, but more so for the market leader. The leader is closer to a high-payoff state, where investments will eventually pay off as profits. The investment incentive is thus stronger for the leader, as is his marginal increase in incentive following a further fall in interest rates. Due to the unequal investment responses, the productivity gap between the leader and the follower widens progressively, and the follower is discouraged from investing due to the low probability of catching up with the leader. The expected marginal value of trying to overtake the leader is thus low relative to the cost of investment. Thus, declining interest rates lead to asymmetric investment responses among firms, widening the productivity gap and enabling the highly productive market leader firms to raise their markups.

The decline in long-term interest rates may therefore act as a single transmission channel which unifies several of the proposed mechanisms driving the rise in market power. Firms with a productivity advantage are able to exploit the falling interest rates to invest in R&D, raise the productivity gap further and consolidate their position as market leaders.

To test whether the observed decline in global interest rates can explain the evolution of markups, I will now explore the relationship between falling interest rates, productivity and markups among Norwegian firms. Formally, I test the following hypothesis:

Figure 17: Scatter Plots of Markups, Productivity and Interest Rates



H_1: *The relationship between the natural rate of interest and markups is more negative in firms with high productivity than in firms with low productivity.*

A stronger negative correlation between interest rates and markups in highly productive firms compared to low-productivity firms is an implication of the discussion above. A decline in global interest rates spurs unequal investment responses, widening the productivity gap between firms, and allows highly productive firms—so-called market leaders—to benefit from rising markups.

Figure 17 provides some motivational evidence. The subplot on the left-hand side plots markups against productivity at the firm level. I use firm-level productivity estimates, which were calculated together with markups. The scatter plot shows a clear positive association between markups and productivity at the micro level. The subplot on the right-hand side in figure 17 plots aggregate markups against the US natural interest rate. It documents that low interest rates are associated with high markups at the macro level. Taken together, the plots in figure 17 might indicate that the secular decline of interest rates triggers productivity growth, at least in some firms with certain characteristics, which in turn allows them to charge higher markups. However, these scatter plots only show reduced form relationships, and correlations at the macro level are not necessarily equal to correlations at the micro level. Testing the hypothesis stated above necessitates a more formal statistical analysis. This is what I will do next.

6.1 ECONOMETRIC MODEL

To formally test the hypothesis of whether the natural rate of interest is more negatively correlated with markups in highly productive firms, I estimate different specifications of the following econometric model:

$$\begin{aligned}\mu_{i,j,t} = {} & \beta_0\mu_{i,j,t-1} + \beta_1\text{age}_{i,j,t} + \beta_2 s_{i,j,t} + \beta_3\text{export}_{i,j,t} + \beta_4\text{exit}_{i,j,t} + \beta_5\omega_{i,j,t} \\ & + \beta_6\text{age}^2_{i,j,t} + \beta_7 s^2_{i,j,t} + \beta_8\text{export}^2_{i,j,t} + \beta_9\omega^2_{i,j,t} \\ & + \beta_{10}\omega_{i,j,t} \times r^*_t \\ & + \alpha_i + \alpha_{j,t} + u_{i,j,t}\end{aligned}$$

where the firm-level markup, $\mu_{i,j,t}$, is the dependent variable. As seen from the econometric expression, the natural interest rate is interacted with firm-level productivity $\omega_{i,j,t}$, which serves as a proxy for firms with inherent market leader advantages. Thus, the main parameter of interest is β_{10}. For the natural rate of interest, r^*_t, the US natural interest rate is used, as estimated by Holston, Laubach, and Williams (2017). This is motivated by the extensive literature on the significance of US interest rates on small, open economies (Gopinath, 2016; Justiniano and Preston, 2010; Adolfson et al., 2005; Christiano et al., 2011). Other measures of international interest rates will subsequently be included as robustness tests. There are several reasons why Norwegian interest rates are not used. First, as a small and open economy, Norway is highly influenced by the transmission of global aggregate shocks (Aastveit et al., 2016; Bergholt, 2015). Second, even if Norwegian rates were to be used, they would most certainly be highly correlated with global interest rates. Finally, as the analysis considers long-term trends rather than short-term cycles, natural interest rates will be used instead of real interest rates, for which there are no satisfactory measures in Norway.

A set of control variables is included to account for firm-specific characteristics and for macroeconomic and sectoral developments. First, I will discuss the control variables at the firm level. The age of firms, as measured by the number of years of existence, is included due to the observed decline in the share of young firms across several countries, as documented by Decker, Haltiwanger, Jarmin, and Miranda (2016) and Furman and Orszag (2018). New evidence from Akcigit and Ates (2019) links the reduction in the number of young firms to the secular increase in market power. Second, I control for the size of firms. This is motivated by the documentation of rising market concentration in several countries, where large firms have captured greater market shares over time (Autor et al., 2017; Grullon et al., 2018; Gutierrez and Philippon, 2016). Higher concentration levels have been interpreted as a symptom of rising markups (Eggertsson et al., 2018). The third firm characteristic which is controlled for is the extent to which firms operate in international markets. This is captured by exports, as measured by a firm's sales accruing from exporting as a share of its total sales. The effect of export intensity has been studied by Haldane et al. (2018), Crespi, Criscuolo, and Haskel (2008) and De Loecker and Warzynski (2012), who find that firms which are relatively more export-oriented experience higher markup growth over time. The selection bias inherent in firms that choose to export could potentially influence the estimates (Melitz, 2003). Fourth, an exit dummy is included to control for the effect on markups from firms leaving the market. The association between markups and firms' exit status may be ambigious (Pavcnik, 2002). On the one hand, firms may choose to leave the market if they fail to obtain profits, i.e.

they have low markups. This would imply a negative correlation between markups and exiting firms. On the other hand, firms about to leave the market may raise markups in an attempt to recoup high fixed costs. In that case, there would be a positive association between markups and exit. Finally, I include lagged markups as a firm characteristic. This is a simple and robust way to control for omitted variables which may influence current markup levels through their effect on historical markups. Note that by including lagged markups I allow for dynamic markup effects from changes in natural interest rates. For these firm-level variables, there could potentially exist non-linear relationships between the characteristics and markups. To control for these, I not only include first-order terms, but also second-order polynomials of the variables.

