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Working Paper

Rising markups, common ownership, and technological capacities

DICE Discussion Paper, No. 340

Provided in Cooperation with:

Düsseldorf Institute for Competition Economics (DICE), Heinrich Heine University Düsseldorf

Suggested Citation: Gibbon, Alexandra J.; Schain, Jan Philip (2020) : Rising markups, common ownership, and technological capacities, DICE Discussion Paper, No. 340, ISBN 978-3-86304-339-1, Heinrich Heine University Düsseldorf, Düsseldorf Institute for Competition Economics (DICE), Düsseldorf

This Version is available at:

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June 2020

IMPRINT

DICE DISCUSSION PAPER

Published by:

Heinrich-Heine-University Düsseldorf,
Düsseldorf Institute for Competition Economics (DICE),
Universitätsstraße 1, 40225 Düsseldorf, Germany
www.dice.hhu.de

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ISSN 2190-9938 (online) / ISBN 978-3-86304-339-1

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Rising Markups, Common Ownership, and Technological Capacities*

Alexandra J. Gibbon[†] Jan Philip Schain[†]

June 2020

Abstract

This paper analyses the impact of common ownership on markups and innovation and adds to the discussion of the recently observed patterns of a long term rise in market power. We shed light on the inconclusiveness of results regarding the effects of common ownership on markups in the existing literature by exploiting industry technology classifications by the European Commission. Using a rich panel of European manufacturing firms from 2005 to 2016, we structurally infer markups and construct a measure of common ownership. Combining propensity score matching with a difference-in-differences estimator, we find an increase of firm markups by 3.1% after the first exposure to common ownership. While this effect is strongly pronounced in low-tech industries, we find no effect on markups in high-tech industries. In contrast, we measure a positive effect of common ownership on innovation activity in high-tech industries and no effect in low-tech industries. Both findings are consistent with recent theoretical findings in López and Vives (2019).

JEL codes: L10, L41, L60, G23, G32, O34

Keywords: Competition, Common Ownership, Market Power, Industry Structure, Antitrust, Innovation

*We would like to thank Joel Stiebale, Frank Verboven, Philipp Schmidt-Dengler, and Tobias Salz for helpful comments and suggestions. This paper also benefited from discussions with participants of the DICE PhD seminar (DFG GRK 1974) in Düsseldorf (2019).

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1 Introduction

The recently observed pattern of a long term rise in market power accompanied by increasing industry concentration (De Loecker et al., 2018; Autor et al., 2017; Syverson, 2019) has sparked worries and interest in the economic consequences and causes of this phenomenon. Simultaneously, the rapidly increasing prevalence of diversified institutional investors has changed industry concentration by creating ownership links between competing companies (Azar et al., 2018). Common ownership, arising in the form of indirect corporate networks connected through common institutional investors, is likely to be one reason that we observe rising markups across many industries and countries.

Investors owning larger shares of an industry are in a position to exert a certain degree of influence on directly competing companies. Economists (for example Azar et al., 2018) argue that in settings of common ownership by institutional investors, firms might no longer take strategic decisions independently. Aligned shareholder value maximisation incentives of firms provide room for possible anti-competitive behaviour regarding prices or innovation.

In total, institutional investors hold over USD 85 trillion of public equity on the worldwide level, as opposed to a total volume of only USD 3 trillion in 1980 (Monopolies Commission, 2016). Institutional investors held on average around 40% of Western European countries' GDP in assets under management in 2018 (OECD, 2019), with common ownership emerging from a concentration of few but large investors within the same industry. Considerable volumes of common ownership can be found in publicly listed companies, for instance in the airline, banking, or pharmacy sector in the USA (Azar et al., 2018), as well as in the chemical sector and car industry in Germany (Seldeslachts et al., 2017). The importance of common ownership has also been recognized by the European Commission (EC) in two recent high-profile merger cases. In both decisions, the EC identifies a high concentration of common ownership in the biotech and agrochemical industry and acknowledges the critical role of common ownership with respect to strategic decisions of firms, such as prices and innovation (European Commission, 2017, 2018).

More empirical research on common ownership and markups is required as the theoretical predictions on competition are ambiguous. Early theoretical papers, such as (Reynolds and Snapp, 1986; Bresnahan and Salop, 1986; Salop and O’Brien, 2000) extend the classical concentration measure Herfindahl-Hirschman Index (HHI) to include ownership links. These papers conclude that common ownership exerts an upward pressure on prices through rivals’ profit internalisation. Firms compete less aggressively as the negative effect on competing firms profit is partly taken into account through the common owners. A relatively new theoretical paper (López and Vives, 2019) calls this the cartelisation effect of common ownership. In addition to these anti-competitive results, the authors find that common ownership can also have a pro-competitive effect. Depending on technological spillovers in a given industry, common ownership can spur innovation by increasing the marginal benefit of innovation. They conclude that in markets with high technological spillovers, firms internalize the spilled over decrease in competitors’ marginal costs caused by their own innovation through common ownership. Thus, this increases the marginal benefit of innovation which leads to higher innovation levels and possibly lower prices. An additional empirical finding by Gutiérrez and Philippon (2017) shows that higher concentration and higher levels of common ownership tend to characterise industries with less investment in capital and R&D (e.g. industries with lower technological capacities). Also adding to the ambiguity, others find no significant effects or challenge the methodologies used for identification of anti-competitive effects (Kennedy et al., 2017; Dennis et al., 2017; O’Brien and Waehrer, 2017; Rock and Rubinfeld, 2017; Patel, 2017; Lambert and Sykuta, 2018; Thomas et al., 2019).

This paper investigates the relationship of common ownership, markups, and innovation on a broad European manufacturing sample of large firms as categorised by the European Commission between 2005 and 2016. Using data from Bureau van Dijk’s Amadeus database we estimate industry specific production functions accounting for input endogeneity following Akerberg et al. (2015) and calculate markups as in De Loecker and Warzynski (2012). Furthermore, we make use of the detailed ownership information available in Amadeus to

construct the modified Herfindahl-Hirschman Index (MHHI), an extension of the classical HHI taking into account ownership links at the industry level, proposed by Bresnahan and Salop (1986) and used in other empirical studies as in Azar et al. (2018). Innovation activity by firms is measured by patents weighted with forward citations. We use an industry classification of technological capacities by the European Commission (2019) and an industry efficiency dispersion measure used in Aghion et al. (2005) to investigate in more detail how the effect of common ownership on markups and innovation varies along these dimensions, and to contribute to the further disambiguation of the effects of common ownership.

We combine propensity score matching with a difference-in-differences estimator and find that on average, firm markups increase by 3.1 percent in industries after the first occurrence of common ownership. This effect is driven by low-tech and medium-low-tech companies as classified by the European Commission. In these industries, we find an increase of 4.5 percent and no effect in high-tech and medium-high-tech industries. In our sample, we find low innovation activity and lower levels of technological spillovers in industries that coincide with the definition of low and medium-low-technology firms. This suggests that in these industries innovation is only a minor strategic variable and thus unlikely to confound the effect of common ownership on firm markups. Our finding of a positive effect of common ownership on markups is consistent with the theoretical result in Lopéz and Vives (2019), who show that in low spillover industries the cartelisation effect of common ownership is dominant. Thus, we would expect that in exactly these industries an increase in markups is most likely to be observed empirically. Furthermore, we also find that the positive effect in the low-tech industries is more pronounced when firms compete in a more neck-and-neck fashion (Aghion et al., 2005) compared to a more dispersed industry in terms of productivity. In contrast to these anti-competitive implications of common ownership, in line with the theoretical predictions by Lopéz and Vives (2019), we also find a positive effect of common ownership on innovation in industries characterised by higher technological capacities. Intuitively, in these industries, innovation is an important strategic variable in addition to prices. In low-

tech and medium-low-tech industries we find no effect of common ownership on innovation which is also consistent with theoretical predictions.

Our paper is related to a large and growing body of literature that recognises the importance of ownership structures involving competing firms and institutional investors.¹ While there are some empirical industry-specific studies that analyse anti-competitive effects of common ownership on prices in the airline and banking industry (Azar et al., 2018, 2016), there is less work on a wider firm panel containing multiple industries. Backus et al. (2019b) perform a calibration exercise with initial markup estimates taken from De Loecker et al. (2018), which are estimated on firms in the S&P500 index. In a recent working paper, Kini et al. (2019) investigate the effect of common ownership on product differentiation of US listed companies. They also analyse firm markups and investment as outcome variables and find no average effect on markups, but a positive effect in industries characterised by high technological spillovers. For investments, they find an average positive effect that is more pronounced in high-spillover industries. The results on investments are consistent with our findings on innovation, but deviate from our results on markups.

This paper is substantially different from Kini et al. (2019) and contributes to the existing literature in four ways. First, we analyse a broad manufacturing sample in Europe that mostly consists of non-listed firms, whereas almost the entire empirical literature on common ownership is based on US listed firms and often focuses on specific industries. Second, our identification methodology does not rely on the extended concentration measure MHHI, but focuses on a propensity score matching strategy. Commonly used strategies of exploiting institutional mergers and stock index inclusion are less appropriate here, as we observe less within-firm variation of common ownership and an insufficient number of firms listed in a stock index. Since the use of the MHHI delta as a measure for common ownership has been criticised due to its large and rather disproportionate range², we define treatment only as

¹Apart from prices, markups, and innovation, researchers have also dealt with managerial incentives (Antón et al., 2018), market entry and exit (Newham et al., 2018; Xie and Gerakos, 2018) and horizontal mergers (Antón et al., 2019) as reactions to common ownership structures in industries.

²As stated by Lambert and Sykuta (2018), it may reach levels up to approximately 28 billion, the

the first exposure of a market to common ownership, not based on values of the MHHI delta. Third, Kini et al. (2019) do not focus solely on innovation activity, but on a wider range of investments as an outcome variable, consisting of capital expenditures, R&D expenditures, and acquisitions. In this paper, we use a direct measure of innovation by analysing citation weighted patents. This is advantageous as the theoretical foundation given in Lopéz and Vives (2019) focuses on innovation spillovers only and may not be trivially extended to general investments in capital. Fourth, on a broader scope, our paper also contributes to the rising market power discussion, as we find a rising markup pattern in our sample. It is striking that this trend cannot only be found in European public firms, but is also reflected in European non-listed firms. We show how much of the rising markups phenomenon can be attributed to the presence of common ownership in our sample.

Our findings are very relevant for competition authorities, as we show in what kind of industries positive price effects and innovation spillovers of common ownership are most likely to occur. This is of considerable importance in mergers between banks, insurances and other institutional investors, where common ownership is created as a by-product of the merger. Our results suggest that in mergers between institutional investors, divestitures of portfolio firms in low-tech and medium-low-tech industries may be necessary as a remedy to counteract anti-competitive price effects. On the other hand, the established ownership links may be beneficial for innovation incentives in high-tech and medium-high-tech industries.

The rest of this paper proceeds as follows. Section 2 gives an overview of the data set and empirical strategy. Correlation evidence is presented in section 3 and results of the difference-in-difference approach follow in section 4. Section 5 discusses the results and concludes. The appendix provides further information on foundations of the concentration measures and productivity and markup estimation used in this paper.

maximum value achieved from their simulations, even when no investor owns more than 5% of a company.

2 Data and Markups

This section presents the data at hand in subsection 2.1. The production function and markup estimation is discussed in subsection 2.2.

2.1 Data

We use a rich firm-level panel from the Amadeus data base by Bureau van Dijk. We rely on the standard definition of large firms by the European Commission, regarding firms with averages of more than 250 employees and over € 50 million in turnover. Large firms follow better reporting standards leading to better data availability and quality, and as has been shown in the literature, institutional investors have a strong preference for large firms (Ferreira and Matos, 2008; Dahlquist and Robertsson, 2001). Small firms are likely to be non-strategic price-takers (Deneckere and Kovenock, 1992), which are targeted less by institutional investors. Assuming monitoring costs by institutional investors, we would expect common ownership to be a more important factor in large firms, as in larger firms the benefit of being active outweighs monitoring costs.

The data set covers the observation period from 2005 to 2016, with a total of 7229 unique firms, operating in the manufacturing industry. Markets are defined on the three-digit NACE code and country level. Common ownership arises when any institutional investor holds any equity share in two or more companies within the same market. The comprehensive collection of financial data and information on corporate structure of European companies also covers non-listed firms, and is regularly updated.

For structural estimation of production functions, one would ideally like to have information on firm-level quantities of output and input factors capital, labour, and materials. Unfortunately, quantities are not widely available. Therefore it is common practice to use accounting data proxies. The data contain sales as a variable approximating output, tangible fixed assets for capital, material expenses for physical materials, and the number of employees as well as costs of employment for labour. In the subsequent estimation, the number of

employees are used as these are quantities and have fewer missing values than the labour expenditures. All of these variables are converted to constant 2010 Euros using a Eurostat dataset on annual producer price indices per two-digit industry and country for the years 2005 to 2016.³

The ideal data set to analyse common ownership networks of firms would report subsidiaries of institutional investors which act in the common interest of a single ultimate owner. Global ultimate ownership in this case is defined as the last legal entity owning over 50% of shares. The ownership entries for the manufacturing firms in Amadeus do not take into account ultimate ownership of invested institutional shareholders, but in order to acknowledge holding structures, different subsidiaries of some of the largest investors are aggregated under the parent investor name. Ownership stakes are consolidated at the corporation level as far as possible, relying on names, the Amadeus data base and other external information. This is justified by the finding that votes are cast on a mutual fund family level and not singularly for individual affiliated funds (He et al., 2019).

Compared to other empirical studies, the lack of price information can be compensated with recent markup estimation strategies using balance sheet data, although these cannot yield perfectly accurate information on firms' marginal cost or price setting behaviour. A large number of missing values also presents a source of potential challenges when constructing variables relating to either financial or ownership data. It is however advantageous to have such a comprehensive, representative data set to conduct a large-scale study of the manufacturing industry in Europe. It should be pointed out that no data set with representative firm-level data across industries provides price data. As common ownership has not been studied thoroughly within this geographical context, the data provide detailed insights on ownership structures of a large number of firms with important players. Wages are calculated as the ratio of the cost of employment and the number of employees. For some companies, information on employment is incomplete, for which then the 4-digit industry-country median

³Short term statistics, code sts_inpp_a, <https://ec.europa.eu/eurostat/web/short-term-business-statistics/data/database>, last accessed: 20.06.2019.

wage is assumed.

Table 1 reports summary statistics of the variables used in the estimation procedure, exhibiting a large dispersion of values for sales and input factors, especially materials and capital as well as investment, all reported in thousand Euros. Around 5% of large firms in our sample are publicly quoted.

Table 1: Summary statistics, firm-level

	Characteristics			
	Mean	SD	Min	Max
Sales	373838.11	1623190.08	23764.94	65657076.00
Labour	1142.74	3362.89	2.00	152408.00
Materials	226449.96	1179973.48	2603.53	53756880.00
Capital	80935.25	330135.46	309.01	12063218.00
Investment	13062.87	66305.38	0.00	4325209.50
Public	0.05	0.21	0.00	1.00
Age	35.47	33.40	0.00	731.00
Wages	45.70	20.07	5.24	110.58
Unique firms	7229			
N	38566			

Note: This table shows summary statistics of the sample at the firm-level. Financial information taken from the Amadeus data base by Bureau van Dijk. Labour denotes the number of employees, materials the material expenditures, and capital tangible fixed assets. Investment is calculated as the change of tangible fixed assets between periods plus depreciation. Wages are calculated as the ratio of costs of employment over number of employees. Sales, material expenditures, tangible fixed assets, investment, and wages in thousand Euro, deflated by 2-digit industry-country-year-specific producer prices.

According to the definition by the European Commission (2019), high and medium-high-technology industries are characterised by higher technological intensities, where industries have higher R&D expenditures, more patent applications, and a larger share of innovating firms on average. The technological intensity of an industry is measured by R&D expenditures over value added (European Commission, 2020). Table 2 reports averages of the number of annual granted patents, patents before 2005, the percentage of innovating firms in the subsample, capital investment in thousand Euros, and levels of technological spillovers (as the pre-sample NACE 2-digit industry average calculated by Bloom et al., 2013) of firms in different subsamples. The measure of technological spillovers in the data set by Bloom

et al. (2013) is calculated using a firm’s position in technology space, which is measured by the patenting distribution across an international classification of technology fields, and serves to determine the distance of rival’s in terms of technological advances. The proximity between firms is used to weight respective R&D stocks, as firms closer to each other have a higher chance to profit from the each other’s R&D (Bloom et al., 2013). In our sample, all numbers decline with the ranking of high to low-technology firms. A high number of patents as well as high spillovers support the prediction of other mechanisms than the cartelisation effect of common ownership being at play in industries with higher technological capacities. These findings suggest that strategic considerations of innovation activities do not confound the anti-competitive effects of common ownership on markups as much in low and medium-low-tech industries.

