Rising Markups, Common Ownership, and Technological Capacities*

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April 2022

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. Using a rich panel of European manufacturing firms from 2005 to 2016, we structurally infer markups and construct a measure of common ownership. We use a propensity score reweighting estimator to eliminate biases due to observational characteristics and find an increase of firm markups ranging up to 3.4% in industries with high technological spillovers after the first exposure to common ownership. For companies directly held by common institutional investors, we also measure a positive effect on citation-weighted patents of up to 9.5% in high-spillover industries. Both findings are consistent with recent theoretical findings in López and Vives (2019). We further exploit industry technology classifications by the European Commission to shed some light on the heterogeneity of the effect of common ownership across the sample.

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

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

* *We would like to thank Willem Boshoff, Allan Collard-Wexler, Jan De Loecker, Florian Ederer, David Gilo, Ángel López, Anton-Giulio Manganelli, Gabriele Rovigatti, Tobias Salz, Martin Schmalz, Philipp Schmidt-Dengler, Jo Seldeslachts, Philip Sutherland, Joel Stiebale, Frank Verboven, and Zhihong Yu for helpful comments and suggestions. This paper also benefited from discussions with participants of the Market Power Trends workshop (Bertelsmann Stiftung & German Monopolies Commission 2020), the RISE3 workshop (Max-Planck Institute Munich, 2020), the DICE PhD seminar (Heinrich-Heine University Düsseldorf, 2019 and 2020, DFG GRK1974), the CCLE webinar at Stellenbosch University (2021), the CRESSE Conference (Crete, 2021), the MaCCI Conference (Mannheim, 2022) and the IIOC Conference (Boston, 2022). Funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) – 235577387/GRK1974.*

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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 and Eeckhout, 2018; Autor et al., 2020; Syverson, 2019) has sparked interest and worries 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, defined as indirect corporate networks of at least two competing firms held by overlapping sets of institutional investors, is potentially 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. Particular cases of interventions by common owners have gained attention from the media[1]. Apart from direct interventions, a reduction in performance-based managerial incentives by common owners constitutes a possible mechanism leading to anti-competitive outcomes (Antón et al., 2021a).

In total, institutional investors held over USD 85 trillion of public equity on the worldwide level in 2014, 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

[1]E.g. the discussions of shareholders with U.S. shale-oil-and-gas producers with the intention of generating larger profits and reducing quantities (https://www.wsj.com/articles/wall-streets-fracking-frenzy-runs-dry-as-profits-fail-to-materialize-1512577420, last accessed: 03.03.2021.). For a comprehensive overview, see Shekita (2020).

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).

Overlapping ownership structures affect the competitive landscape of firms in several dimensions. Early theoretical articles, (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 a modified Herfindahl-Hirschman Index (MHHI), taking into account ownership links at the industry level, and conclude that common ownership exerts an upward pressure on prices through rivals' profit internalisation and may facilitate collusion (Gilo et al., 2006; Shelegia and Spiegel, 2012). Firms compete less aggressively, as the negative effect on competing firms' profit is partly taken into account through the common owners. Bayona et al. (2021) show that even monopoly profits can be replicated allowing for endogenous common ownership links. 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, also described by Shelegia and Spiegel (2015). An additional empirical finding by Gutiérrez and Philippon (2016) shows that higher concentration and higher levels of common ownership tend to characterise industries with less investment in capital and

R&D (i.e. 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; Koch et al., 2021). More empirical research on the effects of common ownership is required, as the theoretical predictions on competition are ambiguous.

This article 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 and accounting for input endogeneity following Ackerberg et al. (2015), we estimate industry-specific production functions and calculate markups as in De Loecker and Warzynski (2012). Innovation activity by firms is measured by patents weighted with forward citations. Furthermore, we use the detailed ownership information available in Amadeus to construct the MHHI as used in other empirical studies (for example Azar et al., 2018), which we exploit as a measure of treatment intensity. We use a measure of technology spillovers by Bloom et al. (2013) at the three-digit NACE industry level as well as an industry classification of technological capacities by the European Commission (2019) 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 use a propensity score reweighting estimator to control for biases due to observational characteristics. We define a binary treatment indicator taking the value one in markets in which at least one additional investment by an institutional investor creates common ownership links between competitors for the first time. This constitutes the first occurrence of common ownership in a given market. Control firms operate in markets that never experience common ownership. Commonly used approaches of exploiting institutional mergers (e.g. He and Huang, 2017; Azar et al., 2018) and stock index inclusion of firms and rivals (e.g. Kennedy et al., 2017; Boller and Scott Morton, 2020) are less appropriate here, as we observe only a small number of firms listed in a stock index relative to the whole sample.

We find a positive effect of common ownership on firm markups that is significantly increasing with technological spillovers and ranges up to 6% in high spillover industries. The positive effect of common ownership on markups becomes stronger with increasing treatment intensity, measured as different percentiles of the distribution of MHHI delta. Splitting the sample into four groups of increasing technological capacities (low, medium-low, medium-high, and high technology) according to the European Commission (2019), we find pronounced effects on markups in low-tech and high-tech industries.

Considering the impact on innovation activity, the emergence of common ownership has in fact a positive and statistically significant effect on citation-weighted patents in high spillover markets for inside firms, which are firms directly held by common investors. For these firms the effect is increasing in spillovers and ranges up to 13% in high-spillover industries. By splitting up the sample with respect to technological capacities as defined by the European Commission (2019), we confirm the finding of a positive effect on inside firms that is increasing with technological capacities. For outside firms, which are competing in the same market with commonly owned firms, we find only insignificant results for innovation activity.