Next, in addition to the firm-specific characteristics mentioned so far, there is a broad range of sectoral and aggregate factors that can potentially be relevant for the evolution of markups and may thus end up in the error term if not included in the model. This may give rise to an omitted variable bias in the estimates. To control for this in a general and robust way, I do the following: first, firm-specific omitted explanatory variables which do not vary over time, such as firms' geographical location and which markets they operate in, are controlled for by the inclusion of firm-specific fixed effects. Second, I include industry-year fixed effects to control for shocks and trends at the sectoral and aggregate level. Examples include macroeconomic cycles, structural trends across sectors and changes in fiscal, monetary and antitrust policy. Note that both time-invariant firm effects and industry-year effects are controlled for in a non-parametric and flexible way. Moreover, the specification implicitly accounts for direct effects of the natural interest rate on markups, both at the aggregate and sectoral level. Finally, all regression models are estimated with Huber-White robust standard errors in order to allow for heteroskedasticity and serial correlation in the residuals. Errors are clustered at the firm level.

In running the regression model, it is important to emphasize that I am estimating correlations conditioned upon several controls. Causal effects should therefore be interpreted with care. For example, there might very well be a simultaneity problem due to a two-way causality between markups and other firm characteristics such as size. Although the estimation will not provide evidence of any clear causal relationships, the results may indeed be a reflection of them. The results from the econometric model is reported in table 3.

In model (1), I estimate a simple regression model which, although in a naive way, attempts to capture the relationship between firm-level markups on the left-hand side and productivity and natural interest rates on the right-hand side. Several patterns emerge from the model. First, the significance and size of the coefficient for lagged markups indicate that there is a relative persistent dynamic in the evolution of markups. Second, productivity is positively correlated with markups, while the natural interest rate is negatively correlated with markups. These estimates are significant at the 1 percent level. The negative coefficient of the natural interest rate (r^*) implies that a falling r^* correlates with increasing markups. However, the specification is sensitive to omitted variables, perhaps particularly at the aggregate level.

Therefore, in model (2), I include firm- and industry-year fixed effects. I do not include r^* in itself, but rather in interaction with productivity. Moreover, a non-linear second-order term for productivity is added to explore whether the effect occurs at a increasing or decreasing rate. This will test the hypothesis of the correlation between r^*

Table 3: Regressions of Natural Interest Rates and Productivity on Markups

	Dependent variable: $\mu_{i,t}$												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
$\mu_{i,t-1}$	0.854***	0.283***	0.272***	0.271***	0.272***	0.271***	0.518***	0.517***	0.747***	0.606***	0.271***	0.253***	0.272***
	(0.021)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.034)	(0.034)	(0.027)	(0.035)	(0.323)	(0.031)	(0.033)
age			-0.003	-0.003	-0.003	-0.003	-0.001	-0.001	0.004	-0.044	-0.003	-0.001	-0.002
			(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.002)	(0.053)	(0.003)	(0.003)	(0.003)
$s_{i,t}$			-5.463***	-5.451***	-5.446***	-5.430***	-1.406*	-1.445*	-1.259*	-0.698	-5.324***	-4.906***	-5.648***
			(1.453)	(1.453)	(1.449)	(1.449)	(0.798)	(0.809)	(0.702)	(0.900)	(1.471)	(1.347)	(1.488)
$export$			6.677***	6.587***	6.666***	6.510***	1.387	1.386	10.838	10.138	6.593***	6.776***	6.419***
			(1.141)	(1.217)	(1.151)	(1.191)	(1.887)	(1.888)	(7.252)	(44.087)	(1.151)	(1.135)	(1.169)
$exit$			0.020*	0.020*	0.020*	0.020*	-0.001	-0.001	0.006	-0.001	0.020*	0.030***	0.020*
			(0.012)	(0.012)	(0.012)	(0.012)	(0.016)	(0.016)	(0.013)	(0.019)	(0.012)	(0.011)	(0.012)
$\omega_{i,t}$	0.025***	0.653***	0.667***	0.648***	0.691***	0.719***	0.247***	0.234***	0.796***	-0.103	0.663***	0.687***	0.632***
	(0.004)	(0.088)	(0.088)	(0.085)	(0.090)	(0.099)	(0.059)	(0.055)	(0.076)	(0.068)	(0.088)	(0.084)	(0.093)
$age \times age$			0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$s_{i,t} \times s_{i,t}$			14.791***	14.639***	14.722***	14.769***	4.461**	4.535**	3.952*	3.432	14.406***	13.078***	15.056***
			(4.062)	(4.065)	(4.032)	(4.075)	(2.217)	(2.230)	(2.034)	(3.101)	(4.052)	(3.623)	(4.059)
$export \times export$			-13.949***	-13.521***	-14.009***	-13.277***	5.395	5.409	-182.427**	-314.759	-13.695***	-14.257***	-13.130***
			(4.009)	(4.075)	(4.026)	(4.043)	(5.814)	(5.817)	(87.059)	(663.062)	(4.026)	(3.774)	(4.049)
$\omega_{i,t} \times \omega_{i,t}$		-0.014	-0.013	-0.013	-0.013		-0.014*	-0.014	-0.014	0.139**	-0.014	-0.016**	-0.010
		(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.055)	(0.054)	(0.008)	(0.008)	(0.009)	
r^*	-0.009***												
	(0.003)												
$r^* \times \omega_{i,t}$		-0.018**	-0.023***	-0.020**	-0.031***	-0.048**	-0.045***	-0.054***	-0.099**	0.029			
		(0.009)	(0.009)	(0.009)	(0.012)	(0.021)	(0.017)	(0.021)	(0.043)	(0.028)			
$p90 = 0$											-0.020**	-0.037***	-0.016
											(0.010)	(0.008)	(0.010)
$p90 = 1$											-0.022**	-0.019**	-0.020**
											(0.009)	(0.008)	(0.009)
Firm FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry x Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$R^2(adjusted)$	0.804	0.478	0.549	0.528	0.530	0.545	0.691	0.694	0.916	0.214	0.541	0.635	0.536
Obs	4,453	4,453	4,453	4,453	4,453	4,453	4,453	4,453	4,453	4,453	4,453	4,453	4,453