Table 2: Technology classification characteristics

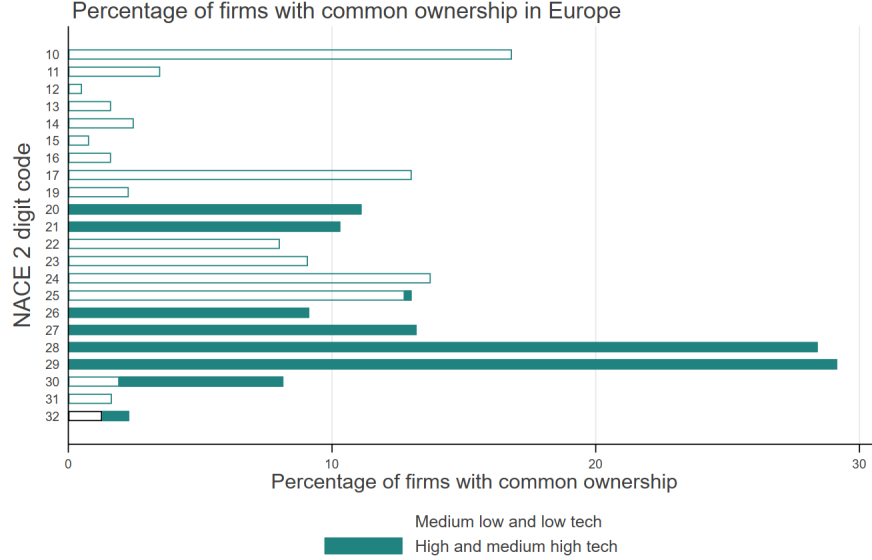
	Patents	Patents before 2005	Percent inno- vating firms	Capital investment	Technological spillovers
High-tech	13.7*** (0.6)	7.4*** (0.4)	41.0*** (0.7)	18364.9*** (1055.7)	6014.7*** (25.1)
Medium-high-tech	6.4*** (0.3)	3.1*** (0.2)	35.0*** (0.4)	13246.7*** (539.2)	4148.1*** (12.8)
Medium-low-tech	2.1*** (0.4)	1.6*** (0.3)	24.2*** (0.4)	13645.6*** (665.2)	3231.9*** (15.8)
Low-tech	0.8** (0.4)	0.6** (0.3)	11.7*** (0.4)	9993.5*** (676.5)	2037.7*** (16.3)
Observations	38566	38566	38566	38566	37842

Note: This table shows sample averages of characteristics indicative for technology classification. Patents, patents before 2005, a dummy for innovation activity, and capital investment (in thousand Euros) are measured at the firm level, and technological spillovers at the two-digit industry-level according to calculations by Bloom et al. (2013). Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 1 shows the percentage of firms with common ownership per NACE 2-digit industry. In the graph, we distinguish between the industries in the high-technology and the low-technology class. We group industries into LOW and HIGH technology subsamples. These are defined by their level of technological capacities, operating either within a

NACE-code industry that is classified as low or medium-low-technology, or within a high or medium-high-technology industry. The highest percentage of common ownership is found in high-tech industries.

Figure 1: Percentage of firms with common ownership in industries



Note: The figure shows the percentage of firms with common ownership by NACE two-digit industry code and technology classification by the European Commission (2019). We use European data from the Amadeus data base by Bureau van Dijk. Common ownership in a market is defined as two competing firms being held by overlapping sets of institutional investors.

2.2 Productivity and Markup Estimation

Productivity

Estimation of markups relies on preceding estimation of total factor productivity (TFP) using the procedure proposed by Akerberg et al. (2015). A Cobb-Douglas technology accounts for substitutability of inputs. A logarithmic specification of this production function is chosen for the estimation of output elasticities. The production function for firm j at time t is designed with the inputs capital k_{jt} , labour l_{jt} , materials m_{jt} , unobserved productivity ω_{jt} ,

and a measurement error ϵ_{jt} , such that

$$q_{jt} = \beta_0 + \beta_k k_{jt} + \beta_l l_{jt} + \beta_m m_{jt} + \omega_{jt} + \epsilon_{jt} \quad (1)$$

In a first stage, predicted output corrects for measurement error without identifying any of the input coefficients. Inverted material input demand is included in the production function, incorporating input factors labour and capital and their squared terms, as well as further control variables MHHI delta, firm age, number of institutional investors, a dummy variable for listing status, and four-digit industry, country, and year fixed effects. The MHHI delta is calculated at the NACE three-digit industry and country level. We follow Collard-Wexler and De Loecker (2016) and correct for measurement error in capital with a two-stage least squares regression using first and second lags of investment and their squared terms as instruments for capital.

Following the assumption of Hopenhayn and Rogerson (1993), and later Olley and Pakes (1996); Levinsohn and Petrin (2003); Akerberg et al. (2015), the serial correlation of productivity is modelled as a controlled first order Markov process. The estimation also allows for common ownership to impact future productivity in an endogenous process, such that it is included in the law of motion of productivity

$$\omega_{jt} = g(\omega_{jt-1}, CO_{jt-1}) + \xi_{jt} \quad (2)$$

where $g(\omega_{jt-1}, CO_{jt-1})$ is a flexible function of lagged productivity and the common ownership measure⁴, and ξ_{jt} is an exogenous productivity shock.

Based on the the optimisation routine by Collard-Wexler and De Loecker (2016), we estimate output elasticities for nine subsets of the manufacturing industry. Constructed with the innovation to productivity $\xi_{jt} = \omega_{jt} - E[\omega_{jt} | \omega_{jt-1}, CO_{jt-1}]$ from the law of motion,

⁴The explicit function used includes a cubic form of both variables and an interaction term

$$\omega_{jt} = \sum_{i=1}^3 \rho_i \omega_{jt-1}^i + \sum_{k=1}^3 \rho_{k+3} CO_{jt-1}^k + \rho_7 \omega_{jt-1} CO_{jt-1} + \xi_{jt}.$$

the objective function minimises the moment conditions

$$E [\xi_{jt}(l_{jt-1}, w_{jt-1}, m_{jt-1}, m_{jt-2}, i_{jt-1}, i_{jt-2})] = 0,$$

where w_{jt-1} is the logarithm of wages. For these moment conditions, the routine calculates the empirical analogue as

$$Q(\beta) = (\boldsymbol{\xi} \mathbf{Z})' (\mathbf{Z}' \mathbf{Z})^{-1} (\boldsymbol{\xi} \mathbf{Z}),$$

with $\boldsymbol{\xi}$ as a vector of productivity shocks ξ_{jt} and \mathbf{Z} as a stacked matrix containing instruments for the input factors (Collard-Wexler and De Loecker, 2016). Results and further detailed discussion of this procedure can be found in the Appendix.

Markups

Markups are computed using the elasticity of output with respect to materials, following De Loecker and Warzynski (2012). The respective input coefficient is related to the revenue share of material expenditures.

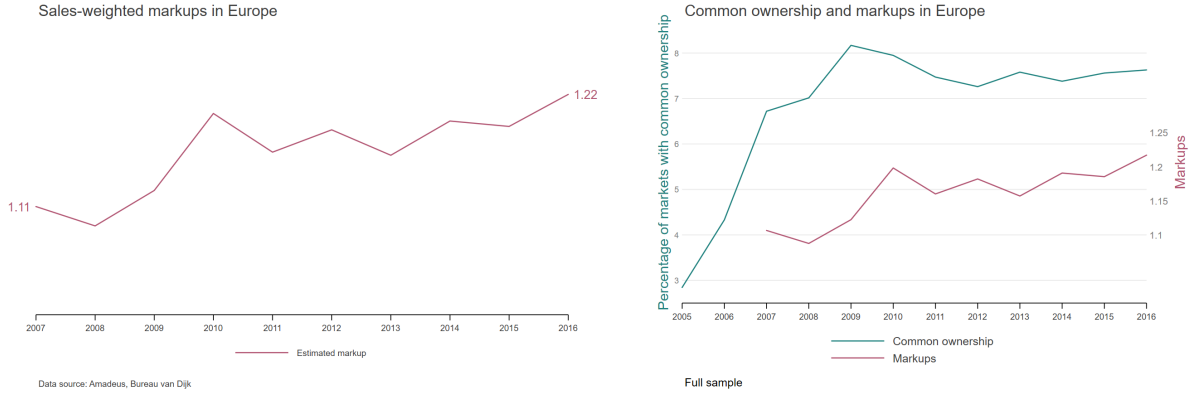
$$\mu_{jt} = \frac{\beta_{jt}^m}{\alpha_{jt}^m} = \left(\frac{P_{jt} Q_{jt}}{w_{jt}^m m_{jt}} \right) \frac{\partial Q_{jt}(\cdot)}{\partial m_{jt}} \frac{m_{jt}}{q_{jt}} \quad (3)$$

In the data, the product of output prices and quantities $P_{jt} Q_{jt}$ is given as sales, and the product of the price and quantities of materials $w_{jt}^m m_{jt}$ is given as material expenditures. The term in parentheses then becomes sales over material expenditures. The second term, $\frac{\partial Q_{jt}(\cdot)}{\partial m_{jt}} \frac{m_{jt}}{q_{jt}}$, denotes the elasticity of output with respect to material inputs, obtained by the previous estimation of the production function and the respective input coefficients.

An error correction is applied to deflated sales in the calculation of the revenue share of the costs of materials, such that

$$\hat{\alpha}_{jt}^m = \frac{\text{materialcosts}_{jt}}{\frac{\text{sales}_{jt}}{\exp(\hat{e}_{jt})}}.$$

Figure 2: Average markups and common ownership, full sample



Note: The figures illustrate the evolution of the average markup and the percentage of markets with common ownership from 2005 to 2016. Markups are estimated using European accounting data from the Amadeus data base by Bureau van Dijk and the method proposed by De Loecker and Warzynski (2012), relying on production function elasticities from the Akerberg et al. (2015) procedure. The average is sales-weighted. Percentage of markets per year in the overall sample, in which common ownership links exist.

Markups are calculated for each firm from the estimated material elasticities, starting in 2007. The years 2005 and 2006 drop out, as two lags of the input variables have been used as instruments in the estimation routine. Following De Loecker and Eeckhout (2017), Figure 2a) shows the average markup, weighted by sales share in the entire sample. The graph is quite revealing of a steady positive trend in markups. Figure 2b) compares the sales-weighted average markup on the right scale to the percentage of markets affected by common ownership on the left scale. Common ownership concentration reveals a similar, increasing pattern in the full sample. We find rising markups in both public and private firms, with a higher level and larger increase in public firms, as can be seen in Figure C.3.

3 Baseline Results

In this section, we provide basic regression results for the effect of common ownership on markups in subsection 3.1, and on patent citations in subsection 3.2.

The variable measuring common ownership in the baseline specifications is the MHHI

delta in the current year, which is the difference between the MHHI and the classical HHI (Salop and O'Brien, 2000),

$$\text{MHHI} = \sum_j \sum_k s_j s_k \frac{\sum_i \beta_{ij} \beta_{ik}}{\sum_i \beta_{ij}^2} = \underbrace{\sum_j s_j^2}_{\text{HHI}} + \underbrace{\sum_j \sum_{k \neq j} s_j s_k \frac{\sum_i \beta_{ij} \beta_{ik}}{\sum_i \beta_{ij}^2}}_{\text{MHHI delta}}.$$

The first part of the equation is the classical HHI as sum of squared market shares s_j of all market participants j , and the second part, MHHI delta, captures the degree of common ownership networks.⁵ Subscripts j and k denote firms and competitors, i indexes the investors, and β_{ij} are ownership shares.⁶ Summing over all combinations of firms and competitors in the industry, the individual profit weights in the fraction are weighted with the product of market shares s_j and s_k of the firm and respective rival.

Corresponding to the market definition partitioning NACE three-digit industry codes per country, the MHHI delta is calculated on a three-digit industry-country level to capture possible competition of firms operating in more than one four-digit industry.

3.1 Markups

To determine a (non-causal) effect of common ownership on firm-level markups, fixed effects regressions are estimated. The main specification estimates a regression of the logarithm of firm j 's markup in market m and period t with year and firm-fixed effects τ_t on the full sample, such that

$$\ln(\mu)_{jmt} = \beta_1 \text{MHHI delta}_{mt} + \beta_2 \text{HHI}_{mt} + \mathbf{X}'_{jmt} \gamma + \tau_t + \nu_j + \epsilon_{jmt}. \quad (4)$$

Firm-fixed effects are included rather than market-specific or industry-specific fixed effects to control for unobserved heterogeneity at the firm level, which might be correlated with the variable measuring common ownership. We therefore analyse only within-firm vari-

⁵For a more detailed derivation of the common ownership measure, please see Appendix D.4.

⁶We assume proportionate control, such that ownership shares equal control shares.

ation. As the explanatory variable of interest is observed at the aggregated market level, unobserved shocks to the markets might lead to correlation of errors of firms in the same market. Standard errors are clustered at the market level to address this concern of biased standard errors (Moulton, 1990). There is a total of 658 unique market clusters. In addition to the year and firm-fixed effects, and the standard concentration measure HHI we control for the logarithm of the firm’s age, and the shares held by institutional investors in \mathbf{X}_{jt} .⁷

We analyse the impact of common ownership, measured by the MHHI delta, on markups on different firm subsamples. We estimate the model on all large firms according to the EU definition. We then split the sample by grouping industries by their level of technological capacities, classifying them as LOW if they operate within a NACE-code industry that is classified as low or medium-low-technology, and HIGH if it is a high or medium-high-technology industry. All regressions rescale the HHI and MHHI delta by dividing by 10,000, such that the HHI ranges between 0 and 1.

Table 3 shows baseline results of panel regressions with firm and year-fixed effects. We consider two functional forms of the dependent variable: the logarithm of estimated markups in columns 1 to 3, and estimated markups in levels in columns 4 to 6. Column 1 shows regression results on the full sample, where a statistically insignificant, negative coefficient on MHHI delta is found. We then split the sample according to the EU technology classification. Firms in the LOW technology subsample in column 2 exhibit a positive and statistically significant effect on markups. The effect in the HIGH technology subsample in column 3 is negative and statistically significant. The results imply that a standard deviation increase in MHHI delta (0.19 and 0.06, respectively) is associated with an increase in average markup of 0.89 percent in LOW tech firms, and a decrease in average markup by 0.2 percent in HIGH tech firms. We find a similar pattern using markups in levels as the dependent variable with

⁷Some further limitations of the panel regressions should be addressed here: The results need to be interpreted only as non-causal relationships. Owing to the properties of the fixed effects estimator, firms with fewer than two observations drop out. In the present case of an unbalanced panel, sample selection problems are introduced if firms drop out of the data non-randomly. Due to many, seemingly random recording errors, such as negative entries for non-negative variables such as material expenses, the probability of observing the observation is likely to be exogenous.

a positive coefficient in the LOW technology firms.

This is consistent with the discussion in the introduction about contrasting competitive effects of common ownership, especially in industries where innovation is a major strategic variable. Therefore, common ownership does not necessarily imply an increase in markups in the HIGH technology sample. On the contrary, the low and medium-low-technology subsample have much lower innovation activity and innovation spills over to a much lesser degree on competitors. Following López and Vives (2019), the cartelisation effect of common ownership dominates in these industries and we would expect to observe quantities to decline and prices to rise. Due to these diverging effects, we find an inconclusive average effect on the full sample.