Both findings for markups and innovation activity are consistent with theoretical findings in López and Vives (2019). Our results are robust with respect to regression and production function specifications as well as a one-to-one propensity score matching approach combined with a difference-in-differences setup.

Our empirical analysis is related to a large and growing body of literature that recognises the importance of ownership structures involving competing firms and institutional investors[2]. Although there are some empirical industry-specific studies that analyse anti-competitive effects of common ownership on prices in the airline and banking industry (Azar

[2]Apart from prices, markups, and innovation, researchers have also dealt with managerial incentives (Antón et al., 2021a), 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. Schmalz (2021); Elhauge (2021) provide comprehensive overviews of the literature on competitive effects of common ownership.

et al., 2018, 2016) and markups in the ready-to-eat cereal industry (Backus et al., 2021), there is less work on a wider firm panel containing multiple industries. Backus et al. (2019) perform a calibration exercise with initial markup estimates taken from De Loecker and Eeckhout (2018), which are estimated on firms in the S&P500 index. In our analysis we abstract from general equilibrium effects as in Azar and Vives (2021a,b). In an unpublished manuscript, 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 our results differ in terms of markups. Antón et al. (2021b) find positive correlations of common ownership in US firms with innovation activities and R&D expenditures, which are amplified differently in settings of either technological or product market spillovers. Kostovetsky and Manconi (2018) show increased intensity of patent citations among firms owned by overlapping institutional investors.

This article is substantially different from the existing literature and contributes in five main 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 data sets of US listed firms and often focuses on specific industries. Non-listed firms constitute around 95.5% of observation in our sample, and account for 85.7% of total deflated sales over our sample period. Effects found in stock listed firms may not be representative for the whole industry. Second, we shed some light on the effect of common ownership on firms which are not directly commonly owned but which, in fact, compete in a market where there are common ownership links between rivals. This aspect has been largely neglected in the literature. Third, we offer a detailed analysis of industry characteristics regarding technological capacities and spillovers that drive the results of common ownership. Fourth, in direct comparison to Kini et al. (2019), this article focuses solely on citation weighted patents as a more precise measure of innovation activity, as opposed to a wider range of investments as an outcome variable, consisting of capital expenditures, R&D expenditures, and acquisitions. This is advantageous, because innovation output is more important for welfare than innovation input, and the theoretical foundation given in López and Vives (2019) focuses on innovation spillovers only and may not be trivially extended to general investments in capital. Fifth, on a broader scale, our article also contributes to the rising market power discussion, as we find a pattern of rising markups 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.

The rest of this article proceeds as follows. Section 2 gives an overview of the data set and markup estimation. The theoretical background of the common ownership measure as well as the identification strategy is presented in Section 3. Results of the propensity reweighting estimator follow in Section 4 and robustness checks are reported in Section 5. Section 6 discusses the results and draws conclusions for future investigations and applications.

2 Data and Markups

This section presents summary statistics of the data at hand in Subsection 2.1. The procedures for the estimation of the production function (according to Ackerberg et al., 2015) and markups (adapted from De Loecker and Warzynski, 2012) are discussed in Subsection 2.2. In this context, we show how the average sales-weighted markup and the percentage of markets with common ownership have developed over time.

2.1 Data Description

Manufacturing Firms' Financial Data

The Amadeus data base by Bureau van Dijk provides a rich firm-level panel of European companies for our analyses. We rely on the standard definition of large firms by the European

Commission, restricting our sample to firms with more than 250 employees and over EUR 50 million in turnover on average. Large firms follow better reporting standards, which leads to better data availability and quality, and institutional investors have a strong preference for large firms, as shown in the literature (Ferreira and Matos, 2008; Dahlquist and Robertsson, 2001). Compared to small and medium enterprises (SMEs), more than twice as many large firms have an institutional owner at some point in our sample, and the average firm revenue weighted by institutionally owned shares of large firms is 32 times larger than of SMEs in the data set. 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.

Amadeus is a comprehensive collection of financial data and information on corporate structure of European companies which also covers non-listed firms, and is regularly updated. This data set includes the observation period from 2005 to 2016, with a total of 7229 unique firms, operating in the manufacturing sector. Markets are defined at 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 ideal data set to analyse common ownership networks of firms would distinguish between ownership and control shares, and report subsidiaries of institutional investors which act in the common interest of a single ultimate owner. We assume proportionate control, where the percentages held in equity are proportional to control rights, as for example in the US, around 90% of publicly listed companies issue shares with equal voting rights with a single class of stock[3]. Global ultimate ownership in this case is defined as the last legal entity owning over 50% of shares. The ownership entries for manufacturing firms in Amadeus do not take into account ultimate ownership of institutional shareholders. In order to acknowledge holding structures, different subsidiaries of some of the largest investors are

[3]Council of Institutional Investors, (2022, February 13). Dual-class stock. Available at https://www.cii.org/dualclass_stock.

manually 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. 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. As quantities are not widely available, 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 costs of employment for labour. 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[4]. It is advantageous to have such a comprehensive, representative data set to conduct a large-scale study of the manufacturing industry in Europe and 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.

Table 1 reports summary statistics of the main variables used in the estimation procedure for productivity and markups, as used in our main analysis in Section 4. These exhibit a large dispersion of values for sales and input factors, all reported in million Euros. Around 5% of large firms in our sample are publicly quoted, and 27% of observations have a positive count of patents in a given year. The average number of patent citations is around 4.

Figure 1 shows the percentage of firms with common ownership per NACE two-digit industry. In the graph, we distinguish between the industries in high, medium-high, medium-

[4]Short term statistics, code sts_inpp_a, https://ec.europa.eu/eurostat/web/short-term-business-statistics/data/database, last accessed: 20.06.2019.