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Column (1) reports the simple first regression model of productivity and the US natural interest rate on markups. Column (2) reports the simple regression model, but which interacts productivity with the interest rate. Column (3) reports the benchmark estimation results. Column (4) reports the robustness test using the natural interest rate of the Euro area as a proxy for global interest rates. Column (5) reports the robustness test using US trend growth as a proxy for interest rates. Column (6) reports the robustness test using European trend growth as a proxy. Column (7) reports the robustness test where the US natural rate is interacted with a dummy for the 90th percentile of the productivity distribution. Column (8) reports the same 90th percentile dummy interacted with the Euro area natural interest rate. Column (9) reports the robustness test using productivity shock instead of productivity level. Column (10) reports the robustness test using the lagged productivity shock. Column (11) reports the benchmark model, but for large firms (90th percentile of the firm size distribution). Column (12) reports the benchmark model, but for the 90th percentile of the markup distribution. Column (13) reports the benchmark model, but for the 90th percentile of the productivity distribution.

and markups being stronger for highly productive firms.

First, it is evident that the positive correlation between productivity and markups holds. It is still significant at the 1 percent level. The second-order term is decreasing, but this non-linear effect is however only significant at the 10 percent level. More interestingly, I find a negative coefficient for the interaction term between productivity and r^*. I thus confirm the hypothesis stating that as r^* declines, markups increase more in firms which are inherently more productive than in firms of low productivity. Note that by non-parametrically controlling for fixed effects, the estimated coefficient of lagged markups falls considerably. This may be explained by the fixed effects capturing all the dynamics in markups that is due to sectoral and macroeconomic developments.

Model (3) is the benchmark model. Here, I also control for the firm-specific characteristics. The estimation shows that the interaction term between productivity and r^* is still negative and significant at the 1 percent level. Moreover, a few insights can be extracted from the coefficients of the firm characteristics. First, there is no significant correlation between firm age and markups. Second, the relation between firm size and markups is highly significant: the coefficient is negative, but at an increasing rate. This implies a U-shape, which indicates that if the firm is large enough, the relationship between firm size and markups will be positive. Given the estimates in model (3), the relationship between firm size and markups is positive if:

$$\frac{\partial \mu_{i,t}}{\partial s_{i,t}} = -5.46 + 2 * 14.79 * s_{i,t} > 0,$$

that is, if $s_{i,t} > 0.18$. However, almost no observations come with firm size of that level. This finding is also consistent with the negative covariance between markups and firm size documented in section 4.2. Third, considering firms' export intensity, the first-order term is positive, while the second-order term is negative. Both are highly significant. But again, there is almost no firms with high enough export intensity so that the second-order effect dominates. The relationship between export intensity and markups is therefore positive, which is consistent with the literature. Fourth, I find that firms which exit the market have somewhat higher markups than others firms. This is consistent with the interpretation that firms about to exit the market increases markups to recoup losses. However, this relationship is only significant at the 10 percent level.

Next, I conduct a battery of robustness tests to investigate how sensitive the interest rate-productivity interaction is to alternative specifications. Model (4) uses the European natural interest rate instead of the US rate. Although US interest rates are considered to be of particular importance for the Norwegian economy, Norway's share of trade with Europe is greater than with the US. The model will thus test whether the results hold for the European natural interest rate, which is obtained from Holston et al. (2017). Indeed, it is shown that the interaction term between the European r^* and productivity is highly significant, with a coefficient similar to the US r^*. The next robustness test is specified in model (5). Here, account is taken of the natural interest rate being non-observable, but rather estimated. As r^* is considered to be highly correlated with trends in GDP growth, I will use US trend growth as a proxy. This series was also obtained from Holston et al. (2017). As is seen from the estimates, the coefficient between trend growth and productivity is still negative and highly significant. In model (6), I substitute the US trend growth with European trend growth and find that the results hold. Next, I want to zoom in on the firms in the upper tail of the productivity distribution. This is done in model (7), where I include a dummy taking the value 1 if the firm is found among the 90th percentile of the productivity distribution, and 0 otherwise. The coefficients show that for the 90th producitvity percentile, the correlation between the US r^* and markups is higher than among firms in the lower productivity percentiles. In model (8), I show that this finding also holds when the European r^* is used.