Table 3: Baseline regressions

Dep. Variable:	ln(Markups)			Markups		
	(1)	(2)	(3)	(4)	(5)	(6)
Technology	Full sample	LOW	HIGH	Full sample	LOW	HIGH
MHHI delta	-0.006 (0.024)	0.047* (0.028)	-0.034** (0.015)	0.014 (0.053)	0.076** (0.031)	-0.015 (0.063)
HHI	0.030 (0.030)	0.048 (0.047)	0.013 (0.039)	0.055 (0.055)	0.077 (0.085)	0.028 (0.074)
ln(Age)	-0.003 (0.017)	0.032 (0.023)	-0.036 (0.024)	0.001 (0.033)	0.065 (0.052)	-0.060 (0.040)
Inst. Holdings	-0.008 (0.013)	0.010 (0.017)	-0.027 (0.017)	-0.009 (0.021)	0.024 (0.028)	-0.041 (0.030)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.95	0.94	0.95	0.93	0.91	0.95
N	17717	8874	8843	17717	8874	8843
Market clusters	658	383	275	658	383	275

Note: Standard errors in parentheses and clustered at the three-digit industry-country level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Market definition: HHI and MHHI delta calculated at the three-digit industry-country level. HHI and MHHI delta are rescaled by division by 10,000, such that the HHI ranges from 0 to 1. Sample split based on EU technology classification. LOW: Low and medium-low technology. HIGH: High and medium-high technology.

3.2 Innovation

The baseline regression model to analyse the effect of common ownership on innovation in industries with varying technological capacities is formulated as a Poisson specification for count data. We use future citation-weighted patents as the main outcome variable to measure innovation. The conditional mean is specified as

$$E[PatCites_{jmt}|x_{jmt}] = \exp(\beta_1 MHHI_{\text{delta}_{mt}} + \beta_2 HHI_{mt} + \mathbf{X}'_{jmt}\gamma + \alpha_j + \iota_j + \tau_t + \epsilon_{jmt}),$$

where firms are denoted by j , markets by m , and years by t . $MHHI_{\text{delta}_{mt}}$ measures common ownership at the market level, and the HHI_{mt} is included to capture market concentration as before. \mathbf{X}_{jmt} is a vector of conditioning variables that comprises average market sales (market size) as a second measure of concentration, 1–Lerner index to capture competition⁸, the logarithm of TFP and age, capital intensity, and the percentage of institutional ownership in a firm. A time-invariant dummy variable indicates whether the firm is publicly quoted. α_j , ι_j , and τ_t are a set of country, two-digit industry, and time-fixed effects. In a nonlinear Poisson model, using pre-sample citation values rather than firm-fixed effects has proven more practicable than firm-fixed effects to deal with unobserved heterogeneity (Blundell et al., 1999). We use the average pre-sample patent citations and a separate dummy variable for firms without citations (i.e. without innovation output) before the sample period. The pre-sample values are calculated from Amadeus data over the period of 1980 to 2004.

For robustness checks, we explore other specifications. We estimate a linear regression model, calculating the dependent variable as $\ln(PatCites)$. Observations with zero citations are assigned a value of 0.000001. In this specification, we include all time-varying controls in \mathbf{X}_{jmt} , time-fixed effects, and firm-fixed effects, consequently omitting time-invariant industry

⁸We base our market-year level measure of competition on Aghion et al. (2005). Competition is

$$C_{mt} = 1 - Lerner_{mt} = 1 - \frac{1}{N_{mt}} \sum_{j \in m} \frac{p_{jt} - c_{jt}}{p_{jt}} = 1 - \frac{1}{N_{mt}} \sum_{j \in m} 1 - \frac{c_{jt}}{p_{jt}} = 1 - \frac{1}{N_{mt}} \sum_{j \in m} 1 - \frac{1}{\frac{p_{jt}}{c_{jt}}} = \frac{1}{N_{mt}} \sum_{j \in m} \frac{1}{\frac{p_{jt}}{c_{jt}}}$$

and country-fixed effects, pre-sample citation variables, and listing status of the firm. We also estimate a zero-inflated Poisson specification, where the logarithm of age, of TFP, the average sales in a market, whether or not a firm has pre-sample citations, and the average number of pre-sample citations are used in the equation that determines whether the count is zero, and the remaining variables of the previous Poisson model serve as covariates.

Table 4 reports the results of the linear model in columns 1 to 3, and the Poisson regression in columns 4 to 6. We find a positive and significant overall effect of MHHI delta on patent citations in the full sample in the linear regression model in column 1. The coefficient on MHHI delta for the LOW technology firms is negative, but not statistically significant. In the HIGH technology industries in column 3, the regression shows a positive and statistically significant association between common ownership and innovation. For the Poisson specification, column 4 indicates an overall positive, highly statistically significant effect in the full sample. A one standard deviation increase in MHHI delta (0.06) implies an increase of average patent citations by 9.6 percent. While the coefficient for LOW tech firms in column 5 is economically large but statistically insignificant, the negative sign can be seen as consistent with predictions by López and Vives (2019), that in lower spillover industries, common ownership has a negative effect on innovation. The positive average effect is clearly driven by the positive and highly statistically significant coefficient in HIGH technology industries, as reported in column 6. This result indicates that a one standard deviation increase in MHHI delta (0.06) is associated with a 4.98 percent increase in average patent citations. These results indicate that in highly innovative industries, where there are larger degrees of technological spillovers, common ownership might possibly have pro-competitive effects, as predicted by López and Vives (2019). The zero-inflated Poisson model supports robustness of these results (see Table B.9).

Nonetheless, one should interpret these results with caution, since possible endogeneity problems arise. The common ownership measure MHHI delta might be biased due to more innovative or productive firms attracting more, and the same, institutional investors.

Table 4: Linear and Poisson model: Patent citations

Dep. Variable:	ln(Patent citations)			Patent citations		
	Linear model			Poisson model		
	(1) Full sample	(2) LOW	(3) HIGH	(4) Full sample	(5) LOW	(6) HIGH
Technology						
MHHI delta	0.171** (0.083)	-0.050 (0.102)	0.336** (0.141)	0.867*** (0.263)	-2.201 (1.661)	0.829*** (0.291)
HHI	-0.120 (0.105)	-0.065 (0.102)	-0.187 (0.185)	0.446 (0.312)	0.769 (0.871)	0.369 (0.320)
1-Lerner	-0.006 (0.054)	0.010 (0.036)	-0.045 (0.107)	-0.869** (0.389)	-0.863 (0.653)	-0.715 (0.436)
Avg. market sales	-0.020 (0.024)	0.014 (0.020)	-0.035 (0.036)	0.558*** (0.140)	0.378* (0.222)	0.568*** (0.154)
ln(TFP)	-0.110 (0.154)	-0.177 (0.201)	-0.085 (0.228)	0.454 (0.618)	-1.130 (0.807)	0.832 (0.699)
Capital intensity	0.032 (0.180)	-0.170 (0.192)	0.126 (0.241)	-9.411 (5.804)	-6.795 (4.865)	-10.041 (6.731)
ln(Age)	0.214*** (0.076)	0.131** (0.063)	0.325** (0.127)	-0.054 (0.108)	-0.002 (0.099)	-0.039 (0.127)
Inst. Holdings	-0.004 (0.042)	-0.009 (0.039)	0.003 (0.074)	0.588 (0.625)	-0.706*** (0.219)	0.757 (0.651)
Publicly quoted				-0.350 (0.256)	0.265 (0.501)	-0.355 (0.249)
No pre-sample cites				-0.069 (0.273)	-0.845*** (0.260)	0.215 (0.309)
Avg. pre-sample cites				0.885*** (0.075)	0.970*** (0.093)	0.870*** (0.082)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	No	No	No
NACE 2 digit FE	No	No	No	Yes	Yes	Yes
Country FE	No	No	No	Yes	Yes	Yes
N	17717	8874	8843	17717	8874	8843
Market clusters	280	179	114	280	179	114

Note: Standard errors in parentheses and clustered at the two-digit industry-country level. * p<0.10, ** p<0.05, *** p<0.01 Market definition: HHI and MHHI delta calculated at the three-digit industry-country level. HHI and MHHI delta are rescaled by division by 10,000, such that the HHI ranges from 0 to 1. Sample split based on EU technology classification. LOW: Low and medium-low technology. HIGH: High and medium-high technology.

4 Identification

This section presents the empirical results of our identification strategy. First, the matching procedure is detailed in subsection 4.1. Subsection 4.2 presents the results of the difference-in-differences estimator on the matched sample. Then subsection 4.3 shows heterogeneous effects regarding direct and indirect effects of common ownership and a sample split with respect to industry efficiency dispersion. Subsection 4.4 shows results regarding the innovation outcome.

4.1 Propensity score matching

The investment strategies of asset managers are clearly not independent of the performance or profitability of their potential portfolio firms. This leads to endogeneity concerns in econometric models where the dependent variable represents any firm characteristics, for example profitability, prices, or markups, and the explanatory variable of interest is related to the level of institutional holdings in a company or a market. In particular, common owners might be motivated to invest in firms operating in markets where they already hold shares in competing firms, as the market is particularly profitable. Additionally, variables based on market shares included in the model, for example the measure of competition HHI, or the MHHI, are endogenous as well. This may lead to a downward bias in the coefficient on MHHI delta. One can imagine a scenario where a non-common owner buys additional shares of its portfolio firm due to increasing expected profitability of the firm, and common owners do not anticipate this effect. Market shares of commonly held firms then decrease, leading to a decrease in MHHI delta in turn. An explanation for a positive bias would be increasing demand on certain markets, which is expected more by passive investors (Azar et al., 2018). More profitable firms with higher markups might also likely become a target of common shareholders, which could possibly lead to simultaneity of the outcome variable and ownership shares. A positive correlation of markups and market shares cannot be excluded, as these are determined simultaneously.

Identification strategies need to account for these endogeneity problems. We combine a propensity score matching approach with a difference-in-differences design. Firms in markets where we observe entry of common ownership are considered to be in the treatment group. By choosing markets' first exposure to common ownership as the treatment indicator, we avoid picking up small variations in MHHI delta induced by short-run changes in sales. We also avoid confounding due to lasting effects in markets with discontinued common ownership. The pool of potential control firms are markets that never experience presence of common ownership in our sample. We discard markets that always show common ownership and that only contain discontinuation of previous common ownership links, and remove observations with periods of discontinuation and second emergence of common ownership in a market. The average change in MHHI delta around treatment is 0.01 with a standard deviation of 0.0350.

The basic idea of matching is to find an adequate control group that can approximate the counterfactual outcome of the treatment group absent treatment. Propensity score matching consists of a two-stage procedure, where in a first step a probit model is estimated to determine treatment probability. The outcome variable is one if in the next year the market experiences entry of common ownership and zero otherwise. We tailor the matching variables to our specific setup. The following firm-level variables are used in the matching procedure to estimate the propensity score: markups, log TFP, age, number of patent citations, labour, capital, and output in logarithms, and share of institutional holdings. Since treatment varies at the market-level (defined by three digit-industry code and country combinations), we do not match on industries and countries directly, but rather on market and industry-level variables HHI, technological spillovers, technological gap between firms, and a dummy for high-tech industries. By including the latter, we can construct the control group on the full sample while ensuring that the matched controls also operate in industries of the same technological capacities as the treated firm. Table 5 shows that almost all covariates significantly determine treatment.

Table 5: Probit regression before matching

	Dependent Variable: Treatment
Markup	0.010 (0.031)
ln(TFP)	-0.225** (0.113)
Age	-0.000 (0.001)
Patent citations	0.001 (0.001)
ln(Capital)	-0.166*** (0.033)
ln(Labour)	0.547*** (0.079)
ln(Sales)	-0.293*** (0.086)
Inst. Holdings	0.246** (0.104)
HHI	-1.181*** (0.224)
Techn. gap	0.734** (0.327)
Techn. ranking	0.001 (0.001)
High-tech	-0.108 (0.083)
Year FE	Yes
<i>N</i>	9934

Note: Standard errors in parentheses and clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. 6 out of 8 year fixed effects are significantly different from zero at the 0.01 percent level. The table shows the results from a Probit regression. The dependent variable takes a value of one if common ownership occurs in the industry for the first time in year $t+1$, and zero otherwise. Market definition: HHI delta calculated at the three-digit industry-country level. HHI rescaled by division by 10,000, such that the HHI ranges from 0 to 1.

After successful matching of propensity scores, treatment and control group do not differ systematically in observables. Table 6 below reports the means for the treatment group and control group before and after the matching in columns 2, 3 and 5, 6, respectively. We see that before the matching there were substantial differences in firm and market characteristics. Columns 4 and 7 show the p-value of a t-test for differences in the mean of the treatment and control group in the unmatched and matched sample. After the matching, the sample is balanced in all variables.

Table 6: Means before and after matching

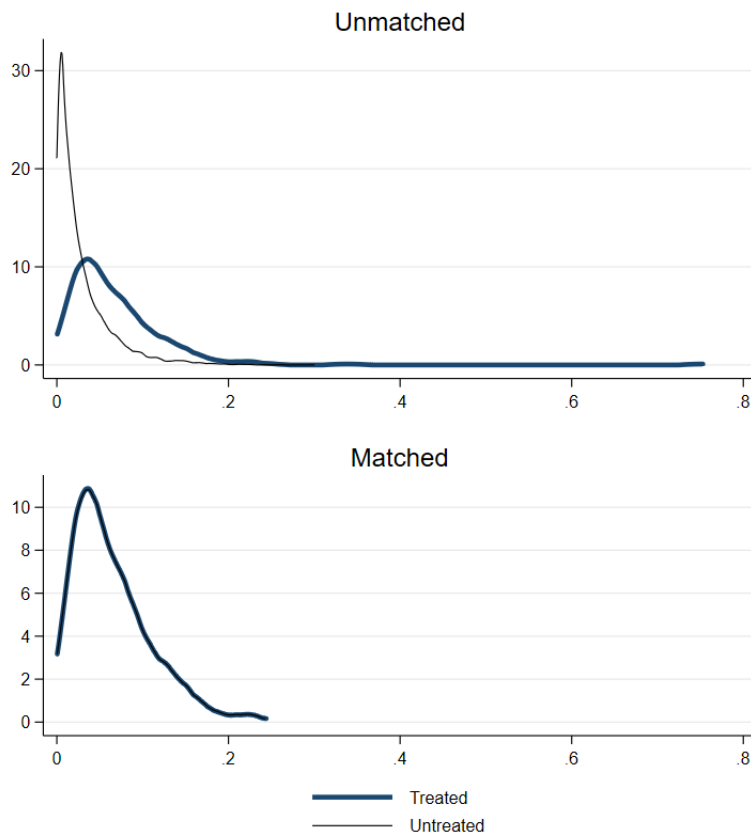
Variable	Before matching			After matching		
	Treated	Control	p-value	Treated	Control	p-value
<i>Firm-level variables</i>						
Propensity score	0.068	0.028	0.000	0.065	0.065	0.998
Markup	1.392	1.227	0.001	1.392	1.387	0.936
ln(TFP)	1.231	1.294	0.002	1.233	1.224	0.759
Age	42.462	36.686	0.007	42.227	45.853	0.401
Patent citations	9.795	2.365	0.000	4.559	6.161	0.478
ln(Capital)	10.161	10.385	0.003	10.135	10.245	0.297
ln(Labour)	10.413	10.116	0.000	10.386	10.441	0.478
ln(Sales)	11.986	12.013	0.652	11.961	12.030	0.415
Inst. holdings	0.123	0.086	0.017	0.121	0.090	0.197
<i>Industry-country-level variables</i>						
HHI	0.179	0.248	0.000	0.180	0.181	0.904
<i>Industry-level variables</i>						
Techn. gap	0.193	0.183	0.084	0.192	0.197	0.559
Techn. ranking	64.628	63.346	0.471	64.632	61.608	0.245
High-tech	0.451	0.394	0.048	0.448	0.406	0.311
Matched observations are also balanced on year dummies.						

Note: Propensity scores are the predicted values from the Probit model in Table 5. Markups and ln(TFP) are estimated using the methods proposed by De Loecker and Warzynski (2012) and Akerberg et al. (2015). Data on patent citations is obtained from the Amadeus patent data base by Bureau van Dijk. Institutional holdings is the share of a firm held by institutional investors. Market definition: HHI calculated at the three-digit industry-country level. Calculation of technological gap based on Aghion et al. (2005), and data on two-digit industry ranking (US SIC codes) according to their technological spillovers obtained from Bloom et al. (2013). High-tech is a dummy that takes a value of one if the firm operates in a two-digit industry classified by the European Commission (2019) as high or medium-high technology, and zero if it operates in a low and medium-low-technology industry.