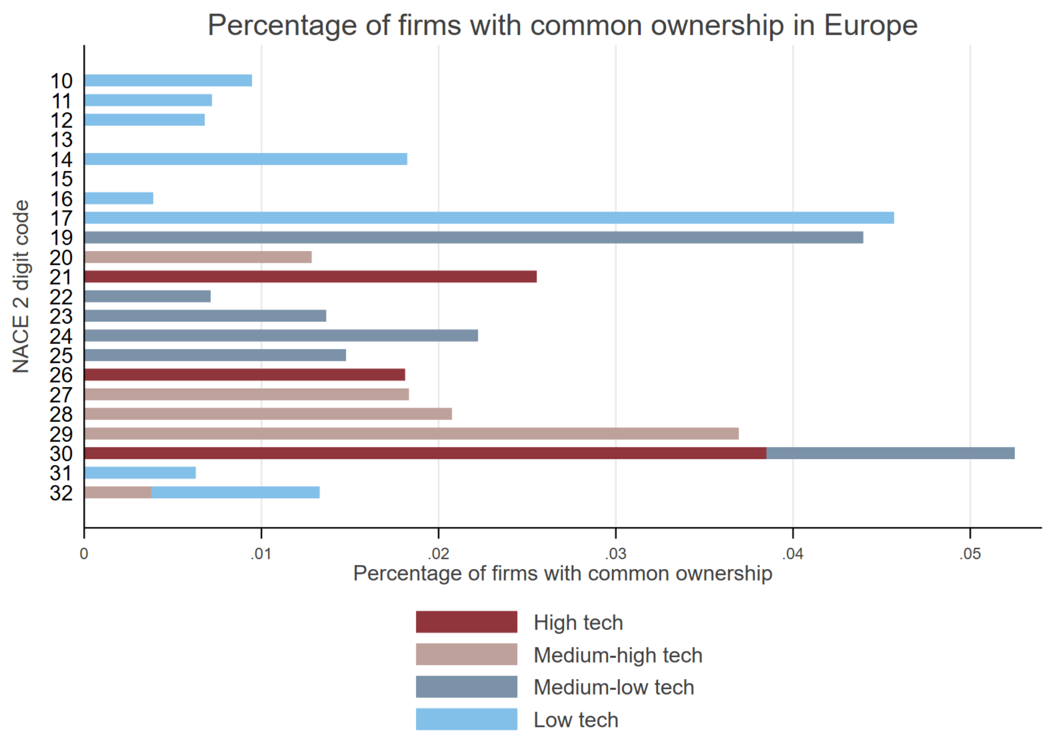
Table 1: Summary statistics, firm-level

	Characteristics			
	Mean	SD	Min	Max
Sales	373.84	1623.19	23.76	65657.08
Labour	52.54	195.34	0.90	13561.66
Materials	226.45	1179.97	2.60	53756.88
Capital	80.94	330.14	0.31	12063.22
Investment	13.06	66.31	0.00	4325.21
Wages	45.70	20.07	5.24	110.58
Age	35.47	33.39	0.00	731.00
Public	0.05	0.21	0.00	1.00
Innovating	0.27	0.44	0.00	1.00
Patent Citations	4.43	71.49	0.00	9938.00
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 costs 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. For some companies, information on employment is incomplete, for which then the two-digit industry-country median wage is assumed. Sales, costs of employees, material expenditures, tangible fixed assets, investment, and wages in million Euro, deflated by two-digit industry-country-year-specific producer prices. Innovating is a dummy variable that takes the value of one if the firm has more than zero patents in a specific year. Patent citations is the number of forward-citation weighted patents in a given year. Public is a dummy variable that takes the value of one if the firm is publicly listed.

low, and low-technology classes. The highest percentage of common ownership is found in medium-high-technology industries.

Figure 1: Percentage of firms with common ownership, by two-digit industry



Note: The figure shows the percentage of manufacturing firms with common ownership by NACE two-digit industry code. We use European ownership 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.

Additional Data Sources

We analyse additional heterogeneous effects, as described further below in Subsection 4.2. For this purpose we employ data on knowledge spillovers and technological capacities of industries. The first data source is made available by Bloom et al. (2013) comprising data on technological spillovers at the three-digit industry-level (US SIC codes) which we concord to the NACE three-digit classification in our main financial data outlined above. Bloom et al. (2013) rely on 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 rivals in terms of technological advances. The proximity between firms is used to weight respective R&D stocks, as firms closer to one another have a higher chance to profit from each other's R&D expenditures (Bloom et al., 2013). Their firm-level measure of technological spillovers is therefore the sum of the firm's competitors' R&D stock (in million USD) weighted with the pairwise degree of overlap in technology. We use the pre-sample average of the R&D stocks that spill over within a NACE three-digit industry.

As an additional measure, we obtain a classification of the technology intensity of the manufacturing industries from the European Commission (2019). According to the definition by the European Commission (2019), two-digit and some three-digit NACE code industries can be categorised by their technological capacities (see Table A.1). The technological intensity of an industry is measured by R&D expenditures over value added (European Commission, 2020). With increasing technological intensity, industries have higher R&D expenditures, more patent applications, and a larger share of innovating firms. Combining this classification with our main financial data from Amadeus, Table A.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 three-digit industry average calculated by Bloom et al., 2013) of firms in different subsamples. In our sample, all characteristics increase with the ranking of low to high-technology firms.