So far, productivity has been used as a continuous variable, i.e. as variation in productivity levels across firms. However, productivity also has a shock, which can be thought of as a shock to innovation. Therefore, in specification (9), I estimate the model conditional on that shock to explore whether the negative relationship between productivity and r^* on markups still hold. To be sure, it is far from obvious that it should. Assuming productivity to be exogenous, i.e. independent from r^*, the relationship should not be significant. However, as the estimates show, I find a strong negative correlation. Indeed, the coefficient is more than doubling. This may indicate that productivity is an endogenous variable which depends on interest rates. This result is consistent with endogenous growth theory, in that as interest rates decline, firms are induced to invest in R&D, raising productivity levels. As a sanity check, in model (10) I test whether the interaction with lagged productivity shocks is significant. This term should not be able to explain markups, as the lagged shock occurred one period ahead. Indeed, the estimate is not significant, and even changes sign. In model (11), I re-estimate the benchmark model, but now with a dummy for firms occupying the 90th percentile of the size distribution. The correlations for firms at either side of the tail is negative and significant, displaying a slightly stronger effect for firms in the 90th percentile. The next percentile I want to zoom in on is the 90th percentile of the markup distribution, estimated in model (12). The correlations are still negative, although somewhat stronger for firms not in the 90th markup percentile. Last, the 90th percentile of the productivity distribution is revisited in model (13), but the specification departs from model (7) in that the dummy is not only interacted with r^*, but also with productivity itself. In so doing, the effect of being in the productivity tail can be quantified. The results show that while the correlation is not significant when the dummy equals 0, the negative correlation holds for the 90th percentile, at the 5 percent level.

To conclude this section, I find a significant negative correlation between markups and the interaction effect between the natural interest rate and productivity, which holds across all model specifications. This is consistent with the hypothesis that declining interest rates lead to heterogenous investment responses at the firm level: highly productive market leaders face a stronger incentive to invest in new technologies, thereby increasing their productivity lead and markups. The results thus fit the story proposed by Liu et al. (2019).

7 Concluding Remarks

This thesis documents the evolution of market power in Norway. Using micro data on all publicly listed Norwegian firms, markups are estimated through a production function approach, yielding a novel dataset of firm-level markups from 1980 to 2017. The results suggest that corporate market power has been rising considerably, as the aggregate markup has increased by about 24 percent since 1980. This secular trend in aggregate markups reveals significant cross-sectional heterogeneity, however. The markup distribution has become increasingly skewed with a fat upper tail of firms being able to extract progressively higher markups, while the median firm has remained at a mostly constant level. These high-markup firms are also documented to be of smaller size, as the covariance between market share and markups is found to be negative.

Several decompositions are performed in order to shed light on the underlying sources of aggregate markup growth. First, the change in markups over time seems to be driven mostly by a pure markup growth within firms, rather than a reallocation of market shares from firms with low markup to those with high markup. Second, at the sectoral level, markups have increased across most industries, with financials and telecommunications experiencing the greatest rise. Due to its sheer size in the Norwegian economy, the oil and gas sector seems to be a considerable contributor to the aggregate markup growth. The rise in aggregate markups is also found to track an increasing trend in the market value of firms as a share of sales, which indicates that the evolution of markups implies higher profitability and a consolidation of market power.

Potential explanations of the secular rise in markups is then explored. As a specific transmission channel, global interest rates are analyzed, motivated by the model put forth by Liu et al. (2019) in which falling interest rates are argued to have driven the increase in global market power. I propose a hypothesis on how the decline in global interest rates is more strongly associated with an increase in markups among highly productive firms relative to low-productivity firms. This relationship is formally tested through an econometric model, where I find a significant negative correlation between natural interest rates and markups in highly productive firms, which confirms my hypothesis. The result is robust to all model specifications. Although my empirical documentation does not necessarily imply a clear causal relationship between markups, productivity and natural interest rates, the results are at least consistent with such causal links, as argued by Liu et al. (2019).

This thesis represents a first step towards understanding markups in Norway. A fruitful avenue for future research will be to study their macroeconomic implications. Recent literature (International Monetary Fund, 2019; Diez et al., 2018; De Loecker and Eeckhout, 2017) has found rising markups to be associated with lower investment rates and productivity, and hence lower output. Moreover, increasing market power has been documented to have negative effects on the labor market, such as a declining labor share, lower labor force participation and hampered labor flows. Relatedly, the implications of rising markups on welfare and inequality is an understudied topic worthy of more attention. Further research on how corporate market power affects these macroeconomic variables in Norway will be valuable in the quest for understanding whether the various secular trends observed in the global economy in recent decades may have had a common cause.

Another extension left for future research is to exploit the broad coverage of the Brønnøysund dataset, which includes the whole population of Norwegian firms. In this thesis, the dataset is used as a robustness test to detect whether the aggregate markups found among publicly listed firms hold for the whole population of firms. Further decompositions based on the dataset can be valuable: to analyze how markups have evolved at the cross-sectional level and across industries, as well as to detect markup patterns in relation to firm size and productivity. Although markups are found to increase at the aggregate level for both datasets, the inclusion of small and privately held firms in the Brønnøysund sample may reveal different pictures at more disaggregate levels.