Figure 3 shows the kernel density estimate of the propensity score before and after the matching procedure. In the matched sample, the density plots are nearly indistinguishable. Together with the covariate means in Table 6, this implies that matching on the estimated propensity score balances the covariates of treated and control group.

Figure 3: Propensity score matching

Kernel density estimate of propensity score

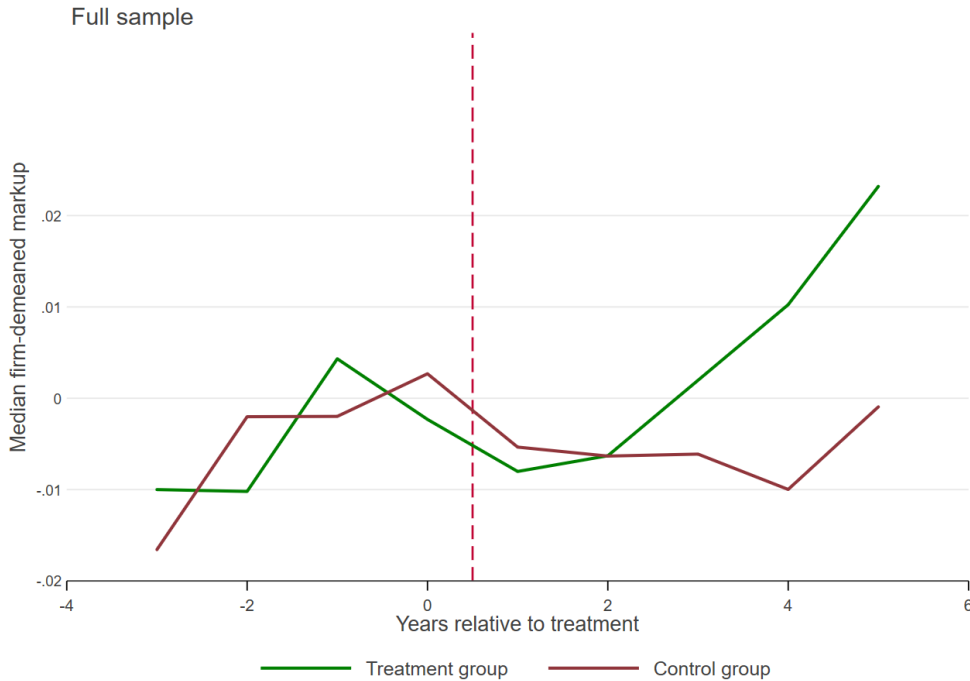


Note: This figure depicts the kernel density estimate of the propensity score distribution before (above) and after (below) the matching procedure with comparison of the treatment group (blue line) and control group (black line) in the full sample. Propensity scores are the predicted values from the Probit model in Table 5, relying on the following covariates: firm-level markup, log TFP, firm age, number of patent citations, capital, labour, and sales in logs, percentage of institutional holdings, HHI, technological gap, technological ranking, and a dummy for operating in a high or medium-high-technology industry. Treatment is defined as the first occurrence of common ownership in a market. Overlap of densities indicates balanced samples.

Plotting markups

For illustration purposes, Figure 4 depicts the progression of median markups for matched treatment and control group in the full sample over time. Markups are demeaned at the firm average level. Both groups show a similar, increasing trend followed by a slight drop just before the treatment. After treatment, this trend continues downwards for the control group. The treatment group shows a clear increase in markups after the first occurrence of common ownership in a market.

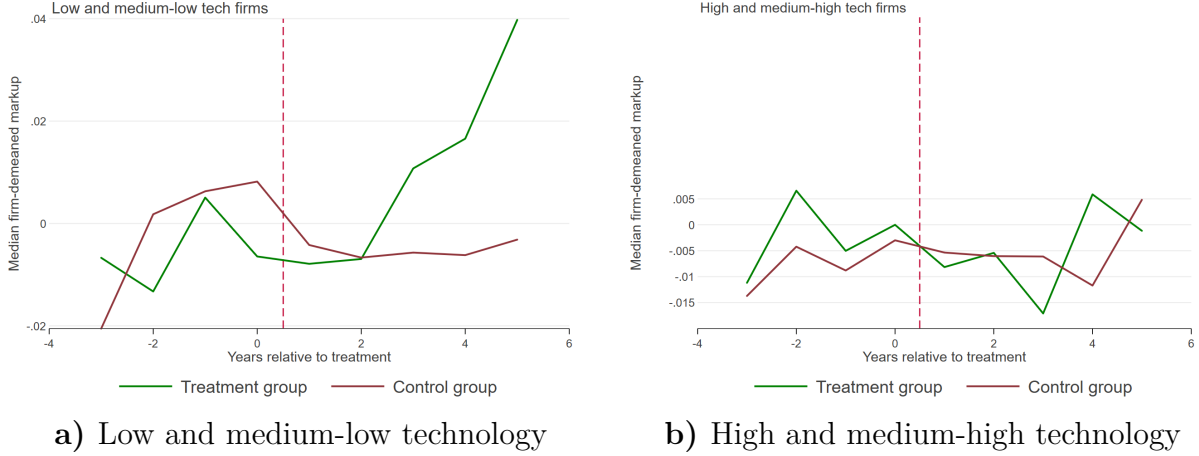
Figure 4: Treatment effects: First occurrence of common ownership, full sample



Note: This figure depicts the progression of median, firm-demeaned markups for matched treatment group (green line) and control group (red line) in the full sample over time. Markups are estimated using European data from the Amadeus data base by Bureau van Dijk and the method proposed by De Loecker and Warzynski (2012), relying on production function elasticities from the Akerberg et al. (2015) procedure. Demeaning refers to subtraction of firm average markup. Treatment is defined as the first occurrence of common ownership in a market, indicated by the dashed line.

Relying on the technology classification of industries, we can split the matched sample by the level of technological capacities. We show the same plot for low and medium-low-technology firms and the high and medium-high technology sample in Figures 5. Treatment

Figure 5: Treatment effects: First occurrence of common ownership, sample split



Note: This figure depicts the progression of median, firm-demeaned markups for matched treatment group (green line) and control group (red line) in the LOW and HIGH technology sample over time. Markups are estimated using European data from the Amadeus data base by Bureau van Dijk and the method proposed by De Loecker and Warzynski (2012), relying on production function elasticities from the Akerberg et al. (2015) procedure. Demeaning refers to subtraction of firm average markup. Treatment is defined as the first occurrence of common ownership in a market, indicated by the dashed line.

and control group of LOW technology class show very similar trends in the pre-treatment period, where markups in the control group decrease slightly and stabilise shortly after treatment, and the treatment group exhibits strongly upward sloping median, firm-demeaned markups. In the HIGH technology industries, median, firm-demeaned markups of control and treatment group follow very similar patterns with no clear trend.

4.2 Treatment Effects

After matching, we use difference-in-differences estimation to determine the average treatment effect on the treated of common ownership on the logarithm of markups.

$$\ln(\mu)_{jt} = \delta_1 \text{Treat}_j \times \text{Post}_t + \delta_2 \text{Post}_t + \tau_t + \nu_j + \epsilon_{jt}. \quad (5)$$

In addition to the difference-in-differences coefficient $\text{Treat}_j \times \text{Post}_t$ and year-fixed effects τ_t , we control for the post period with Post_t , as treatment time varies across individual firms. We include firm-fixed effects ν_j . The indicator variable for the Treat_j group is subsumed by

the firm-fixed effects. We cluster standard errors at the market level.

Table 7 shows the results of the difference-in-differences estimator on the matched sample. On the full sample, we find a statistically significant, positive effect. When firms are first exposed to common ownership in the market, average markups increase by 3.1 percent. The sample split again shows the same pattern for LOW technology firms as in the fixed effect regression analysis. The effect in this subsample is larger and also statistically significant, and indicates that treatment increases the average markup in these industries by 4.5 percent. In the HIGH tech industries, we find no significant effect of common ownership on markups. As treatment varies on industry-country-year level, it is important to account for heterogeneous country and industry time trends. Table B.2 replicates table 7 including additional year-country or year-industry fixed effects. The results of a positive effect on the entire matched sample, which is driven by LOW tech industries, remains unchanged.

Table 7: Treatment effects: $\ln(\text{Markup})$

Dep. Variable:	$\ln(\text{Markups})$		
	(1)	(2)	(3)
Technology	Full sample	LOW	HIGH
Treat \times Post	0.031*** (0.009)	0.045*** (0.011)	0.011 (0.016)
Post	-0.016** (0.007)	-0.022** (0.009)	-0.005 (0.011)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adj. R^2	0.94	0.94	0.95
N	2743	1630	1113
Market clusters	177	100	77

Note: Standard errors in parentheses and clustered at the three-digit industry-country level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Market definition: HHI and MHHI delta calculated at the three-digit industry-country level. HHI and MHHI delta are rescaled by division by 10,000, such that the HHI ranges from 0 to 1. Sample split based on EU technology classification. LOW: Low and medium-low technology. HIGH: High and medium-high technology.

Time-varying treatment effects

The treatment effect shown in Table 7 represents an average across treatment markets and across time. It is necessary to analyse time heterogeneous treatment effects to rule out that the average effect is driven by some extreme values in few periods that may also outweigh negative effects in other periods. More generally, any non-smooth time pattern of the treatment effect would raise doubt in our identification strategy. We estimate the difference-in-difference specifications for the LOW tech and HIGH tech subsamples and allow the treatment effect to vary over time.

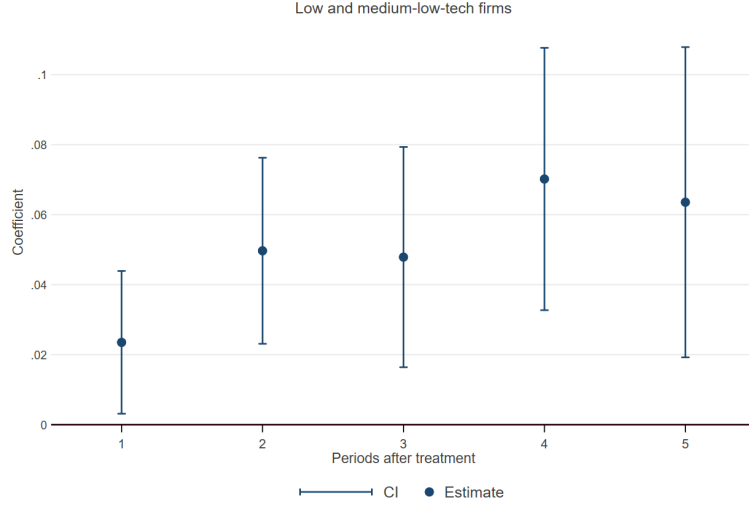
Figure 6 plots separate coefficients for each period after the treatment in the LOW subsample. We normalise the treatment time such that treatment occurs between $t = 0$ and $t = 1$. As indicated by the confidence intervals around the estimates in each year, all coefficients are highly statistically significant. Interestingly, the effect is smaller in the first period after treatment and grows in the subsequent periods. This seems intuitive, as the new equilibrium with common ownership and corresponding effects may take time to emerge.⁹ It can be seen that the 95 percent confidence interval grows larger each period. By construction, there are fewer observations available to identify the effect, the further away the time of treatment is.¹⁰

We perform the same exercise for the HIGH subsample. The reasoning remains the same as for low-tech industries. We want to rule out that the insignificant average effect is driven, for example, by significantly positive and negative effects that cancel each other out. The results for the high-tech industries are shown in Figure 7. In all periods, the confidence interval around the estimate includes zero. The point estimates do not exhibit large jumps and remain slightly above zero.

⁹Similarly, post-merger increases in rival markups also have been shown to be small shortly after the merger, but increase over time (Stiebale and Szücs, 2019).

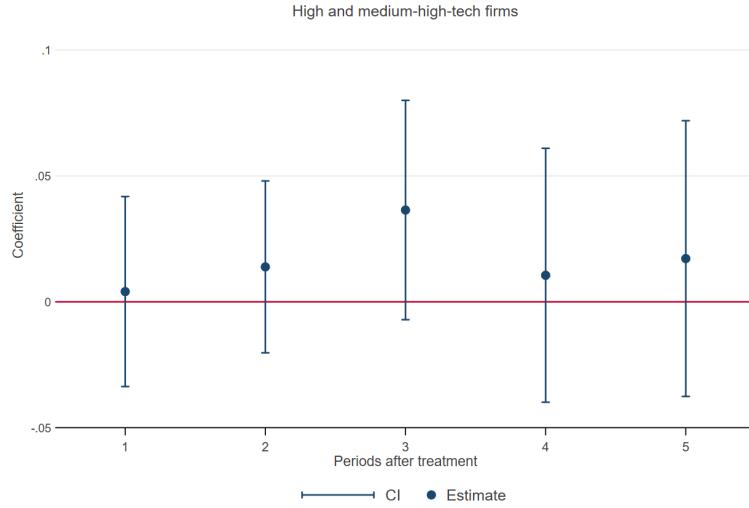
¹⁰For example, only firms that are treated in 2011 or earlier can potentially have a fifth period after treatment time.

Figure 6: Estimated treatment coefficients by post-treatment periods, LOW technology



Note: The graph plots the estimated coefficients of common ownership entry treatment indicator interacted with post-treatment period fixed effects in the low and medium-low-technology subsample, and respective confidence intervals. We control for HHI at the three-digit industry country level, the logarithm of age, share of institutional holdings, firm and year-fixed effects and cluster standard error at the three-digit industry-country level. The red line indicates zero.

Figure 7: Estimated treatment coefficients by post-treatment periods, HIGH technology



Note: The graph plots the estimated coefficients of common ownership entry treatment indicator interacted with post-treatment period fixed effects in the high and medium-high-technology subsample, and respective confidence intervals. We control for HHI at the three-digit industry country level, the logarithm of age, share of institutional holdings, firm and year-fixed effects and cluster standard error at the three-digit industry-country level. The red line indicates zero.

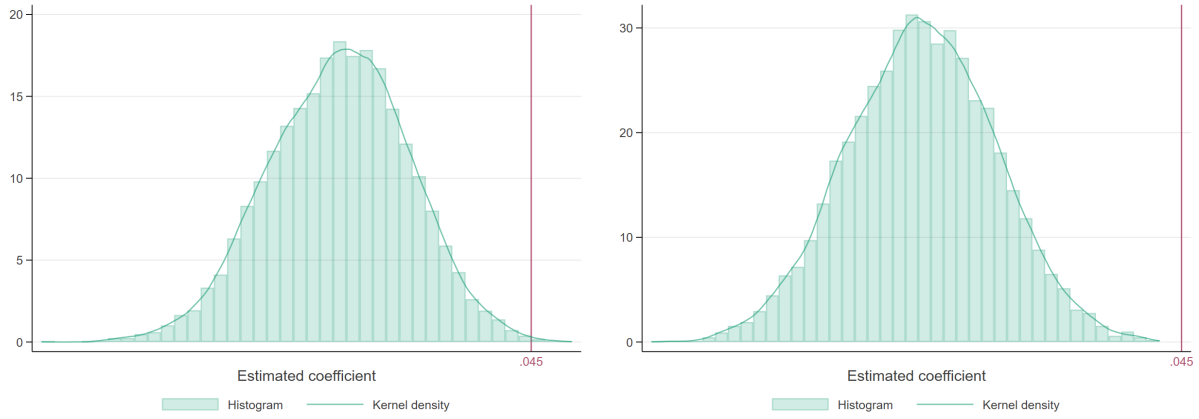
Placebo tests

One might be concerned that what we pick up as a treatment effect is actually a pre-treatment trend that differs in treatment and control group. In order to rule this out, we randomly assign treatment time, discarding the actual treatment period and all actual post-treatment years. If a pre-treatment trend was driving the regression results, it should also show in this placebo test. Another concern may be that the effects in the treatment group appear by pure chance. To address this in a second placebo test, we keep the correct treatment time to define pre-treatment and post-treatment periods, but randomly assign treatment to firms. In both tests, we repeat this 10,000 times and estimate the same difference-in-difference model for the three sample definitions as in Table 7 in each draw.

Figure 8 plots the results of the two tests for the LOW technology firms. Both graphs show that the draws yield normally-distributed coefficients with a mean of -0.015 and roughly zero and standard deviations between 0.01 and 0.02. The previously estimated coefficient with the correct definition of treatment time and treatment group is marked in red in both graphs. If we neither pick up a pre-treatment time trend nor do the estimated effects of the treatment group occur by chance, we would expect the red lines to lie far outside the distribution in both histograms. This can be confirmed in Figure 8.