2.2 Productivity and Markup Estimation

Productivity

Estimation of markups relies on preceding estimation of total factor productivity (TFP) using the procedure proposed by Ackerberg et al. (2015). A Cobb-Douglas technology accounts for substitutability of inputs and a logarithmic specification of this production function is chosen for the estimation of output elasticities. The production function of firm j in market m (note that each firm only operates in one market m, their main line of business) and year t for output q_{jmt} is designed with the inputs capital k_{jmt}, labour l_{jmt}, materials m_{jmt}, unobserved productivity ω_{jmt}, and a measurement error ϵ_{jmt}, such that

$$q_{jmt} = \beta^0 + \beta^k k_{jmt} + \beta^l l_{jmt} + \beta^m m_{jmt} + \omega_{jmt} + \epsilon_{jmt}. \tag{1}$$

In the 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. The output prediction incorporates a third order polynomial in input factors labour, capital, and materials, and country fixed effects.

Following the assumption of Hopenhayn and Rogerson (1993), and later Olley and Pakes (1996); Levinsohn and Petrin (2003); Ackerberg 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

$$\omega_{jmt} = g(\omega_{jmt-1}, \mathrm{MHHIdelta}_{mt-1}, \mathrm{HHI}_{mt-1}) + \xi_{jmt} \tag{2}$$

where $g(\omega_{jmt-1}, \mathrm{MHHIdelta}_{mt-1}, \mathrm{HHI}_{mt-1})$ is a flexible function of cubic lagged productivity, the common ownership measure, and the HHI, both of which are measured at the market level. ξ_{jmt} is an exogenous firm-level productivity shock.

We estimate output elasticities for nine subsets of the manufacturing industry. For ease of notation, we omit the subscript of the industry subsets for the estimated elasticities. Information on the pooled industry subsets and the results of the production function estimation can be found in Table B.1 in the Appendix. We follow Collard-Wexler and De Loecker (2020) and correct for measurement error in capital, using lagged investment as an instrument for capital[5]. Constructed with the innovation to productivity $\xi_{jmt} = \omega_{jmt} - E[\omega_{jmt}|\omega_{jmt-1}, \mathrm{MHHIdelta}_{mt-1}, \mathrm{HHI}_{mt-1}]$ from the law of motion, the objec-

[5]For one subset of industries, we additionally include i_{jmt-2} as an instrument for capital.

tive function minimises the moment conditions

$$E\left[\xi_{jmt}(l_{jmt}, m_{jmt-1}, i_{jmt-1})\right] = 0.$$

The empirical analogue for these moment conditions is

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

with $\boldsymbol{\xi}$ as a vector of productivity shocks ξ_{jmt} and $\boldsymbol{Z}$ as a stacked matrix containing instruments for the input factors (Collard-Wexler and De Loecker, 2016, 2020).

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, such that

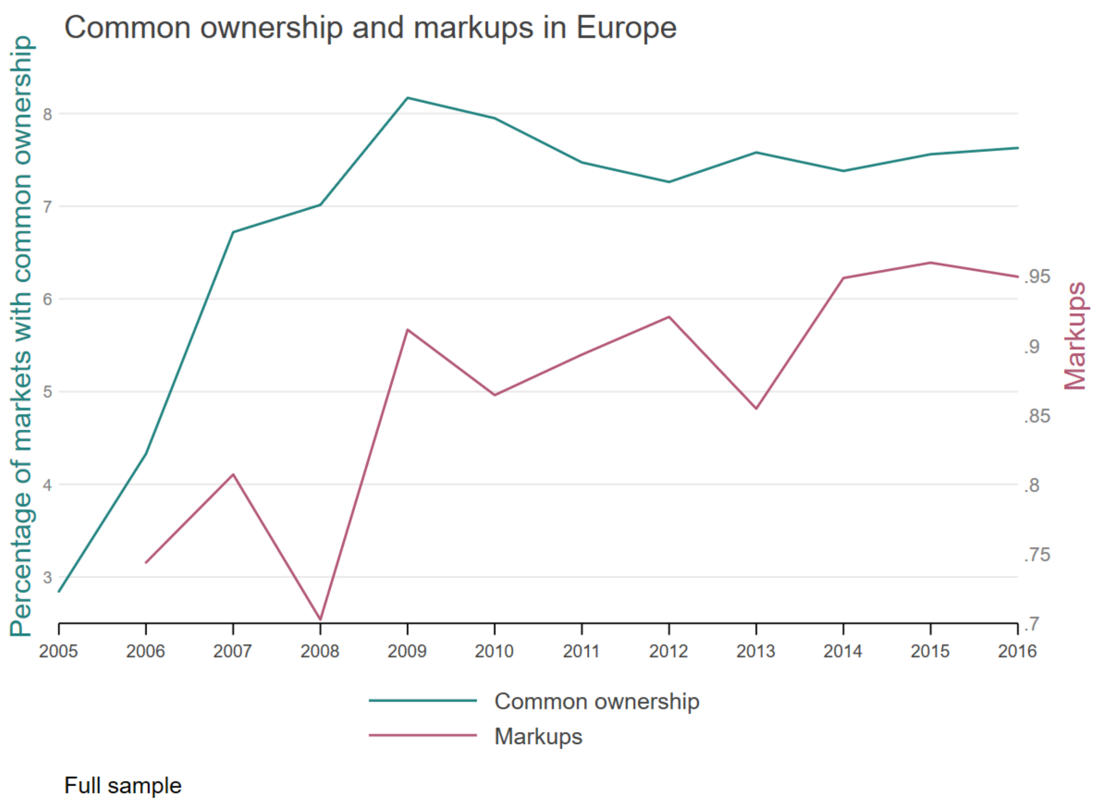
$$\mu_{jmt} = \frac{\beta^m}{\hat{\alpha}^m_{jmt}} = \left(\frac{P_{jmt}Q_{jmt}}{w^m_{jmt}m_{jmt}}\right)\frac{\partial Q_{jmt}(\cdot)}{\partial m_{jmt}}\frac{m_{jmt}}{Q_{jmt}}, \tag{3}$$

where μ_{jmt} is the markup of firm j at time t. In the data, the product of output prices and quantities $P_{jmt}Q_{jmt}$ is given as sales, and the product of the price and quantities of materials $w^m_{jmt}m_{jmt}$ is given as material expenditures. The term in parentheses then becomes sales over material expenditures. The second term, $\frac{\partial Q_{jmt}(\cdot)}{\partial m_{jmt}}\frac{m_{jmt}}{Q_{jmt}}$, 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

$$\hat{\alpha}^m_{jmt} = \frac{m_{jmt}}{\frac{P_{jmt}Q_{jmt}}{exp(\hat{\epsilon}_{jmt})}}.$$