Apart from leaving the macroeconomic implications relatively untouched, the thesis may suffer from two main limitations. First, a careful treatment of firms' fixed costs could have provided insight into their potential role in increasing markups. As firms' fixed costs have been documented to increase on average across many countries, I could have conducted several robustness tests where I could include them in the production function either as part of variable costs as in Traina (2018) or as another factor of production, as in De Loecker and Eeckhout (2017). Such a robustness test could further confirm that increasing markups reflect market power and not only rising fixed costs. Second, the thesis could possibly benefit from a more in-depth analysis of the dynamics at the industry level. Instead of just treating the industry level as one of several decompositions, I could have analyzed each industry separately by providing insights into sector-specific developments over time, important M&As and case-studies of particular firms dominating each sector.

The increasing market power detected in Norway and across a broad range of advanced economies in recent decades is important for several reasons. Greater markups imply higher prices and lower output, as well as a less efficient allocation of production between firms. Furthermore, it implies that income is redistributed from consumers and wage earners to business owners, further exacerbating the inequality of income and wealth evident across many countries. Attention should therefore be directed towards possible policy measures that can curb the exercise of market power and level the competitive market ground. Antitrust regulations overseen by the competition authorities should better correspond to the global nature of driving forces behind the evolution of markups. As global drivers have been documented to have a significant impact on markups, a greater degree of policy coordination across countries might be warranted. Moreover, central banks should take note of the changing nature of market power, as higher markups may have implications for the conduct of monetary policy.

REFERENCES

Aastveit, K., H. C. Bjørnland, and L. A. Thorsrud (2016, January). The World is Not Enough! Small Open Economies and Regional Dependence. *The Scandinavian Journal of Economics 118*(1), 168–195.

Adolfson, M., S. Lasen, J. Lind, and M. Villani (2005). Bayesian estimation of an open economy DSGE model with incomplete pass-through. Working paper series 179, Sveriges Riksbank.

Aghion, P., N. Bloom, R. Blundell, R. Griffith, and P. Howitt (2005). Competition and Innovation: an Inverted-U Relationship. *The Quarterly Journal of Economics 120*(2), 701–728.

Akcigit, U. and S. T. Ates (2019, April). What Happened to U.S. Business Dynamism? CEPR Discussion Papers 13669, C.E.P.R. Discussion Papers.

Alvaredo, F., A. B. Atkinson, T. Piketty, and E. Saez (2013, Summer). The Top 1 Percent in International and Historical Perspective. *Journal of Economic Perspectives 27*(3), 3–20.

Arellano, M. and S. Bond (1991). Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. *Review of Economic Studies 58*(2), 277–297.

Autor, D., D. Dorn, L. Katz, C. Patterson, and J. Van Reenen (2017, May). The Fall of the Labor Share and the Rise of Superstar Firms. CEPR Discussion Papers 12041, C.E.P.R. Discussion Papers.

Baker, J. and S. Salop (2015, January). Antitrust, Competition Policy, and Inequality. *SSRN Electronic Journal 104*.

Baltagi, B. H. (2005). *Econometric Analysis of Panel Data*. Hoboken, New Jersey: John Wiley & Sons, Ltd.

Barkai, S. (2018). Declining Labor and Capital Shares. Technical report, London Business School.

Bekes, G., C. Hornok, and B. Murakozy (2016). Globalization and the markups of European firms. Kiel Working Papers 2044, Kiel Institute for the World Economy (IfW).

Bergholt, D. (2015). Foreign Shocks. Working Paper 2015/15, Norges Bank.

Bessen, J. (2017). Information technology and industry concentration. *Boston Univ. School of Law, Law and Economics Research Paper 17-41*.

Blanchard, O. (2009, May). The State of Macro. *Annual Review of Economics 1*(1), 209–228.

Bloom, N. and J. Van Reenen (2010, Winter). Why Do Management Practices Differ across Firms and Countries? *Journal of Economic Perspectives 24*(1), 203–224.

Blundell, R. and S. Bond (2000). GMM Estimation with persistent panel data: an application to production functions. *Econometric Reviews 19*(3), 321–340.

Brandt, L., J. V. Biesebroeck, L. Wang, and Y. Zhang (2017, September). WTO Accession and Performance of Chinese Manufacturing Firms. *American Economic Review 107*(9), 2784–2820.

Calligaris, S., C. Criscuolo, and L. Marcolin (2018). Mark-ups in the digital era. OECD Science, Technology and Industry Working Papers 2018/10, OECD Publishing.

Christiano, L. J., M. Trabandt, and K. Walentin (2011). Introducing financial frictions and unemployment into a small open economy model. *Journal of Economic Dynamics and Control 35*(12), 1999–2041.

Council of Economic Advisers (2016, April). Benefits of Competition and Indicators of Market Power. Technical report. https://obamawhitehouse.archives.gov/sites/default/files/page/files/20160414 (accessed February 28, 2019).

Crespi, G., C. Criscuolo, and J. Haskel (2008, May). Productivity, exporting, and the learning-by-exporting hypothesis: direct evidence from UK firms. *Canadian Journal of Economics 41*(2), 619–638.

Dao, M. C., M. Das, Z. Koczan, and W. Lian (2017). Why Is Labor Receiving a Smaller Share of Global Income? Theory and Empirical Evidence. Working Paper 2017/169, International Monetary Fund.

De Loecker, J. and J. Eeckhout (2017, August). The Rise of Market Power and the Macroeconomic Implications. NBER Working Papers 23687, National Bureau of Economic Research, Inc.

De Loecker, J. and J. Eeckhout (2018, June). Global Market Power. NBER Working Papers 24768, National Bureau of Economic Research, Inc.