We also repeat both placebo tests in the HIGH technology sample. The results of the placebo tests are plotted in Figure 9. It becomes apparent that the estimated difference-in-difference coefficient of 0.011 with the correct definition of treatment time and treatment group, outlined in red, lies relatively centered in the middle of both distributions of estimates, as expected. This reinforces our findings of a strong positive effect in LOW technology industries, and no or ambiguous effects in industries with HIGH technological capacities and possibly innovation activity.

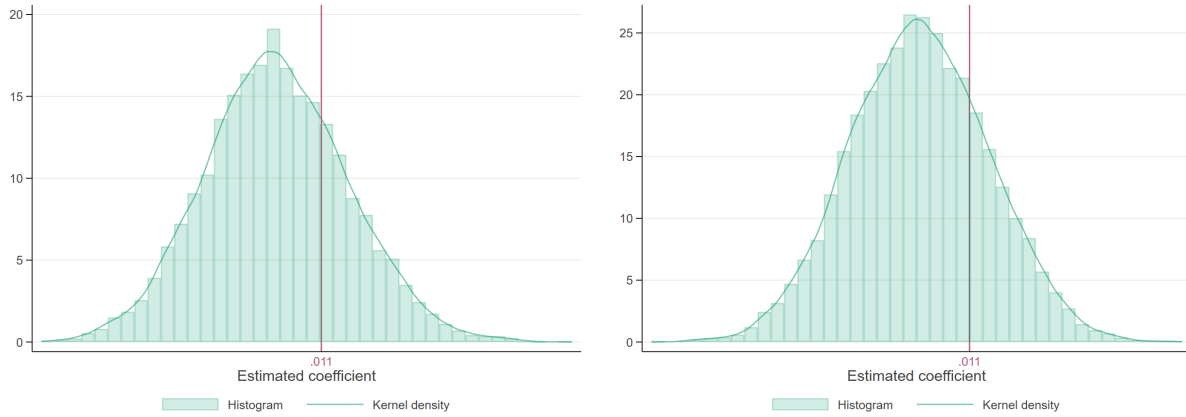
Figure 8: Placebo tests, LOW technology



a) Random assignment of treatment time b) Random assignment to treatment group

Note: The figures plot histograms of the estimated difference-in-difference coefficients of two different placebo tests in the low and medium-low-technology subsample. In Figure 8a), we randomly assign treatment time of treated firms, discarding the actual treatment period and all post-treatment years. In Figure 8b), we keep the treatment time to define pre- and post-periods, but randomly assign treatment to firms. We repeat this 10,000 times each and estimate the same difference-in-difference model for the three sample definitions as in Table 7 in each draw. The red line indicates the estimated main treatment effect in the low and medium-low-technology subsample.

Figure 9: Placebo tests, HIGH technology



a) Random assignment of treatment time b) Random assignment to treatment group

Note: The figures plot histograms of the estimated difference-in-difference coefficients of two different placebo tests in the high and medium-high-technology subsample. In Figure 9a) we randomly assign treatment time of treated firms, discarding the actual treatment period and all post-treatment years. In Figure 9b), we keep the treatment time to define pre- and post-periods, but randomly assign treatment to firms. We repeat this 10,000 times each and estimate the same difference-in-difference model for the three sample definitions as in Table 7 in each draw. The red line indicates the estimated main treatment effect in the high and medium-high-technology subsample.

4.3 Heterogeneous effects

Direct and indirect effects of common ownership

Since we define treated firms as all firms operating in a market first exposed to common ownership, we would expect different responses of firms directly or only indirectly affected by common ownership. We define directly affected firms, or insiders, as competitors in the same market which are acquired by the same institutional investor in the same period, resulting in a common ownership link between these firms. Indirectly affected firms, or outsiders, operate in the same market as these jointly held firms, but do not have any common owners and are therefore not directly linked to another rival firm. One would expect that the direct effect of common ownership on markups would be more pronounced than the indirect effect. We interact the treatment effect with two dummies indicating an insider and outsider status, and find that the positive effect of treatment on log markups differs in strength between inside and outside firms. We find no significant effect on inside firms, but a highly significant and positive effect of common ownership for outside firms in the full sample. In both classes in the LOW tech industries, common ownership shows a highly significant and positive coefficient, where the effect on insiders is stronger by around 50 percent. The first exposure to common ownership increases log markups of directly affected firms by 6.5 percent, whereas competing firms that are indirectly affected show a 4.4 percent increase in markups. We find no effect in HIGH tech firms.

Table 8: DiD regressions: Inside vs outside firms

Dep. Variable:	ln(Markups)		
	(1)	(2)	(3)
Technology	Full sample	LOW	HIGH
Treat \times Post \times Insider	0.009 (0.026)	0.065*** (0.022)	-0.080 (0.048)
Treat \times Post \times Outsider	0.032*** (0.010)	0.044*** (0.011)	0.015 (0.016)
Post	-0.016** (0.007)	-0.022** (0.009)	-0.006 (0.011)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adj. R^2	0.94	0.94	0.95
N	2743	1630	1113
Market clusters	177	100	77

Note: Standard errors in parentheses and clustered at the three-digit industry-country level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Market definition: HHI and MHHI delta calculated at the three-digit industry-country level. HHI and MHHI delta are rescaled by division by 10,000, such that the HHI ranges from 0 to 1. Sample split based on EU technology classification. LOW: Low and medium-low technology. HIGH: High and medium-high technology. Insider firms are defined as directly affected by common ownership, i.e. firms that are acquired by the same institutional investor in the same period. Outside firms are indirectly affected by common ownership, i.e. firms which operate in the same market as other jointly held firms, but do not have any common owners and are therefore not directly linked to another rival firm.

Technological Gap

We construct a within-industry measure of the technological gap between firms based on Aghion et al. (2005). Industries with a small technological gap are considered as competing in a neck-and-neck fashion, while a large technological gap represents larger dispersion between firms' cost structures. The technological spread measures the average distance in TFP to the level of TFP of the firm at the technological frontier. This firm has the highest level of TFP in the industry. Following Aghion et al. (2005), we calculate

$$m_{jt} = (TFP_{Ft} - TFP_{jt})/TFP_{Ft}, \quad (6)$$

with the frontier firm denoted by F , and the other firms denoted by j . We then calculate the average technological gap of an industry per year. Neck-and-neckness of an industry decreases in the average technological spread m_{jt} , indicating that firms get closer in terms of the technological frontier. A large technological spread m_{jt} is characteristic for industries with more laggard firms.

Interestingly, we are able to identify that the industry structure in terms of cost dispersion plays a crucial role for the magnitude of the positive effect of common ownership on markups. Table 9 shows difference-in-differences regressions where we split up the full sample, the low and medium-low, and the high and medium-high samples according to a efficiency dispersion measure. The smaller the measure, the more pronounced is neck-and-neck competition between firms. The results show that the effect of common ownership on markups is more pronounced in the neck-and-neck industries, compared to a more dispersed industry structure where we find no effects. The coefficient implies that on average, the first occurrence of common ownership links in a market increases markups by 4.5 percent. If we further split up the sample with respect to technological capacities, we find again that the effect is driven in low and medium-low-technology industries, especially with neck-and-neck competition (see Table B.4 for supporting panel fixed-effects regressions). In these industries, entry of common ownership increases average markups by 5.3 percent. Even in more dispersed industries, we find a significant increase in markups by 2.6 percent due to the exposure to common ownership. In table B.8, after using the same matched treatment and control group as for log markups, we also find a positive and statistically significant effect in the neck-and-neck industries without splitting up the sample according to technological capacities.

We find this more pronounced effect in the neck-and-neck industries economically intuitive. If firms are further away from each other in terms of costs, the degree of competition between those firms is likely to be much lower. In the limit, these firms do not compete with each other at all. For instance, in a simple perfect Bertrand setting with two firms, the more efficient firm may not even be price constrained at all by the less efficient firm and can set its

price at monopoly level. If the cost of the less efficient firm is below the monopoly price of the efficient firm, the efficient firm will match its price to the costs of the less efficient firm. A full merger in this setting results in monopoly prices, but the price level in this case may not change a lot if firms are technologically far away from each other. The same reasoning applies to a simple Cournot setting with two firms and heterogeneous costs. In the limit of diverging costs, the more efficient firm will set its quantities close to the monopoly quantity. Also here a full merger would not change the total quantity and thus the equilibrium price much.

Table 9: Treatment Effects (ln(Markup): Efficiency dispersion split

	Dependent Variable: ln(Markups)					
	Full sample		LOW		HIGH	
	(1)	(2)	(3)	(4)	(5)	(6)
Technological gap	Neck-and-neck	Dispersed	Neck-and-neck	Dispersed	Neck-and-neck	Dispersed
Treat \times Post	0.045*** (0.013)	0.011 (0.012)	0.053*** (0.016)	0.026* (0.015)	0.015 (0.032)	-0.002 (0.018)
Post	-0.021* (0.013)	-0.005 (0.011)	-0.027 (0.016)	-0.005 (0.011)	-0.011 (0.018)	-0.004 (0.015)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.94	0.96	0.94	0.95	0.92	0.96
N	1306	1315	951	630	355	684
Market clusters	109	109	73	54	36	55

Note: Standard errors in parentheses and clustered at the three-digit industry-country level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Market definition: HHI and MHHI delta calculated at the three-digit industry-country level. HHI and MHHI delta are rescaled by division by 10,000, such that the HHI ranges from 0 to 1. Sample split based on EU technology classification. LOW: Low and medium-low technology. HIGH: High and medium-high technology.

4.4 Innovation

We also identify a treatment effect on the logarithm of patent citations in a linear difference-in-differences model. Since innovation acts more as an additional strategic variable in industries that are classified as HIGH technology compared to LOW technology industries, we expect to find more pronounced effects of common ownership on innovation outcomes

in firms with higher technological capacities. Table 10 displays the difference-in-difference estimation results on the matched sample. While the full and the LOW technology samples do not show significant results in columns 1 to 6, the treatment effect in the HIGH technology firms is positive and significant including firm, year and year-country or year-two-digit industry fixed effects in columns 8 and 9, respectively. Allowing for time-heterogeneous trends, treatment induces average patent citations to increase between 15.1 and 17.8 percent in these industries. This result is consistent with the Poisson and OLS regressions from the baseline results and follows the theoretical predictions in López and Vives (2019).

Table 10: Treatment Effects: $\ln(\text{Patent citations})$

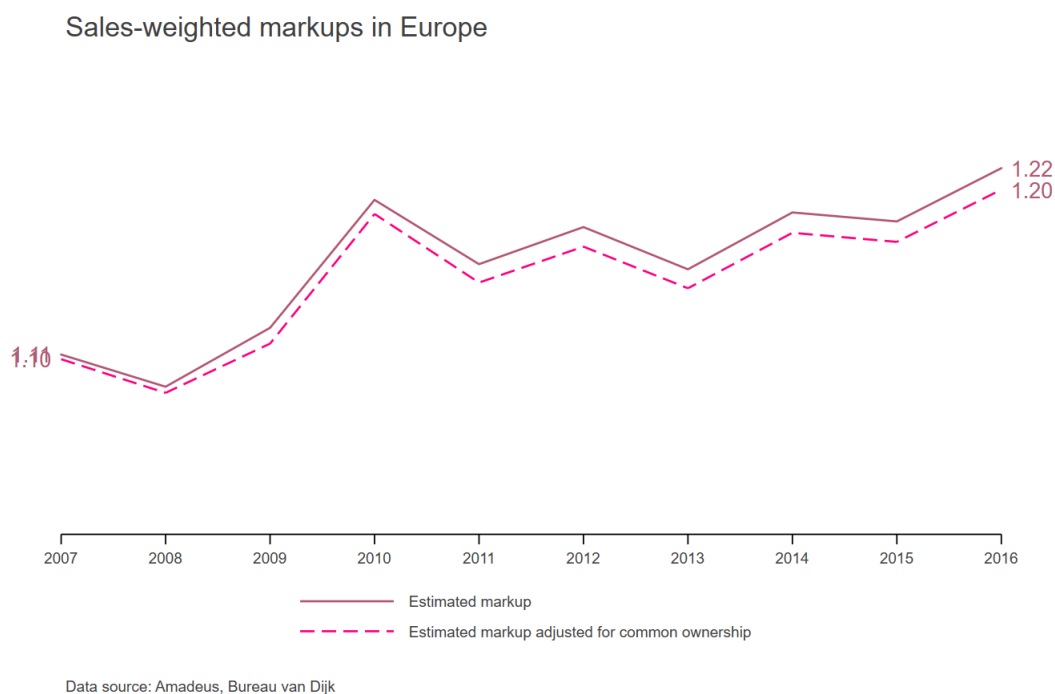
Technology	Dependent Variable: $\ln(\text{Patent citations})$								
	Full sample			LOW			HIGH		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treat \times Post	0.019 (0.045)	0.060 (0.045)	0.044 (0.054)	-0.058 (0.041)	-0.017 (0.053)	-0.068 (0.053)	0.147 (0.090)	0.178** (0.077)	0.151* (0.088)
Post	-0.016 (0.037)	-0.023 (0.040)	0.007 (0.040)	0.029 (0.039)	0.030 (0.046)	0.065 (0.046)	-0.090 (0.071)	-0.112 (0.083)	-0.072 (0.073)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	Yes	No	No	Yes	No	No
Year-Country FE	No	Yes	No	No	Yes	No	No	Yes	No
Year-NACE2 FE	No	No	Yes	No	No	Yes	No	No	Yes
Adj. R^2	0.70	0.70	0.71	0.64	0.63	0.65	0.73	0.71	0.73
N	3813	3795	3810	2251	2206	2243	1562	1549	1552
Market clusters	182	181	182	103	98	103	79	77	78

Note: Standard errors in parentheses and clustered at the three-digit industry-country level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Market definition: HHI and MHHI delta calculated at the three-digit industry-country level. HHI and MHHI delta are rescaled by division by 10,000, such that the HHI ranges from 0 to 1. Sample split based on EU technology classification. LOW: Low and medium-low technology. HIGH: High and medium-high technology.

4.5 Counterfactual markups

After having identified the treatment effect of common ownership entry on markups, we can construct the evolution of sales-weighted average markups absent common ownership. The counterfactual is depicted as the dotted line “Markups adjusted for common ownership” in Figure 10. For this purpose, we deduct the treatment effect of 3.1 percent of a firm’s estimated markup, if common ownership links exist in that firm’s respective market. It becomes apparent that a part of the rising trend in markups can be attributed to increases due to common ownership.

Figure 10: Markups adjusted for common ownership



Note: The figure illustrates the evolution of the average markup from 2007 to 2016. Markups are estimated using European accounting data from the Amadeus data base by Bureau van Dijk and the method proposed by De Loecker and Warzynski (2012), relying on production function elasticities from the Akerberg et al. (2015) procedure. The average is sales-weighted. The dotted line “Estimated markup adjusted for common ownership” is the counterfactual average sales-weighted markup that we calculate from estimated markups in the absence of common ownership.

5 Conclusion

This paper analyses the relationship of common ownership, markups, and innovation using a broad manufacturing sample in Europe, including both listed and non-listed firms. We use balance sheet variables to estimate firm-level productivity, recover markups, and construct a measure of common ownership using detailed firm ownership information. As an additional outcome, citation-weighted patents measure the innovation output of firms. Using an industry classification by the European Commission (2019), we distinguish between effects in industries characterised by low and high technological capabilities. We combine propensity score matching with a difference-in-differences estimator to estimate the effect of common ownership on markups. By defining treatment based on the first exposure of a market to common ownership, we shift the focus away from a commonly used, but also criticised measure of common ownership.

We find a positive effect of common ownership on markups that is driven by firms classified as low and medium-low technology. These results are consistent with theoretical predictions of a pronounced cartelisation effect of common ownership in industries with low technological spillovers. Analysing the effect within low-technology markets affected by common ownership, we find that while both the markups of commonly firms held as well as their rivals increase, firms held in common ownership portfolios exhibit a more pronounced increase. Industry structure also plays a main role for the size of the effect. We find that in industries where firms compete in a more neck-and-neck fashion, the effect is the largest, compared to a more dispersed industry structure. This paper suggests that part of the rising markups pattern observed in many industries and countries can be explained by the rise in common ownership.