Markups are calculated for each firm from the estimated material elasticities, starting in

Figure 2: Average markups and common ownership, full sample



Note: The figure illustrates the evolution of the average sales-weighted 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 Ackerberg et al. (2015) procedure. The percentage of markets, in which common ownership links exist, is calculated per year and for the overall sample.

2006[6]. Following De Loecker et al. (2020), we weight the average markup by sales share in the entire sample, and compare it on the right scale to the percentage of markets affected by common ownership on the left scale in Figure 2. The graph is quite revealing of a steady positive trend in markups. Common ownership concentration shows a similar, increasing pattern in the full sample.

[6]The year 2005 drops out, due to the lag specification in the estimation routine.

3 Empirical Strategy

This section presents a measure of common ownership, and the identification strategy employed to determine its effect on markups and patent citations. In Subsection 3.1, we introduce the MHHI as a measure of common ownership. The propensity score reweighting procedure following Guadalupe et al. (2012) is detailed in Subsection 3.2, including the construction of propensity score weights and a discussion of reweighted regressions.

3.1 A Measure for Common Ownership

We introduce a frequently used measure for common ownership, the MHHI. The MHHI delta reflects common ownership concentration in a market and is constructed as the difference between the MHHI and the classical HHI (Salop and O'Brien, 2000), such that for a single market at a given point in time

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

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. Subscripts j and k denote firms and competitors, i indexes the investors, and β_{ij} are ownership shares.[7] Summing over all combinations of firms and competitors in the industry, the individual profit weights between each pair of commonly owned firms 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. Whereas other

[7]We assume proportionate control, such that ownership shares equal control shares.

articles exploit exogenous variation in the MHHI due to mergers at the investor level, we use the MHHI as a measure for treatment intensity.

3.2 Identification Strategy

The investment strategies of asset managers are clearly not independent of the performance or profitability of their potential portfolio firms. Institutional investors do not randomly select competing firms in the same market to invest in. It seems plausible that they may choose firms that have initially high markups, or that are more productive or innovative. Determinants of the investment decision at the market level are also possible: firms may invest in markets where they already hold shares in competing firms, or choose a market in which larger investments by other institutional investors signal profitability.

Identification strategies need to account for these potential biases. We apply a propensity score reweighting approach following Guadalupe et al. (2012) using weighted panel fixed effects regressions. Fixed-effects models control for time-constant characteristics and identify the effects using only within-firm variation. The propensity score controls for selection on time-varying observed covariates, as the observables and treatment assignment are independent conditional on the propensity score under the unconfoundedness assumption (Rosenbaum and Rubin, 1983; Heckman et al., 1997).

Propensity score reweighting assigns weights corresponding to the inverse probability of treatment to observations in order to construct a sample with a control group that can approximate the counterfactual outcome of the treatment group absent treatment (Hirano and Imbens, 2001; Hirano et al., 2003; Imbens, 2004). In our application, firms in markets where we observe new occurrences of common ownership links are considered to be in the treatment group. For a clearly defined treatment group, 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. We also remove NACE two-digit industries and countries that never experience common ownership. The average change in MHHI delta around treatment is 0.01 which constitutes $\frac{1}{4}$ standard deviation of the total variation of the MHHI delta.

Propensity score reweighting encompasses a two-stage procedure: In a first stage, a probit model is estimated to determine the propensity towards exposure to treatment given the observed covariates. Treatment probabilities are used to assign corresponding inverse probability weights to the observations. In the second stage, weighted least squares regressions using the inverse probability weights are estimated to determine the average treatment effect (ATE) (Hirano and Imbens, 2001; Imbens, 2004; Guadalupe et al., 2012).

We closely follow the identification strategy employed by Guadalupe et al. (2012). In the first stage probit model, the outcome variable is one if the market experiences the first occurrence of common ownership in the following year, and zero otherwise. Only pre-treatment covariates are used for the treated firms. The following firm-level variables are used in the matching procedure to estimate the propensity score: the logarithm of markups, the logarithm of TFP, firm age, number of patent citations, labour, capital, and output in logarithms, and the share of institutional holdings. As treatment varies at the market-level (defined by three-digit-industry code and country combinations), we also include market and industry-level covariates HHI, technological spillovers and technological gap between firms. A year trend is also included, following Guadalupe et al. (2012). Observations belonging to treatment group and control group are pooled together, but two separate probit models are estimated for firms in low-tech and high-tech industries to allow for the relationship to vary across these categories. Table C.1 shows that the majority of covariates significantly determine treatment when clustering standard errors at the firm level.

Following Hirano and Imbens (2001); Guadalupe et al. (2012), we calculate the propensity score $\hat{p}$ as the estimated treatment probability of new common ownership links in the market, conditional on having no common ownership in the period before, from the probit regressions. The propensity scores can be transformed into inverse probability weights. To obtain an estimate of the ATE in the second stage weighted regressions, treated firms are assigned weights of $1/\hat{p}$, and weights for the control observations are $1/(1-\hat{p})$.