De Loecker, J., C. Fuss, and J. Van Biesebroeck (2018, October). Markups and price dynamics: linking micro to macro. Working Paper Research 357, National Bank of Belgium.

De Loecker, J. and F. Warzynski (2012, October). Markups and Firm-Level Export Status. *American Economic Review 102*(6), 2437–2471.

Decker, R. A., J. Haltiwanger, R. S. Jarmin, and J. Miranda (2016). Where has all the skewness gone? The decline in high-growth (young) firms in the U.S. *European Economic Review 86*(C), 4–23.

di Giovanni, J., A. A. Levchenko, and I. Mejean (2018). Foreign Shocks as Granular Fluctuations. *Forthcoming*.

Diez, F. J., D. Leigh, and S. Tambunlertchai (2018). Global market power and its macroeconomic implications. Working Paper 2018/137, International Monetary Fund.

Eggertsson, G. B., J. A. Robbins, and E. G. Wold (2018, February). Kaldor and Pikettys Facts: The Rise of Monopoly Power in the United States. NBER Working Papers 24287, National Bureau of Economic Research, Inc.

Ennis, S., P. Gonzaga, and C. Pike (2017). Inequality: a hidden cost of market power. Technical report, OECD Competition Division. www.oecd.org/daf/competition/inequality-a-hidden-cost-of-market-power.htm (accessed March 6, 2019).

Furman, J. and P. Orszag (2018, June). Slower Productivity and Higher Inequality: Are They Related? Working Paper Series WP18-4, Peterson Institute for International Economics.

Gopinath, G. (2016). The international price system. *Jackson Hole Symposium Proceedings*.

Grullon, G., Y. Larkin, and R. Michaely (2018). Are U.S. Industries Becoming More Concentrated? *Forthcoming, Review of Finance*.

Gutierrez, G. and T. Philippon (2016, November). Investment-less Growth: An Empirical Investigation. CEPR Discussion Papers 11673, C.E.P.R. Discussion Papers.

Haldane, A. G., T. Aquilante, and S. Chowla (2018, August). Market power and monetary policy. Technical report, Bank of England.

Haltiwanger, J. (1997, May). Measuring and analyzing aggregate fluctuations: the importance of building from microeconomic evidence. *Federal Reserve Bank of St. Louis Review*, 55–78.

Harberger, A. (1964, July). Taxation, Resource Allocation, and Welfare. In *The Role of Direct and Indirect Taxes in the Federal Reserve System*, NBER Chapters, pp. 25–80. National Bureau of Economic Research, Inc.

Hirschman, A. O. (1964, September). The Paternity of an Index. *American Economic Review 54*(5), 761–762.

Holston, K., T. Laubach, and J. C. Williams (2017). Measuring the natural rate of interest: International trends and determinants. *Journal of International Economics 108*(S1), 59–75.

International Monetary Fund (2019). World Economic Outlook 2019: Growth Slowdown, Precarious Recovery. Technical report, IMF.

Justiniano, A. and B. Preston (2010, May). Can structural small open-economy models account for the influence of foreign disturbances? *Journal of International Economics 81*(1), 61–74.

Karabarbounis, L. and B. Neiman (2014). The Global Decline of the Labor Share. *The Quarterly Journal of Economics 129*(1), 61–103.

Kehrig, M. and N. Vincent (2017). Growing Productivity without Growing Wages: The Micro-Level Anatomy of the Aggregate Labor Share Decline. 2017 Meeting Papers 739, Society for Economic Dynamics.

Kose, M. A., C. Otrok, and C. H. Whiteman (2003, September). International Business Cycles: World, Region, and Country-Specific Factors. *American Economic Review 93*(4), 1216–1239.

Liu, E., A. Mian, and A. Sufi (2019, January). Low Interest Rates, Market Power, and Productivity Growth. NBER Working Papers 25505, National Bureau of Economic Research, Inc.

Martins, J. O., S. Scarpetta, and D. Pilat (1996, January). Mark-Up Ratios in Manufacturing Industries: Estimates for 14 OECD Countries. OECD Economics Department Working Papers 162, OECD Publishing.

Melitz, M. J. (2003, November). The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity. *Econometrica 71*(6), 1695–1725.

Nygaard, V. M. (2013). Input-output analysis of the Norwegian economy. Staff Memo 2013/17, Norges Bank.

OECD (2011). *Divided We Stand: Why Inequality Keeps Rising*. Paris: OECD Publishing.

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

Pavcnik, N. (2002). Trade Liberalization, Exit, and Productivity Improvements: Evidence from Chilean Plants. *Review of Economic Studies 69*(1), 245–276.

Philippon, T. (2018). A Primer On Concentration, Investment and Growth. Technical report, Jackson Hole Symposium. https://www.kansascityfed.org/ /media/files/publicat/sympos/2018/papersandhandouts /824180819philipponhandout.pdf?la=en (accessed December 9, 2018).

Piketty, T. (2014). *Capital in the Twenty-First Century*. Cambridge, Massachusetts: The Belknap Press of Harvard University Press.

Ramey, V. (2018). Increasing Differences between Firms: Market Power and the Macro-Economy. Technical report, Jackson Hole Symposium.

Roodman, D. (2009, March). How to do xtabond2: An introduction to difference and system GMM in Stata. *Stata Journal 9*(1), 86–136.

Shapiro, C. (2018). Antitrust in a time of populism. *International Journal of Industrial Organization 61*(C), 714–748.