Our findings also help to shed light on the ambiguous effects of common ownership on markups and innovation. While a large part of the literature has focused on anti-competitive implications, our results contribute to a further disambiguation of the influence of common ownership structures. Pro-competitive effects can be found in industries that are charac-

terised by higher technological spillovers, supporting the theoretical predictions by López and Vives (2019). In these industries, common ownership leads to an increase in patent citations.

Our findings have direct policy implications for competition authorities. First, common ownership may have economically meaningful anti-competitive effects for the entire industry. In the future, regulations on the degree of common ownership may be required to tackle this issue. Second, when competition authorities are confronted with mergers between institutional investors, portfolio firms of the parties have to be carefully analysed, as the merger could lead to more common ownership. Our results suggest that especially in low and medium-low-tech industries, divestitures of portfolio firms may be required to prevent markups to rise as a by-product of the merger. On the other hand we observe a larger innovation activity induced by common ownership in high and medium-high-tech industries.

Appendices

A Technology Classification

According to the definition of the European Commission, NACE 2-digit and 3-digit industries are grouped into the following technology classes as can be seen in Table A.1.

Table A.1: Technology classification

NACE 2 digit	NACE 3 digit	Description
<i>High-technology</i>		
21		Basic pharmaceutical products and pharmaceutical preparations
26		Computer, electronic and optical products
	30.3	Air and spacecraft and related machinery
<i>Medium-high-technology</i>		
20		Chemicals and chemical products
	25.4	Weapons and ammunition
27		Electrical equipment
28		Machinery and equipment not elsewhere classified
29		Motor vehicles, trailers and semi-trailers
30	(excl. 30.1, 30.3)	Other transport equipment
	32.5	Medical and dental instruments and supplies
<i>Medium-low-technology</i>		
19		Coke and refined petroleum products
22		Rubber and plastic products
23		Other non-metallic mineral products
24		Basic metals
25	(excl. 25.4)	Fabricated metal products, except machinery and equipment
	30.1	Building of ships and boats
<i>Low-technology</i>		
10		Food products
11		Beverages
12		Tobacco products
13		Textiles
14		Wearing apparel
15		Leather and related products
16		Wood and products of wood and cork
17		Paper and paper products
31		Furniture
32	(excl. 32.5)	Other manufacturing

B Tables

B.1 Robustness of main results

Heterogeneous time trends

In Table B.2, we account for time-heterogeneous trends by adding more fixed effects to the models, using the same three sample definitions as before. Columns (1), (3), and (5) add year-country fixed effects, and columns (2), (4), and (6) include additional year-two-digit industry fixed effects. In both cases, the results yield highly significant effects of common ownership on markups in the full sample and the LOW technology sample, slightly smaller in magnitude in the cases with year-two-digit industry fixed effects.

Table B.2: Treatment effects: Additional FE

Technology	Dependent Variable: $\ln(\text{Markups})$					
	Full sample		LOW		HIGH	
	(1)	(2)	(3)	(4)	(5)	(6)
Treat \times Post	0.037*** (0.011)	0.024** (0.011)	0.042*** (0.014)	0.031** (0.013)	0.024 (0.019)	0.013 (0.018)
Post	-0.019** (0.008)	-0.020*** (0.008)	-0.023** (0.010)	-0.027*** (0.009)	-0.009 (0.011)	-0.008 (0.011)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Country FE	Yes	No	Yes	No	Yes	No
Year-NACE2 FE	No	Yes	No	Yes	No	Yes
Adj. R^2	0.94	0.95	0.94	0.94	0.95	0.95
N	2718	2732	1593	1614	1101	1100
Market clusters	171	177	93	100	75	76

Note: Standard errors in parentheses and clustered at the three-digit industry-country level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Market definition: HHI and MHHI delta calculated at the three-digit industry-country level. HHI and MHHI delta are rescaled by division by 10,000, such that the HHI ranges from 0 to 1. Sample split based on EU technology classification. LOW: Low and medium-low technology. HIGH: High and medium-high technology.

Table B.3: Treatment Effects (ln(Markup): Efficiency dispersion split, individual cutoff values

	Dependent Variable: ln(Markups)					
	Full sample		LOW		HIGH	
	(1)	(2)	(3)	(4)	(5)	(6)
Technological gap	Neck-and-neck	Dispersed	Neck-and-neck	Dispersed	Neck-and-neck	Dispersed
Treat \times Post	0.045*** (0.013)	0.011 (0.012)	0.039** (0.019)	0.014 (0.016)	0.023 (0.031)	-0.016 (0.020)
Post	-0.021* (0.013)	-0.005 (0.011)	-0.053*** (0.015)	0.001 (0.009)	0.005 (0.014)	0.003 (0.017)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.94	0.96	0.94	0.95	0.93	0.96
N	1306	1315	801	779	527	531
Market clusters	109	109	60	67	50	44

Note: Standard errors in parentheses and clustered at the three-digit industry-country level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Market definition: HHI and MHHI delta calculated at the three-digit industry-country level. HHI and MHHI delta are rescaled by division by 10,000, such that the HHI ranges from 0 to 1. Sample split based on EU technology classification. LOW: Low and medium-low technology. HIGH: High and medium-high technology.

B.2 More correlation evidence

Table B.4: Baseline regressions ($\ln(\text{Markup})$): Efficiency dispersion split

	Dependent Variable: $\ln(\text{Markups})$					
	Full sample		LOW		HIGH	
	(1)	(2)	(3)	(4)	(5)	(6)
Technological gap	Neck-and-neck	Dispersed	Neck-and-neck	Dispersed	Neck-and-neck	Dispersed
MHHI delta	0.085 (0.086)	-0.009 (0.023)	0.137*** (0.049)	0.004 (0.041)	-0.134 (0.114)	-0.020 (0.014)
HHI	-0.001 (0.032)	0.073 (0.057)	-0.038 (0.046)	0.226** (0.114)	0.001 (0.051)	0.075 (0.059)
$\ln(\text{Age})$	0.016 (0.028)	-0.017 (0.024)	0.043* (0.025)	0.009 (0.038)	-0.081* (0.041)	-0.035 (0.032)
Inst. Holdings	0.023 (0.018)	-0.034** (0.017)	0.058** (0.027)	-0.040 (0.026)	-0.031 (0.022)	-0.013 (0.023)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.94	0.96	0.95	0.95	0.94	0.96
N	8463	8537	4190	4224	4168	4182
Market clusters	471	328	258	224	220	163

Note: Standard errors in parentheses and clustered at the three-digit industry-country level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Market definition: HHI and MHHI delta calculated at the three-digit industry-country level. HHI and MHHI delta are rescaled by division by 10,000, such that the HHI ranges from 0 to 1. Sample split based on EU technology classification. LOW: Low and medium-low technology. HIGH: High and medium-high technology.

B.3 Level markups

DiD

Table B.5: Propensity score and DiD regressions

	Dependent Variable: Markups		
	Full sample	Technology split	
	(1) Full sample	(2) LOW	(3) HIGH
Treat \times Post	0.044** (0.020)	0.050** (0.023)	0.033 (0.037)
Post	-0.018 (0.014)	-0.022 (0.020)	-0.009 (0.016)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adj. R^2	0.92	0.91	0.93
N	2743	1630	1113
Market clusters	177	100	77

Note: Standard errors in parentheses and clustered at the three-digit industry-country level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Market definition: HHI and MHHI delta calculated at the three-digit industry-country level. HHI and MHHI delta are rescaled by division by 10,000, such that the HHI ranges from 0 to 1. Sample split based on EU technology classification. LOW: Low and medium-low technology. HIGH: High and medium-high technology.

Inside firms

Table B.6: Propensity score and DiD regressions: Inside firms

Technology	Dependent Variable: Markups		
	Full sample	Technology split	
	(1) Full sample	(2) LOW	(3) HIGH
Treat \times Post \times Insider	-0.002 (0.035)	0.070*** (0.022)	-0.117 (0.077)
Treat \times Post \times Outsider	0.046** (0.021)	0.049** (0.024)	0.040 (0.039)
Post	-0.018 (0.014)	-0.022 (0.020)	-0.010 (0.016)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adj. R^2	0.92	0.91	0.93
N	2743	1630	1113
Market clusters	177	100	77

Note: Standard errors in parentheses and clustered at the three-digit industry-country level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Market definition: HHI and MHHI delta calculated at the three-digit industry-country level. HHI and MHHI delta are rescaled by division by 10,000, such that the HHI ranges from 0 to 1. Sample split based on EU technology classification. LOW: Low and medium-low technology. HIGH: High and medium-high technology.

Technological gap

Table B.7: Baseline regressions: Efficiency dispersion split

	Dependent Variable: Markups					
	Full sample		LOW		HIGH	
	(1)	(2)	(3)	(4)	(5)	(6)
Technological gap	Neck-and-neck	Dispersed	Neck-and-neck	Dispersed	Neck-and-neck	Dispersed
MHHI delta	0.098 (0.103)	0.014 (0.056)	0.184*** (0.058)	0.058 (0.058)	-0.220 (0.197)	0.014 (0.066)
HHI	0.008 (0.047)	0.098 (0.102)	-0.053 (0.062)	0.363 (0.237)	0.042 (0.094)	0.070 (0.123)
ln(Age)	0.016 (0.058)	0.008 (0.041)	0.026 (0.042)	0.112 (0.104)	-0.122* (0.067)	-0.054 (0.065)
Inst. Holdings	0.050* (0.028)	-0.058* (0.034)	0.101** (0.048)	-0.040 (0.041)	-0.015 (0.025)	-0.045 (0.047)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.94	0.94	0.93	0.90	0.93	0.97
N	8463	8537	4190	4224	4168	4182
Market clusters	471	328	258	224	220	163

Note: Standard errors in parentheses and clustered at the three-digit industry-country level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Market definition: HHI and MHHI delta calculated at the three-digit industry-country level. HHI and MHHI delta are rescaled by division by 10,000, such that the HHI ranges from 0 to 1. Sample split based on EU technology classification. LOW: Low and medium-low technology. HIGH: High and medium-high technology.

Table B.8: Treatment Effects: Efficiency dispersion split

	Dependent Variable: Markups					
	Full sample		LOW		HIGH	
	(1)	(2)	(3)	(4)	(5)	(6)
Technological gap	Neck-and-neck	Dispersed	Neck-and-neck	Dispersed	Neck-and-neck	Dispersed
Treat \times Post	0.073*** (0.020)	-0.006 (0.028)	0.065** (0.030)	-0.031 (0.028)	0.058 (0.073)	-0.017 (0.033)
Post	-0.046** (0.021)	0.014 (0.025)	-0.089*** (0.029)	0.033 (0.033)	0.003 (0.024)	0.003 (0.026)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.94	0.92	0.93	0.90	0.88	0.96
N	1306	1315	801	779	527	531
Market clusters	109	109	60	67	50	44

Note: Standard errors in parentheses and clustered at the three-digit industry-country level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Market definition: HHI and MHHI delta calculated at the three-digit industry-country level. HHI and MHHI delta are rescaled by division by 10,000, such that the HHI ranges from 0 to 1. Sample split based on EU technology classification. LOW: Low and medium-low technology. HIGH: High and medium-high technology.

B.4 Innovation

The zero-inflated Poisson model in Table B.9 shows a positive effect of MHHI delta on the number of patent citations in the full sample, a large and negative significant effect in the low and medium-low-tech industries, and a positive effect in the medium-high and high-tech sample. All coefficients are statistically significant. In the full sample, the equation modelling whether the count is zero is significant in parameters for the logarithm of age and TFP, the indicator for pre-sample citations and average number of pre-sample citations.

The last Table B.11 reports a Poisson model, splitting all three samples according to the median technological gap. Common ownership shows a positive significant association with innovation in the full sample and the high-tech sample, only in industries that are more dispersed in terms of efficiency.

Table B.9: Zero-inflated Poisson model: Patent citations

Technology	Dependent Variable: Patent citations		
	Full sample	Technology split	
	(1) Full sample	(2) LOW	(3) HIGH
NumPatCite			
MHHI delta	1.626** (0.743)	-4.413* (2.510)	1.580* (0.819)
HHI	1.125* (0.652)	-0.365 (1.172)	1.281** (0.640)
1–Lerner	-1.653* (0.891)	-1.345 (1.119)	-1.553 (1.021)
Capital intensity	-17.881** (6.999)	-9.934*** (1.937)	-18.957** (8.049)
Inst. Holdings	0.393 (0.912)	-0.797*** (0.205)	0.572 (0.997)
Publicly quoted	1.094** (0.429)	-0.239 (0.271)	1.197*** (0.442)
inflate			
ln(Age)	0.075 (0.057)	0.064 (0.106)	0.034 (0.072)
ln(TFP)	0.512** (0.219)	0.230 (0.317)	0.037 (0.463)
Avg. market sales	0.079 (0.097)	0.135 (0.149)	0.093 (0.126)
No pre-sample cites	1.686*** (0.142)	1.651*** (0.193)	1.570*** (0.196)
Avg. pre-sample cites	-0.595*** (0.052)	-0.730*** (0.079)	-0.531*** (0.067)
Year FE	Yes	Yes	Yes
NACE 2 digit FE	Yes	Yes	Yes
N	17717	8874	8843
Zero	15042	8092	6950
Market clusters	280	179	114

Note: Standard errors in parentheses and clustered at the two-digit industry-country level. * p<0.10, ** p<0.05, *** p<0.01 Market definition: HHI and MHHI delta calculated at the three-digit industry-country level. HHI and MHHI delta are rescaled by division by 10,000, such that the HHI ranges from 0 to 1. Sample split based on EU technology classification. LOW: Low and medium-low technology. HIGH: High and medium-high technology.

Table B.10: Linear and Poisson model: Patent citations

Dep. Variable:	ln(Patent citations)			Patent citations		
	Linear model			Poisson model		
	(1) Full sample	(2) LOW	(3) HIGH	(4) Full sample	(5) LOW	(6) HIGH
Technology						
MHHI delta \times Insider	0.628*** (0.154)	-0.773 (0.525)	0.839*** (0.212)	1.483*** (0.524)	-4.410 (6.558)	1.395** (0.564)
MHHI delta \times Outsider	-0.071 (0.071)	0.221** (0.090)	0.035 (0.153)	-1.322 (1.633)	-1.835 (1.783)	-0.954 (1.432)
insider	0.055 (0.129)	-0.157** (0.069)	0.156 (0.173)	-1.073* (0.611)	-0.709 (0.782)	-0.985 (0.681)
outsider	0.067 (0.046)	-0.061* (0.031)	0.146*** (0.055)	-0.011 (0.093)	-0.469** (0.209)	0.037 (0.106)
HHI \times Insider	-0.359 (0.549)	0.676 (0.414)	-0.959 (0.680)	1.325* (0.756)	5.990*** (1.353)	1.037 (0.869)
HHI \times Outsider	-0.284 (0.187)	0.096 (0.149)	-0.540*** (0.201)	-0.185 (0.418)	0.044 (0.873)	-0.374 (0.429)
HHI	-0.071 (0.110)	-0.088 (0.088)	-0.082 (0.180)			
1-Lerner	-0.004 (0.053)	0.005 (0.036)	-0.039 (0.104)	-0.731* (0.411)	-0.647 (0.792)	-0.527 (0.445)
Avg. market sales	-0.020 (0.023)	0.015 (0.020)	-0.033 (0.035)	0.556*** (0.144)	0.286 (0.250)	0.537*** (0.165)
ln(TFP)	-0.098 (0.158)	-0.188 (0.193)	-0.062 (0.234)	0.129 (0.787)	-1.003 (0.826)	0.488 (0.927)
Capital intensity	0.023 (0.177)	-0.182 (0.190)	0.078 (0.230)	-9.392* (5.626)	-6.624 (4.510)	-10.027 (6.477)
ln(Age)	0.217*** (0.078)	0.128** (0.063)	0.332** (0.132)	-0.015 (0.110)	0.023 (0.093)	-0.011 (0.138)
Inst. Holdings	-0.005 (0.044)	-0.011 (0.039)	-0.008 (0.081)	0.643 (0.585)	-0.728*** (0.252)	0.800 (0.598)
Publicly quoted				-0.041 (0.240)	0.127 (0.524)	-0.041 (0.275)
No pre-sample cites				0.064 (0.353)	-0.901*** (0.232)	0.372 (0.390)
Avg. pre-sample cites				0.914*** (0.096)	0.937*** (0.089)	0.906*** (0.105)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	No	No	No
NACE 2 digit FE	No	No	No	Yes	Yes	Yes
Country FE	No	No	No	Yes	Yes	Yes
N	17717	8874	8843	17717	8874	8843
Market clusters	280	179	114	280	179	114

Note: Standard errors in parentheses and clustered at the two-digit industry-country level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Market definition: HHI and MHHI delta calculated at the three-digit industry-country level. HHI and MHHI delta are rescaled by division by 10,000, such that the HHI ranges from 0 to 1. Sample split based on EU technology classification. LOW: Low and medium-low technology. HIGH: High and medium-high technology.