Following (Guadalupe et al., 2012), we only use observations that fulfil the common support condition and sum over the firms to generate weights for control observations that are used multiple times. Finally, weights are winsorised at the 99^{th} percentile to account for large outliers in the weights.

After reweighting the sample with propensity scores, treatment and control group should not differ systematically in observables. We test the balancing condition for pre-treatment variables on the full sample. Table 2 below reports the difference in pre-treatment means for the treatment group and control group for the unweighted and the weighted sample after demeaning at the year level. In the unweighted sample, there are substantial differences in firm and market characteristics. Reweighting observations with their inverse treatment probability weights leads to an active correction, as this sample shows no significant difference in means. Figures C.1, C.2 in the Appendix plot the empirical cumulative distribution functions of the pre-treatment covariates in the unweighted and weighted sample for the treatment group and control group. In the weighted sample, the distributions of the treated firms lie very close to those of the control firms. Compared to the unweighted sample, balancing is clearly improved.

Figure 3 shows yearly averages[8] of markups and patent citations in logarithms. For the treatment group, only pre-treatment observations are taken into account. The yearly means for the treatment group follow a similar pattern as the control markets, not giving rise to concerns of diverging pre-treatment trends.

Having obtained the propensity score weights, we estimate weighted fixed effects regressions in the second stage to determine the effects of common ownership on the outcome variables. The main specification with firm j's logarithm of markups in market m[9] and

[8]Both variables are demeaned at the company level before averaging at a yearly level. For the logarithm of patent citations, we additionally control for zero patent citations.

[9]In the data, firms are only assigned to a single market, therefore $ln(\mu)_{jmt} = ln(\mu)_{jt}$, $\text{Inst}_{jmt} = \text{Inst}_{jt}$ and $\nu_{jm} = \nu_j$.

Table 2: Balancing property - unweighted and weighted sample

	Balancing	
Sample	Unweighted	Weighted
ln(Markup)	0.149**	0.076
	(0.058)	(0.096)
ln(TFP)	-0.152	-0.076
	(0.136)	(0.147)
Age	1.635	1.469
	(2.174)	(2.681)
Patent citations	3.424**	0.181
	(1.483)	(0.993)
ln(Capital)	-0.284***	-0.038
	(0.104)	(0.193)
ln(Labour)	0.107*	0.043
	(0.059)	(0.076)
ln(Sales)	-0.123*	-0.056
	(0.065)	(0.142)
Inst. Holdings	0.021**	0.023
	(0.010)	(0.020)
HHI	-0.070***	-0.013
	(0.025)	(0.043)
Techn. gap	0.024	0.019
	(0.027)	(0.036)
Techn. ranking	4.746	1.513
	(4.906)	(6.022)

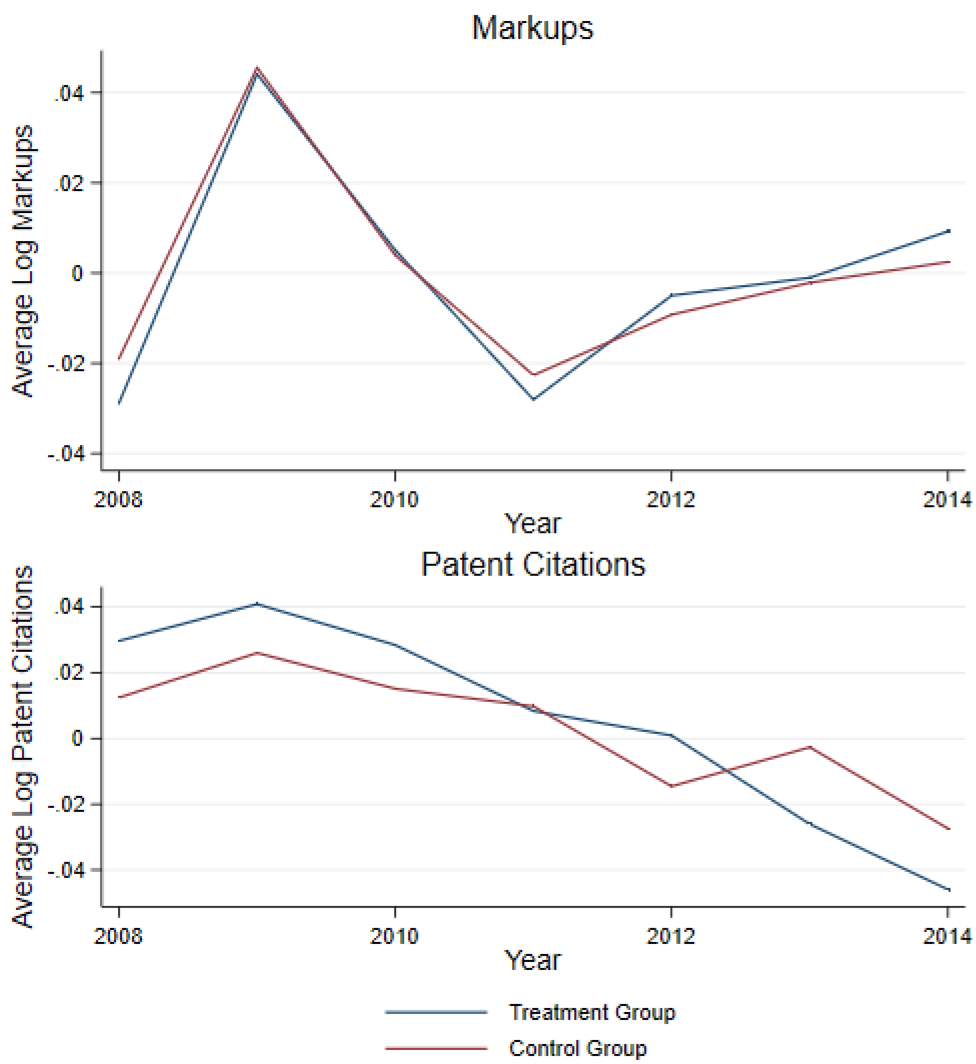
Note: Standard errors in parentheses and clustered at the market level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. The table shows the differences in pre-treatment means between treatment and control group after controlling for year fixed effects. Propensity scores are the predicted values from the Probit model in Table C.1. Markups and TFP are estimated using the methods proposed by De Loecker and Warzynski (2012) and Ackerberg et al. (2015). Data on patent citations is obtained from the Amadeus patent data base by Bureau van Dijk. Institutional holdings are the shares held by institutional investors per firm. Calculation of technological gap is based on Aghion et al. (2005), and data on three-digit industry ranking (US SIC codes) according to their technological spillovers is obtained from Bloom et al. (2013). Market definition: HHI calculated at the three-digit industry-country level and rescaled by division by 10,000, such that it ranges from 0 to 1.