Statistics Norway (2019). Share capital, received dividends and received previously paid-up capital. https://www.ssb.no/en/statbank/table/10504 (accessed March 19, 2019).

Syverson, C. (2019, January). Macroeconomics and Market Power: facts, Potential Explanations and Open Questions. Brookings economics studies report, Brookings Institution.

The World Bank (2017). Market Capitlization of Listed Domestic Companies. https://data.worldbank.org/indicator/CM.MKT.LCAP.GD.ZS?locations=NO (accessed March 2, 2019).

Tirole, J. (1988). *The Theory of Industrial Organization*. Cambridge, Massachusetts: The MIT

Press.

Traina, J. (2018). Is Aggregate Market Power Increasing? Production Trends using Financial Statements. Technical report, Chicago Booth mimeo.

Weche, J. P. and A. Wambach (2018, January). The fall and rise of market power in Europe. Working Paper Series in Economics 379, University of Lneburg, Institute of Economics.

Wolff, E. N. (2014, December). Household Wealth Trends in the United States, 1962-2013: What Happened over the Great Recession? NBER Working Papers 20733, National Bureau of Economic Research, Inc.

APPENDIX

A AGGREGATE MARKUPS, AVERAGE MARKUPS, AND FIRM SIZE

Here I derive the link between aggregate and average markups used in the main text. One point of departure is the difference between these two measures:

$$\mathcal{M}_t - \bar{\mathcal{M}}_t = \sum_{i=1}^{N_t} s_{i,t}\mathcal{M}_{i,t} - \frac{1}{N_t}\sum_{i=1}^{N_t}\mathcal{M}_{i,t}$$

The right-hand side can be expanded in the following way:

$$\begin{aligned}
\mathcal{M}_t - \bar{\mathcal{M}}_t &= \sum_{i=1}^{N_t} s_{i,t}\mathcal{M}_{i,t} - \frac{1}{N_t}\sum_{i=1}^{N_t}\mathcal{M}_{i,t} - \bar{s}_t\bar{\mathcal{M}}_t N_t + \bar{s}_t\bar{\mathcal{M}}_t N_t \\
&= \sum_{i=1}^{N_t} s_{i,t}\mathcal{M}_{i,t} - \bar{\mathcal{M}}_t\sum_{i=1}^{N_t} s_{i,t} - \bar{s}_t\sum_{i=1}^{N_t}\mathcal{M}_{i,t} + \sum_{i=1}^{N_t}\bar{s}_t\bar{\mathcal{M}}_t \\
&= \sum_{i=1}^{N_t}\left(s_{i,t} - \bar{s}_t\right)\left(\mathcal{M}_{i,t} - \bar{\mathcal{M}}_t\right)
\end{aligned}$$

This is the expression in the main text. Moreover, the last summation is proportional to the sample covariance between firm size and firm markups, the latter being given by,

$$\frac{1}{N_t - 1}\sum_{i=1}^{N_t}\left(s_{i,t} - \bar{s}_t\right)\left(\mathcal{M}_{i,t} - \bar{\mathcal{M}}_t\right).$$

B A DERIVATION OF WITHIN, BETWEEN, AND NET ENTRY COMPONENTS OF AGGREGATE MARKUPS

Here I derive the decomposition of aggregate markups used in the text. Importantly, it accounts for the fact that the dataset is unbalanced, since some firms enter and exit the market in each period. Variants of this decomposition have been used in different contexts, see, for example, the application to productivity by Haltiwanger (1997). The point of departure is the definition of aggregate markups, $\mathcal{M}_t = \sum_{i=1}^{N_t} s_{i,t}\mathcal{M}_{i,t}$. Its growth rate can be decomposed into three parts, each with a particular interpretation:

$$\begin{aligned}
\Delta\mathcal{M}_t &= \sum_{i=1}^{N_t} s_{i,t}\mathcal{M}_{i,t} - \sum_{i=1}^{N_{t-1}} s_{i,t-1}\mathcal{M}_{i,t-1} \\
&= \left(\sum_{i=1}^{N_{1,t}} s_{i,t}\mathcal{M}_{i,t} + \sum_{i=1}^{N_{2,t}} s_{i,t}\mathcal{M}_{i,t}\right) - \left(\sum_{i=1}^{N_{1,t}} s_{i,t-1}\mathcal{M}_{i,t-1} + \sum_{i=1}^{N_{3,t-1}} s_{i,t-1}\mathcal{M}_{i,t-1}\right) \\
&= \sum_{i=1}^{N_{1,t}}\left(s_{i,t}\mathcal{M}_{i,t} - s_{i,t-1}\mathcal{M}_{i,t-1}\right) + \sum_{i=1}^{N_{2,t}} s_{i,t}\mathcal{M}_{i,t} - \sum_{i=1}^{N_{3,t-1}} s_{i,t-1}\mathcal{M}_{i,t-1}
\end{aligned}$$

The split into sub-samples is defined as follows: first, regarding period t, there are $N_t = N_{1,t}+N_{2,t}$ firms active. The number of incumbent firms (those that exist both in period t and $t-1$) is denoted