Table B.11: Poisson model: Efficiency diversion split

	Dependent Variable: Patent citations					
	Full sample		LOW		HIGH	
	(1)	(2)	(3)	(4)	(5)	(6)
Technological gap	Neck-and-neck	Dispersed	Neck-and-neck	Dispersed	Neck-and-neck	Dispersed
MHHI delta	-0.171 (1.632)	0.760** (0.359)	-1.541 (2.923)	-1.076 (1.809)	1.666 (1.540)	0.702** (0.336)
HHI	0.110 (0.500)	0.626 (0.419)	-1.205* (0.728)	0.391 (1.156)	0.393 (0.272)	0.514 (0.421)
1–Lerner	-0.361 (0.472)	-1.036* (0.557)	-2.020** (1.021)	-0.664 (0.717)	-0.168 (0.471)	-0.970 (0.805)
Avg. market sales	0.549*** (0.209)	0.644*** (0.130)	1.175*** (0.289)	-0.160 (0.239)	0.251 (0.206)	0.791*** (0.164)
ln(TFP)	0.817 (0.828)	0.037 (0.758)	-0.974 (0.653)	-0.405 (1.156)	2.401*** (0.630)	-0.791 (0.811)
Capital intensity	-12.774** (5.950)	-7.703 (5.590)	-7.303** (3.687)	-6.895 (7.772)	-11.742* (6.264)	-8.783 (6.105)
ln(Age)	-0.071 (0.093)	-0.063 (0.133)	-0.123 (0.158)	0.238 (0.201)	0.020 (0.140)	-0.231* (0.134)
Inst. Holdings	0.658 (0.704)	0.522 (0.544)	-0.390 (0.299)	-0.833*** (0.274)	0.746 (0.752)	0.728 (0.535)
Publicly quoted	-0.863*** (0.257)	0.012 (0.229)	-0.335 (0.486)	0.193 (0.677)	-0.532* (0.291)	-0.037 (0.191)
No pre-sample cites	-0.025 (0.467)	0.060 (0.340)	-0.776*** (0.238)	-1.094** (0.442)	0.359 (0.452)	0.222 (0.418)
Avg. pre-sample cites	0.962*** (0.098)	0.876*** (0.065)	0.862*** (0.086)	0.943*** (0.106)	0.936*** (0.090)	0.888*** (0.078)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
NACE 2 digit FE	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
N	8822	8895	4448	4426	4457	4386
Market clusters	228	208	145	146	102	98

Note: Standard errors in parentheses and clustered at the two-digit industry-country level. * p<0.10, ** p<0.05, *** p<0.01 Market definition: HHI and MHHI delta calculated at the three-digit industry-country level. HHI and MHHI delta are rescaled by division by 10,000, such that the HHI ranges from 0 to 1. Sample split based on EU technology classification. LOW: Low and medium-low technology. HIGH: High and medium-high technology.

C Additional Figures

Figure C.1: Common ownership and markups, medium-low and low-tech sample

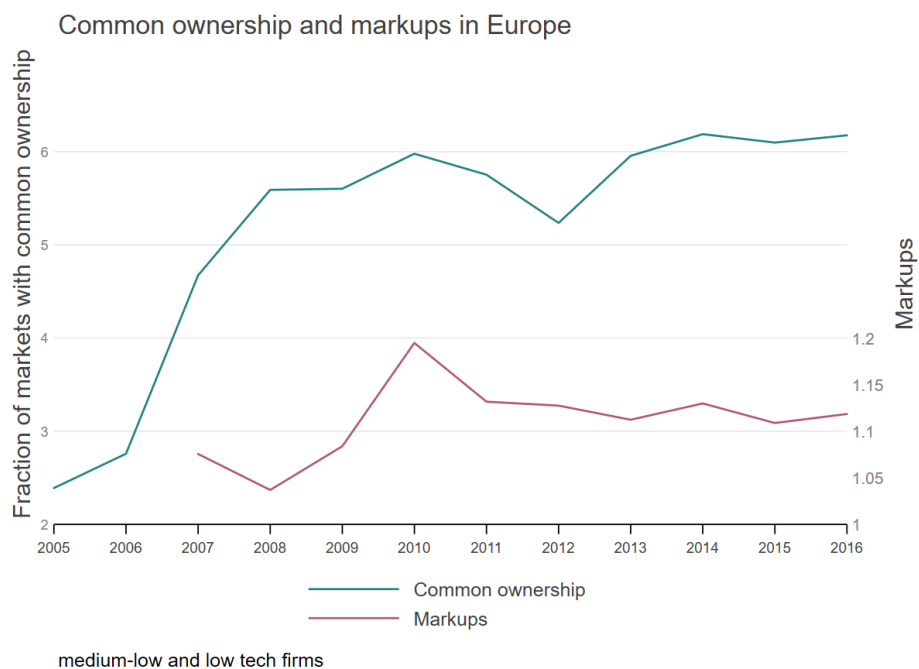


Figure C.2: Markups by technology category

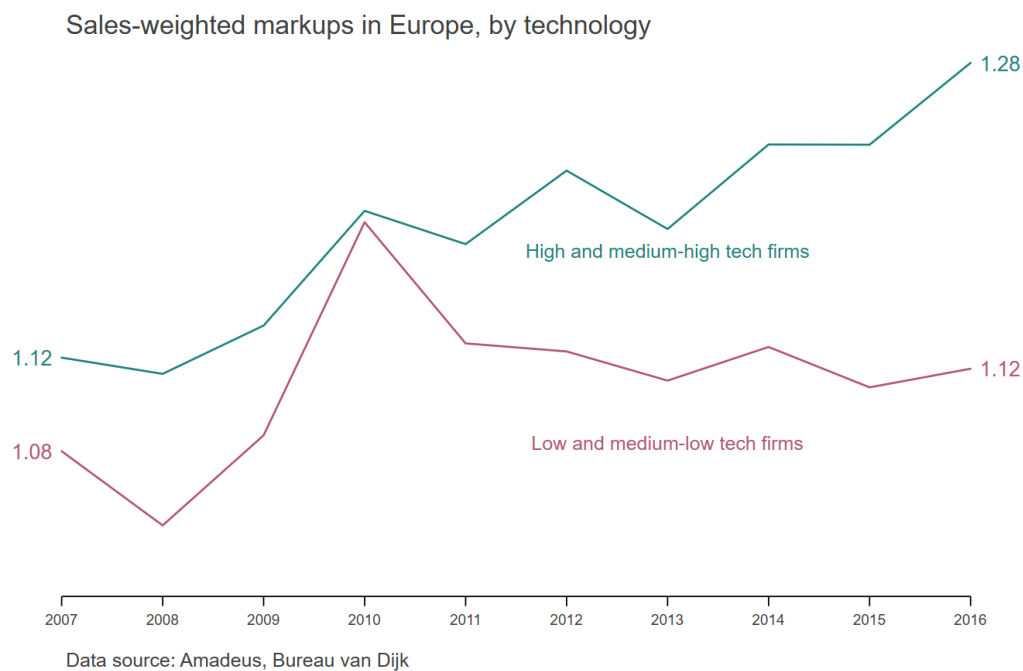
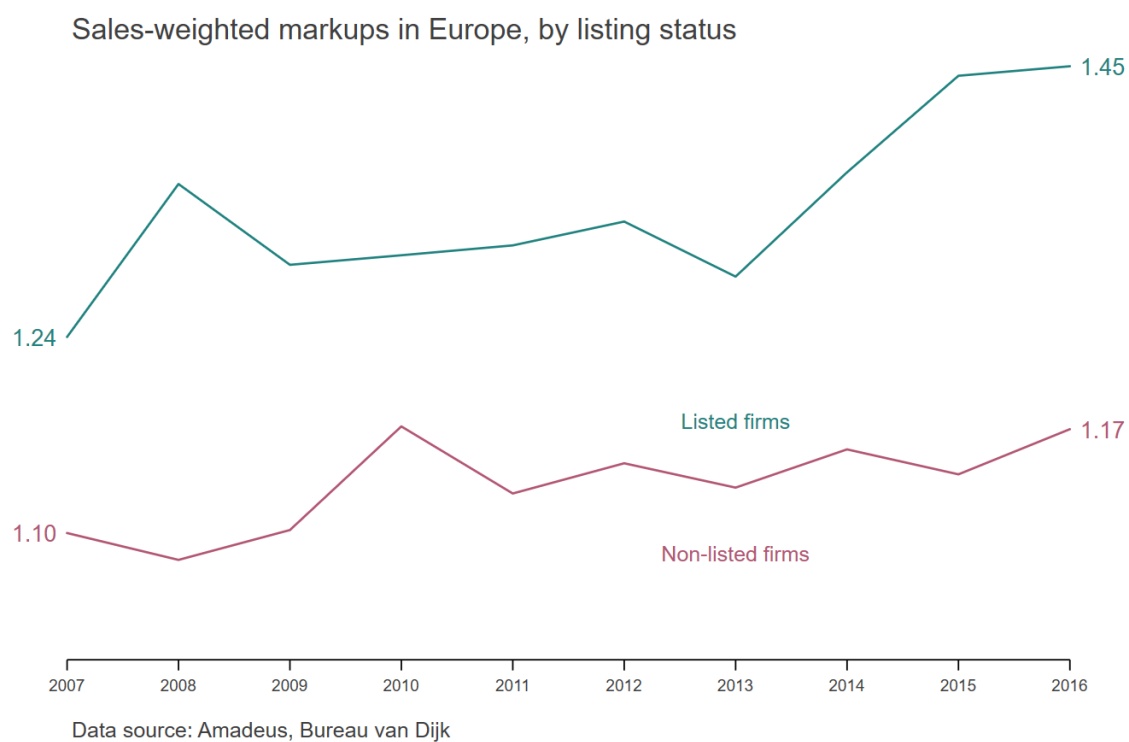


Figure C.3: Markups, by listing status



D Formal Methods

D.1 Pooled Industries

For estimation of output elasticities, nine subsets of the data were regarded separately, pooling the NACE 2-digit codes detailed in Table D.12.

Table D.12: Pooled 2-digit industries

NACE 2-digit code	Industries
10, 11, 12	Food, beverages, tobacco
13, 14, 15	Textiles, wearing apparel, leather
16, 17, 18	Wood, paper, print
19, 20, 21	Coke, chemicals, pharmaceuticals
22, 23	Rubber, plastic, minerals
24, 25	Basic, fabricated metals
26, 27	Computer, electronic, electrical eq.
28, 29, 30	Machinery, motor, transport
31, 32, 33	Furniture, other manufacturing

D.2 Production Function Estimation

Productivity

Estimation of markups relies on preceding estimation of TFP using the procedure proposed by Akerberg et al. (2015). A Cobb-Douglas technology accounts for substitutability of inputs. A logarithmic specification of this production function is chosen for the estimation of output elasticities. The production function for firm j at time t is designed with the inputs capital k_{jt} , labour l_{jt} , materials m_{jt} , unobserved productivity ω_{jt} , and a measurement error ϵ_{jt} , such that

$$q_{jt} = \beta_0 + \beta_k k_{jt} + \beta_l l_{jt} + \beta_m m_{jt} + \omega_{jt} + \epsilon_{jt} \quad (7)$$

The underlying assumption of using these production functions is that firms maximise profits with respect to the input factors employed for production (Marschak and Andrews,

1944). Firms make investments to accumulate capital with the prospect of maximising future discounted cash flows (Olley and Pakes, 1996). Also, firms decide on quantities of labour and materials to maximise short-run profits (Doraszelski and Jaumandreu, 2013; Akerberg et al., 2015). The endogeneity problem due to the correlation of input factors and the unobserved productivity term (Marschak and Andrews, 1944) is accounted for with the control function estimator by Akerberg et al. (2015).

A first stage corrects for measurement error by predicting the output variable without identifying any coefficients of the production function due to the functional dependence of productivity on inputs. Predicted values of output are obtained from an OLS regression, where inverted material input demand is included in the production function, incorporating input factors labour and capital and their squared terms to approximate the function for unobserved productivity. Further control variables are MHHI delta, firm age, number of institutional investors, a dummy variable for listing status, and four-digit industry, country, and year fixed effects. The MHHI delta is calculated at the NACE three-digit industry and country level

$$\begin{aligned} q_{jt} &= \beta_0 + \beta_k k_{jt} + \beta_l l_{jt} + \beta_m m_{jt} + \tilde{f}_t^{-1}(k_{jt}, l_{jt}, m_{jt}) + \epsilon_{jt} \\ &= \hat{\Phi}_t(k_{jt}, l_{jt}, m_{jt}) + \epsilon_{jt}. \end{aligned} \tag{8}$$

After eliminating the measurement error in output by predicting fitted values, a common problem in productivity estimation remains the occurrence of measurement errors in the input variables. Collard-Wexler and De Loecker (2016, CWDL) discuss especially the problem of measurement error in the input factor capital, which can result in production function estimations suffering from possibly biased and attenuated capital coefficients. We employ their extension as productivity estimation within the scope of this paper relies on accounting data. In this case, lagged investment can be used to instrument for current capital, since it contains information about values of current capital. One caveat in using this particular

data set is that no information on firm-level investments in tangible fixed assets is available explicitly. The investment values have to be calculated from the data using the capital book values and recorded depreciation using the perpetual inventory method. Although it is calculated from mismeasured capital book values, investment serves to eliminate cross-sectional variation in the measurement error. Investment decided in period $t - 1$ becomes productive in period t (Doraszelski and Jaumandreu, 2013), and is therefore calculated as

$$investment_{jt} = tfa_{jt} - tfa_{jt-1} + depr_{jt} \cdot \frac{tfa_{jt}}{fa_{jt}}$$

where tfa_{jt} is the stock of tangible fixed assets of firm j at t , $depr_{jt}$ measures total depreciation and amortisation of fixed assets, and fa_{jt} denotes total fixed assets. $depr_{jt}$ measures both depreciation of tangible assets as well as amortisation of intangible assets. Therefore, it is multiplied with the ratio of tangible assets to total fixed assets. Following CWDL, a two-stage least squares regression, using first and second lags of investment and their squared terms as instruments for capital, is conducted to obtain predicted values of output net of measurement error, $\hat{\Phi}_{jt}$.

Afterwards, the optimisation routine by Collard-Wexler and De Loecker (2016) estimates output elasticities for nine subsets of the manufacturing industry. A second OLS regression of $q_{jt} = \beta_k k_{jt} + \beta_l l_{jt} + \beta_m m_{jt}$ is conducted to obtain initial values for input coefficients. These values are used to obtain preliminary estimates of empirically unobserved productivity ω_{jt} as the difference, i.e. as a residual, of production net of the measurement error and the coefficients of the second OLS regressions multiplied with the input factors

$$\omega_{jt} = \hat{\Phi}_{jt} - \hat{\beta}_k k_{jt} - \hat{\beta}_l l_{jt} - \hat{\beta}_m m_{jt}.$$

The serial correlation of productivity over time is modelled as a controlled first order Markov process (Hopenhayn and Rogerson, 1993). The estimation also explicitly allows for common ownership to impact future productivity in an endogenous process. Such factors

can be included in the process if a firm anticipates their influence on future productivity and therefore future revenues by either reducing production costs or increasing demand, whereas unforeseen effects would enter the error term ξ_{jt} (De Loecker, 2013). In the present case, the MHHI delta at the three-digit industry country level is included in the law of motion of productivity

$$\omega_{jt} = g(\omega_{jt-1}, CO_{jt-1}) + \xi_{jt} \quad (9)$$

where $g(\omega_{jt-1}, CO_{jt-1})$ is a flexible function of lagged productivity and the common ownership measure, and ξ_{jt} is an exogenous productivity shock. The explicit function used for estimation includes a cubic form of both variables and an interaction term

$$\omega_{jt} = \sum_{i=1}^3 \rho_i \omega_{jt-1}^i + \sum_{k=1}^3 \rho_{k+3} CO_{jt-1}^k + \rho_7 \omega_{jt-1} CO_{jt-1} + \xi_{jt}.$$

The estimate yields a mean-zero error ξ_{jt} . These innovations to productivity are uncorrelated with lagged productivity, as they are obtained as residuals from this regression (Akerberg et al., 2015). When accounting for unobserved productivity with the endogenous Markov process, the production function then becomes

$$q_{jt} = \beta_0 + \beta_k k_{jt} + \beta_l l_{jt} + \beta_m m_{jt} + g(\omega_{jt-1}, CO_{jt-1}) + \xi_{jt} + \epsilon_{jt}.$$

From this regression, fitted values $\hat{\omega}_{jt} = E[\omega_{jt} | \omega_{jt-1}, CO_{jt-1}]$ are predicted and residuals $\xi_{jt} = \omega_{jt} - E[\omega_{jt} | \omega_{jt-1}, CO_{jt-1}]$ are obtained from the preliminary estimates of productivity and the fitted values from the first order Markov process.