period t as the outcome variable includes year and firm-fixed effects τ_t and ν_j, such that

$$ln(\mu)_{jmt} = \beta_1 \mathbf{1}[\text{MHHI delta} > 0]_{mt} + \beta_2 \text{HHI}_{mt} + \beta_3 \text{Inst}_{jmt} + \tau_t + \nu_{jm} + \epsilon_{jmt}. \tag{4}$$

$\mathbf{1}[\text{MHHI delta} > 0]_{mt}$ is the common ownership treatment indicator variable, taking the

Figure 3: Pre-treatment averages of outcome variables



Note: The figures show yearly averages of markups and patent citations in logarithms. 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 Ackerberg et al. (2015) procedure. Data on patent citations is obtained from the Amadeus patent data base by Bureau van Dijk. Both variables are demeaned at the company level before averaging at the yearly level. For patent citations, we also control for also zero citations. For the treatment group, only observations before treatment are used. For the control group, the yearly averages contain all observations.

value of one for MHHI delta$_{mt} > 0$, i.e. a market with common ownership, and zero for a market without common ownership, where MHHI delta$_{mt} = 0$. Firm-fixed effects rather than market-specific or industry-specific fixed effects are included 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 variation. In addition to the year and firm-fixed effects, we control for the standard concentration measure HHI at the NACE three-digit-country level and the shares held by institutional investors per firm. By including additional control variables, the precision of the weighted least squares model is enhanced (Imbens, 2004). As the treatment indicator varies 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 471 unique market clusters.

We incorporate an analysis of treatment intensity effects by estimating the model in several subsets of the data. We always keep all control observations, but discard treated firms with an MHHI delta below different percentiles of the distribution of non-zero MHHI delta. We first regard the full sample, and then only keep treated firms above the 5^{th}, 10^{th}, 15^{th}, 20^{th} and above the 25^{th} percentile of MHHI delta larger than zero. As an additional robustness check on treatment intensity, we estimate a model on the full sample and include dummy variables for different values of MHHI delta in the regression, indicating observations below 15% of the distribution of positive MHHI delta, between 15 and 25%, and above 25%.

Our second outcome variable is innovation output measured by citation-weighted patents. We follow Hausman et al. (1984) by replacing zero patent citations with unity before taking the logarithm and consequently adding a dummy variable indicating zero citations in the regression. The regression specification for patent citations as the outcome variable is richer than for markups, as additional control variables $\mathbf{X}_{jmt}$ are introduced. The firm-level covariates included are the logarithm of TFP, capital intensity measured as the ratio of capital to labour, firm age, and the indicator of zero citations. As market-level control variables, we also include market size measured by average market sales, and as an additional measure for competition, $1 - Lerner$ at the market level. For innovation output, we estimate the model

$$ln(cites)_{jmt} = \beta_1 \mathbf{1}[\text{MHHI delta} > 0]_{mt} + \beta_2 \text{HHI}_{mt} + \beta_3 \text{Inst}_{jmt} + \mathbf{X}_{jmt} + \tau_t + \nu_j + \epsilon_{jmt}. \quad (5)$$

We repeat the exercise using the same subsets and indicator variables as before to account for treatment intensity along different values of the distribution of non-zero MHHI delta.

4 Empirical Results

The empirical results relying on the propensity score reweighting method by Guadalupe et al. (2012) are reported in this section. Subsection 4.1 presents the results of the reweighting estimator, where we test whether upon emergence of new common ownership links in the market, firms set higher markups, and engage in more innovation activity. We account for treatment intensity and show average direct and indirect effects of common ownership. In Subsection 4.2, we explore the interaction of the effect of common ownership with the level of technological spillovers in an industry, and analyse further heterogeneity with respect to technological capacities of specific industries.