$N_{1,t}$, and the number of new firms (entrants) is denoted by $N_{2,t}$. Second, regarding period $t-1$, there were $N_{t-1} = N_{1,t} + N_{3,t-1}$ firms active in that period. Of these, $N_{1,t}$ firms were also active in period t while the number of firms that exited after period $t-1$ is denoted by $N_{3,t-1}$. The net change in the number of firms between the two periods is, therefore, $\Delta N_t = N_{2,t} - N_{3,t-1}$. To proceed, I first expand the sum involving firms that exist in both periods:

$$\begin{aligned}
\sum_{i=1}^{N_{1,t}} (s_{i,t}\mathcal{M}_{i,t} - s_{i,t-1}\mathcal{M}_{i,t-1}) &= \sum_{i=1}^{N_{1,t}} (s_{i,t-1}\Delta\mathcal{M}_{i,t} + \Delta s_{i,t}\mathcal{M}_{i,t}) \\
&= \sum_{i=1}^{N_{1,t}} (s_{i,t-1}\Delta\mathcal{M}_{i,t} + \Delta s_{i,t}\mathcal{M}_{i,t-1} + \Delta s_{i,t}\Delta\mathcal{M}_{i,t}) \\
&= \sum_{i=1}^{N_{1,t}} [s_{i,t-1}\Delta\mathcal{M}_{i,t} + \Delta s_{i,t}(\mathcal{M}_{i,t-1} - \mathcal{M}_{t-1}) + \Delta s_{i,t}\Delta\mathcal{M}_{i,t}] \\
&\quad + \sum_{i=1}^{N_{1,t}} \Delta s_{i,t}\mathcal{M}_{t-1}
\end{aligned}$$

The last equality adds and subtracts $\sum_{i=1}^{N_{1,t}} \Delta s_{i,t}\mathcal{M}_{t-1}$, for reasons that will be clear below. The next step is to expand the sum capturing firm entry:

$$\sum_{i=1}^{N_{2,t}} s_{i,t}\mathcal{M}_{i,t} = \sum_{i=1}^{N_{2,t}} s_{i,t}(\mathcal{M}_{i,t} - \mathcal{M}_{t-1}) + \sum_{i=1}^{N_{2,t}} s_{i,t}\mathcal{M}_{t-1}$$

Here, $\sum_{i=1}^{N_{2,t}} s_{i,t}\mathcal{M}_{t-1}$ is added and subtracted. Third, I expand the sum with exiting firms:

$$\sum_{i=1}^{N_{3,t-1}} s_{i,t-1}\mathcal{M}_{i,t-1} = \sum_{i=1}^{N_{3,t-1}} s_{i,t-1}(\mathcal{M}_{i,t-1} - \mathcal{M}_{t-1}) + \sum_{i=1}^{N_{3,t-1}} s_{i,t}\mathcal{M}_{t-1}$$

Now, $\sum_{i=1}^{N_{3,t-1}} s_{i,t}\mathcal{M}_{t-1}$ is added and subtracted. Finally, I combine all pieces and express the aggregate markup change in the following way:

$$\begin{aligned}
\Delta\mathcal{M}_t = &\sum_{i=1}^{N_{1,t}} [s_{i,t-1}\Delta\mathcal{M}_{i,t} + \Delta s_{i,t}(\mathcal{M}_{i,t-1} - \mathcal{M}_{t-1}) + \Delta s_{i,t}\Delta\mathcal{M}_{i,t}] \\
&+ \sum_{i=1}^{N_{2,t}} s_{i,t}(\mathcal{M}_{i,t} - \mathcal{M}_{t-1}) - \sum_{i=1}^{N_{3,t-1}} s_{i,t-1}(\mathcal{M}_{i,t-1} - \mathcal{M}_{t-1}) \\
&+ \sum_{i=1}^{N_{1,t}} \Delta s_{i,t}\mathcal{M}_{t-1} + \sum_{i=1}^{N_{2,t}} s_{i,t}\mathcal{M}_{t-1} - \sum_{i=1}^{N_{3,t-1}} s_{i,t-1}\mathcal{M}_{t-1}
\end{aligned}$$

Note that the three sums in the last row above add to zero, since

$$\mathcal{M}_{t-1}\left(\sum_{i=1}^{N_{1,t}} \Delta s_{i,t} + \sum_{i=1}^{N_{2,t}} s_{i,t} - \sum_{i=1}^{N_{3,t-1}} s_{i,t-1}\right) = \mathcal{M}_{t-1}\left(\sum_{i=1}^{N_t} s_{i,t} - \sum_{i=1}^{N_{t-1}} s_{i,t-1}\right) = 0$$

Once this is taken into account, I arrive at the decomposition used in the text:

$$\Delta\mathcal{M}_t = \sum_{i=1}^{N_{1,t}} s_{i,t-1}\Delta\mathcal{M}_{i,t} \qquad \text{(within)}$$

$$+\sum_{i=1}^{N_{1,t}} \Delta s_{i,t} \left(\mathcal{M}_{i,t-1} - \mathcal{M}_{t-1}\right) \qquad \text{(reallocation)}$$

$$+\sum_{i=1}^{N_{1,t}} \Delta s_{i,t} \Delta \mathcal{M}_{i,t} \qquad \text{(cross)}$$

$$+\sum_{i=1}^{N_{2,t}} s_{i,t} \left(\mathcal{M}_{i,t} - \mathcal{M}_{t-1}\right) \qquad \text{(entry)}$$

$$-\sum_{i=1}^{N_{3,t-1}} s_{i,t-1} \left(\mathcal{M}_{i,t-1} - \mathcal{M}_{t-1}\right) \qquad \text{(exit)}$$

Following De Loecker and Eeckhout (2017), I define as "between" the sum of reallocation and cross, while "net entry" is defined as entry minus exit.

Norges miljø- og biovitenskapelige universitet
Noregs miljø- og biovitskapelege universitet
Norwegian University of Life Sciences

Postboks 5003
NO-1432 Ås
Norway