Exogenous variables as well as valid instruments are needed to fulfil identification requirements of the estimation. Due to the timing assumptions of ACF, the dynamic variable capital is exogenous, as it is determined by investments in period $t - 1$. Endogeneity issues arise due to correlation of labour and materials in the current period with productivity and therefore also the productivity shock in the current period. Instruments for the endogenous input variables have to be uncorrelated with changes in productivity ξ_{jt} , but not necessarily

with the level of productivity ω_{jt} (Akerberg et al., 2015). Lagged values of these input variables can be used as instruments, as ξ_{jt} in period t is unanticipated by the firm in the decision making process of workforce and materials in $t - 1$ (Akerberg et al., 2015). The endogenous variable l_{jt} is instrumented with l_{jt-1} and the logarithm of firm-level wages as lagged input prices, w_{jt-1} (Doraszelski and Jaumandreu, 2013), m_{jt} is instrumented with m_{jt-1}, m_{jt-2} , and lags of the logarithm of *investment*, i_{jt-1} and i_{jt-2} are used for k_{jt} .

The endogenous productivity process with the common ownership variable and the optimisation algorithm are based on the routine provided by Collard-Wexler and De Loecker (2016). The algorithm updates the estimates $\hat{\beta}_k, \hat{\beta}_l, \hat{\beta}_m$, and consequently also ω_{jt} and residuals such that the objective function, as described in the following, is minimised. To conduct the estimation, moment conditions formed from the innovation to productivity ξ_{jt} and the vector of aforementioned suitable instruments \mathbf{Z} (Akerberg et al., 2015)

$$\frac{1}{T} \frac{1}{N} \sum_t \sum_j \hat{\xi}_{jt}(\beta_k, \beta_l, \beta_m) \mathbf{Z} = E[\hat{\xi}_{jt}(\beta_k, \beta_l, \beta_m) \mathbf{Z}] = 0.$$

For these moment conditions, the routine calculates the empirical analogue as

$$Q(\beta) = (\boldsymbol{\xi} \mathbf{Z})' (\mathbf{Z}' \mathbf{Z})^{-1} (\boldsymbol{\xi} \mathbf{Z}),$$

with $\boldsymbol{\xi}$ as a vector of productivity shocks ξ_{jt} and \mathbf{Z} as a matrix containing instruments for the input factors.

Total factor productivity of firms is then calculated as

$$TFP_{jt} = \exp(q_{jt} - \hat{\beta}_k k_{jt} - \hat{\beta}_l l_{jt} - \hat{\beta}_m m_{jt}).$$

Markups

Subsequent to the productivity estimation, firm-level markups can be recovered from the production data. Due to a possible correlation between markups and firm decisions on

inputs, markups cannot be estimated without controlling for unobserved productivity (De Loecker and Warzynski, 2012). De Loecker and Warzynski (2012, DLW) introduce a method for estimating markups with a control function to estimate the industry-level production function coefficients on a variable input similarly to ACF. Markups are computed using the elasticity of output with respect to materials, following De Loecker and Warzynski (2012). The respective input coefficient is related to the revenue share of material expenditures.

$$\mu_{jt} = \frac{\beta_{jt}^m}{\alpha_{jt}^m} = \left(\frac{P_{jt}Q_{jt}}{w_{jt}^m m_{jt}} \right) \frac{\partial Q_{jt}(\cdot)}{\partial m_{jt}} \frac{m_{jt}}{q_{jt}} \quad (10)$$

In the data at hand, output prices times quantities of output $P_{jt}Q_{jt}$ is given as sales, and the price of materials times quantity of materials $w_{jt}^m m_{jt}$ is given as material expenditures. The term in parentheses then becomes sales over material expenditures. The second term, $\frac{\partial Q_{jt}(\cdot)}{\partial m_{jt}} \frac{m_{jt}}{q_{jt}}$, denotes the elasticity of output with respect to material inputs, obtained by the previous estimation of the production function and the respective input coefficients.

An error correction is applied to deflated sales in the calculation of the revenue share of the costs of materials, such that

$$\hat{\alpha}_{jt}^m = \frac{\text{materialcosts}_{jt}}{\frac{\text{sales}_{jt}}{\exp(\hat{e}_{jt})}}.$$

Results

The production function coefficients are estimated separately for nine larger subsets of the data, pooling some of the industries together (documented in Table D.12). Table D.13 reports elasticities of output obtained from a simple OLS regression for reference, and the ACF procedure. In agreement with Collard-Wexler and De Loecker (2016), correcting for the measurement error in capital increases capital coefficients compared to the OLS estimates in most estimations. The labour coefficients increase in five and decrease in four cases. The material coefficients decrease in five of nine industries. With a Cobb-Douglas production function, returns to scale amount to the sum of output elasticities with respect to the inputs

capital, labour, and materials ($RTS = \beta_k + \beta_l + \beta_m$). In industries 10-12, 13-15, 19-21, and 28-30, returns to scale are constant and close to constant in the other five industry subsets. The average returns to scale obtained in the nine estimations are around 0.99. The estimated TFP in logarithms has a mean of 1.24. The dispersion between the 90th and 10th percentile (after Syverson, 2004) is around 0.887.

Table D.13: Production function elasticities

	OLS and ACF production function estimates							
	OLS			ACF				
	β_k	β_l	β_m	β_k	β_l	β_m	RTS	N
NACE 10-12	0.079	0.354	0.562	0.115	0.334	0.556	1.005	2585
NACE 13-15	0.033	0.483	0.540	0.022	0.529	0.513	1.064	637
NACE 16-18	0.133	0.362	0.466	0.133	0.341	0.484	0.958	962
NACE 19-21	0.105	0.375	0.540	0.101	0.355	0.552	1.009	2239
NACE 22-23	0.061	0.342	0.544	0.038	0.346	0.547	0.931	2060
NACE 24-25	0.062	0.324	0.594	0.057	0.319	0.605	0.981	2612
NACE 26-27	0.035	0.334	0.613	0.028	0.346	0.607	0.981	2149
NACE 28-30	0.053	0.319	0.616	0.058	0.336	0.618	1.011	4941
NACE 31-33	0.005	0.369	0.568	0.008	0.377	0.562	0.947	452

Note: This table presents output elasticities obtained from production function estimation (Cobb-Douglas). The endogenous productivity process incorporates the MHHI delta. For comparison, results of a simple OLS regression of the log of sales on input factors in logs are displayed. Returns to scale (RTS) amount to the sum of output elasticities with a Cobb-Douglas technology.

Markups are calculated for each firm from the estimated output elasticities, starting in 2007. The years 2005 and 2006 drop out, as two lags of the input variables have been used as instruments in the estimation routine.

D.3 Derivation of Profit Weights

Consider an industry with $N \geq 2$ firms, where k indexes all firms in the market and $j \in \{1, \dots, N\}$ denotes individual firms. Suppose firm j competes in quantities, and each of j 's competitors is denoted by $k \neq j$. Furthermore, there exists a set of investors $i \in \{1, \dots, I\}$

that choose to invest shares of $\beta_{ij} \in [0, 1]$ in firm j and $\beta_{ik} \in [0, 1]$ in firm j 's competitors k . With common ownership, suppose that at least one common investor i owns a percentage of $\beta_{ij} > 0$ in firm j , and simultaneously holds a stake of $\beta_{ik} > 0$ in at least one of k . that are included in the calculations of profit functions The profit function of shareholder i in Equation (11) is the sum over the profits π_j of each portfolio firm j , weighted with the ownership share β_{ij} , which corresponds to cash-flow rights (Backus et al., 2019a, pp. 5 f.)

$$\pi_i = \sum_j \beta_{ij} \pi_j. \quad (11)$$

The portfolio firms' individual profit functions include the share of control which the investor is able to exert on corporate governance processes. Firm j itself puts a weight γ_{ij} on the interest, i.e. profits π_i , of investor i . This serves the purpose of Pareto-weighting all investors' interests in the firm's objective function Q_j , as investors of the same firm might have diverging motives regarding its strategy. Firms' profits depend on their own strategic decisions x_j and on their rivals' behaviour x_{-j} . Following Salop and O'Brien (2000); Azar et al. (2018); Backus et al. (2019a), the objective function of firm j becomes

$$Q_j(x_j, x_{-j}) = \sum_i \gamma_{ij} \cdot \pi_i(x_j, x_{-j}) \quad (12)$$

$$\begin{aligned} &= \sum_i \gamma_{ij} \cdot \left(\sum_k \beta_{ik} \pi_{j,k}(x_j, x_{-j}) \right) \\ &= \sum_i \gamma_{ij} \beta_{ij} \pi_j + \sum_i \gamma_{ij} \sum_{k \neq j} \beta_{ik} \pi_k \\ &\propto \pi_j + \underbrace{\sum_{k \neq j} \left(\frac{\sum_i \gamma_{ij} \beta_{ik}}{\sum_i \gamma_{ij} \beta_{ij}} \right)}_{\equiv \kappa_{jk}(\gamma_j, \beta)} \pi_k. \end{aligned} \quad (13)$$

Plugging in (11) for all assets in Equation (12) yields a profit maximisation problem of firm j , nesting the ownership share-weighted sum of profits π_j of all of i 's assets. Rearranging by factoring out firm j 's own profits π_j , the profit function now includes rivals' profits through overlapping investors i , weighted by a ratio of ownership and control shares. This ratio is

represented by the profit weights

$$\kappa_{jk} = \frac{\sum_{\forall i} \gamma_{ij} \beta_{ik}}{\sum_{\forall i} \gamma_{ij} \beta_{ij}}. \quad (14)$$

$$\kappa_{jk} = \begin{cases} \frac{\sum_i \gamma_{ij} \beta_{ik}}{\sum_i \gamma_{ij} \beta_{ij}} & \text{if } k \neq j \wedge \gamma_{ij}, \beta_{ij}, \beta_{ik} > 0 \\ 0 & \text{if } k \neq j \wedge (\gamma_{ij} \vee \beta_{ij} \vee \beta_{ik}) = 0 \\ 1 & \text{if } k = j \wedge \gamma_{ij}, \beta_{ij}, \beta_{ik} > 0. \end{cases}$$

As before, β_{ij} and β_{ik} refer to the ownership weights, equal to the stake investor i holds in firms j and k . γ_{ij} is the control share accruing to investor i in company j . The pairwise products of the respective control and ownership shares ($\gamma_{ij} \beta_{ik}$) are added up over all investors which own positions in the two companies. If $\gamma_{ij}, \beta_{ij}, \beta_{ik} > 0$, and $k \neq j$ common ownership arises (Backus et al., 2019a, p. 6). Empirically, control shares γ_{ij} are not always observed simultaneously with ownership shares β_{ij} . The proportional control assumption is commonly employed in the literature and sets $\gamma_{ij} = \beta_{ij}$. The profit weight κ_{jk} for any company-competitor combination is only larger than zero if there is a common ownership link between the two firms operating in the same industry through one or several investors. Therefore, the firm incorporates the profits of competitors weighted by the respective κ_{jk} in its own profit maximising function only if these firms are commonly held. κ_{jj} is normalised to one (Backus et al., 2019a, pp. 5 ff.).

Now suppose that with non-zero profit weights, firm j undercuts any jointly held firm k 's price. Average prices in the industry decrease. Then, investor i gains profits by firm j 's increasing market share through a larger number of units sold, but simultaneously loses even more through the foregone profits of k . The joint producer rent of firm i and j decreases at the expense of investor i . Intuitively, investor i benefits from joint monopolistic pricing (Azar et al., 2018, p. 1521).

D.4 A Measure of Common Ownership

Standard models of oligopolistic markets do not take into account firm connections through diversified, overlapping shareholders. Commonly regarded profit maximisation problems pertain to firms which are not jointly held (Azar, 2012). Conversely, it is a well-established fact that investors construct their portfolio based on risk and return of positions, and maximise profits through portfolio diversification (Markowitz, 1952; Rotemberg, 1984; Hansen and Lott, 1996). Common ownership puts institutional investors in a position to obtain information about firms and increases concentration of voting power, as voting guidelines are often established at the mutual fund family level (He et al., 2019). Allowing for common ownership accounts for settings in which shareholders are diversified within the same industry. Investor returns then depend on the combined profits of their portfolio firms, weighting the different assets by corresponding ownership shares in the investors' profit functions. The general profit maximisation problem of the model incorporates the investors' individual profit functions in the firms' objective functions.¹¹

Also, the European Commission acknowledges that classical market concentration measures, such as the Herfindahl-Hirschman Index (HHI) neglect non-coordinated effects within industries. To account for indirect ownership links between competing firms, extensions to incorporate ownership levels of influential investors are required (European Commission, 2017, Dow/DuPont).

The measure most commonly used to quantify the common ownership concentration of a market in the literature is the Modified Herfindahl-Hirschman Index by Salop and O'Brien (2000), based on Bresnahan and Salop (1986).¹² The MHHI is modelled with market shares of firms and rivals, as well as control and ownership shares of institutional investors in these companies. The calculation of the MHHI consists of two parts,

¹¹A more detailed description of the profit maximisation problem can be found in Appendix D.

¹²Used for example by Azar et al. (2018); Gutiérrez and Philippon (2017); Antón et al. (2019).

$$\text{MHHI} = \text{HHI} + \text{MHHI delta}.$$

The first part of the equation is the classical HHI, derived from the sum of squared market shares s_j of all market participants j , and determines the general level of market concentration (Azar et al., 2018)

$$\text{HHI} = \sum_j s_j^2.$$

The second part, MHHI delta, captures the degree of common ownership networks. It is the difference between the MHHI and the HHI. In a market where no two firms share even only a single investor, MHHI delta is equal to zero. Thus, for markets without any firms connected by common ownership, $\text{MHHI} = \text{HHI}$. Subscripts j and k denote firms and competitors, i indexes the investors, and β_{ij} are ownership shares.¹³ Summing over all combinations of firms and competitors in the industry, the individual profit weights in the fraction are weighted with the product of market shares s_j and s_k of the firm and respective rival. Following the derivation of Salop and O'Brien (2000),

$$\text{MHHI} = \sum_j \sum_k s_j s_k \frac{\sum_i \beta_{ij} \beta_{ik}}{\sum_i \beta_{ij}^2} = \underbrace{\sum_j s_j^2}_{\text{HHI}} + \underbrace{\sum_j \sum_{k \neq j} s_j s_k \frac{\sum_i \beta_{ij} \beta_{ik}}{\sum_i \beta_{ij}^2}}_{\text{MHHI delta}}.$$

In the standard Cournot setting with separate ownership of firms, the HHI and the market share-weighted average markup (Lerner Index) show a monotonic relationship. With common ownership, the market concentration measure also incorporates the MHHI delta, such that MHHI over price elasticity equals Lerner Index (Salop and O'Brien, 2000)

$$\frac{1}{\eta} \sum_j \sum_k s_j s_k \kappa_{jk} = \sum_j s_j \frac{P - C'_j}{P}$$

$$\frac{\text{MHHI}}{\eta} = \text{Lerner Index}.$$

¹³We assume proportionate control, such that ownership shares equal control shares.

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Universitätsstraße 1, 40225 Düsseldorf

ISSN 2190-992X (online)
ISBN 978-3-86304-339-1