4.1 Treatment Intensity

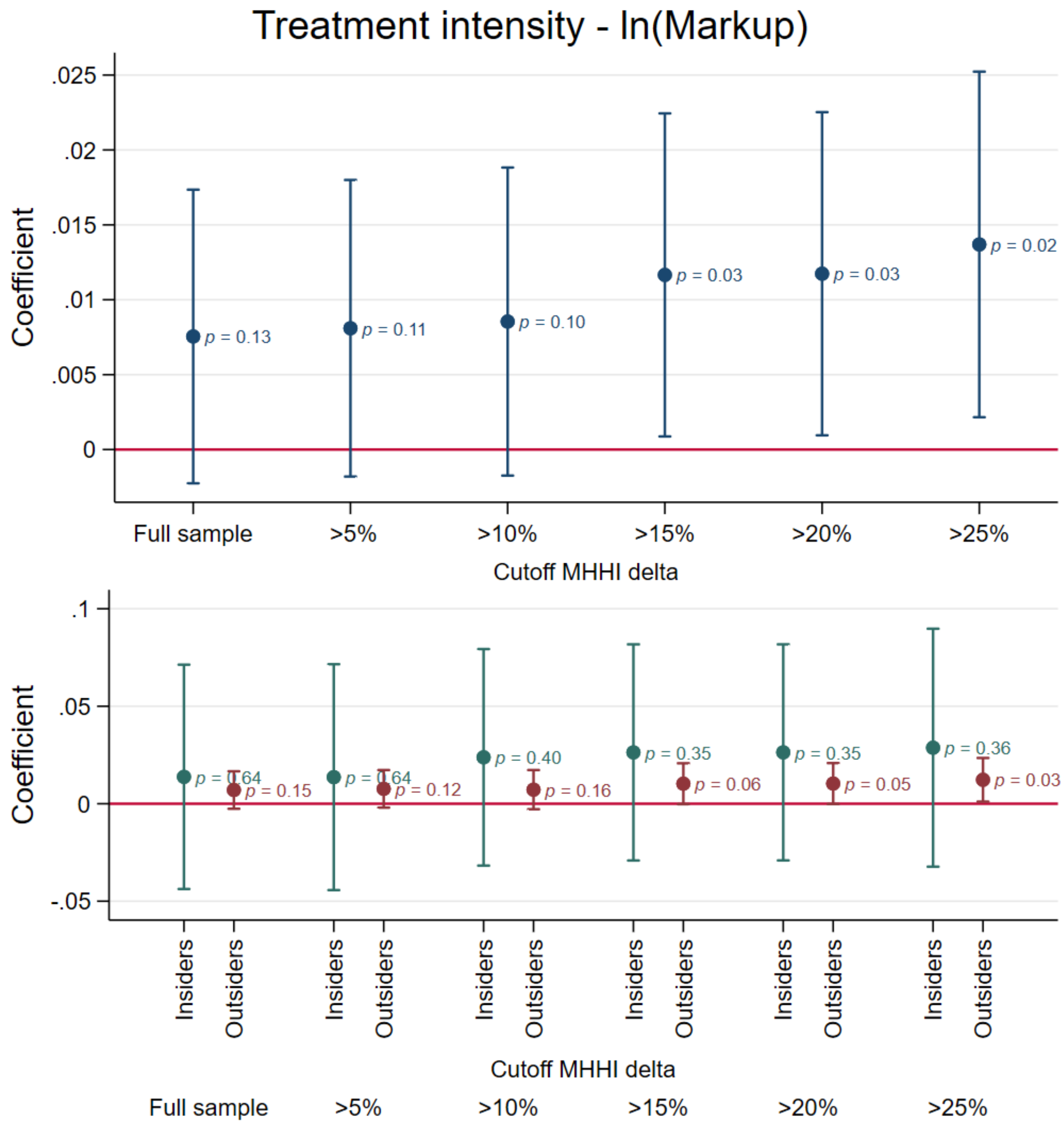
Markups

Turning to markups first, Figure 4 shows the effect of the treatment indicator for new common ownership links in the market, as estimated from firm-level propensity score reweighted regressions of the logarithm of markups on the common ownership treatment dummy. Observations are assigned weights according to their treatment group status as described in Subsection 3.2. To examine how the effect changes with increasing treatment intensity, the different coefficients are estimated in subsamples where we keep control observations with MHHI delta equal to 0 and treated observations with positive MHHI delta above the indicated percentile of the distribution of MHHI delta. In all subsets, we control for HHI at the three-digit industry country level, share of institutional holdings, firm and year-fixed effects. By including firm fixed effects, we account for selection based on time-invariant firm idiosyncrasies. Standard errors are clustered at the three-digit industry-country level. The positive average treatment effect is increasing in treatment intensity and becomes statistically significant when discarding the lower 15% of the distribution of positive MHHI delta. The effect size implies a 0.8 to 1.4% increase in markups after a market's first exposure to common ownership.

As we define treated firms as all firms operating in a market that is first exposed to common ownership, we would expect different responses of firms directly and only indirectly affected by common ownership. There is only little known in the literature about the effects of common ownership on outsiders. Papadopoulos (2021) shows in a model with cross-ownership that firms that are not part of a cross-ownership scheme always benefit from their competitors that are forming cross-ownership links. The authors show that outsiders increase output as a response to the change in market structure. We define directly affected firms, or insiders, as competitors in the same market which are held by overlapping sets of institutional investors 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 is more pronounced than the indirect effect. We interact the treatment effect with two dummies indicating the insider and outsider status in the different subsamples as before, and find that the positive effect of treatment on log markups differs in strength between inside and outside firms, and also increases with treatment intensity. In all subsamples, the direct effect for inside firms is always larger than the indirect effect for the competing firms, and ranges from 1.4 to 2.9%. The effect for outside firms lies between 0.7 and 1.2%.

Table C.2 and C.3 in the Appendix show the corresponding weighted least squares regression results.

Figure 4: Reweighting estimator: Coefficients of treatment indicator by cutoffs, ln(Markup)



Note: The graph plots the estimated coefficients of the treatment indicator and respective confidence intervals and p-values. The different coefficients are estimated in subsamples where we keep control observations with MHHI delta equal to 0 and treated observations with positive MHHI delta above the indicated percentile of the distribution of MHHI delta. Treatment is defined as the first occurrence of common ownership, i.e. a non-zero MHHI delta. Insiders are defined as directly commonly owned firms. Outsiders are non-commonly owned competitors in the same market. We control for HHI at the three-digit industry country level, share of institutional holdings, firm and year-fixed effects and cluster standard errors at the three-digit industry-country level. The red line indicates zero.

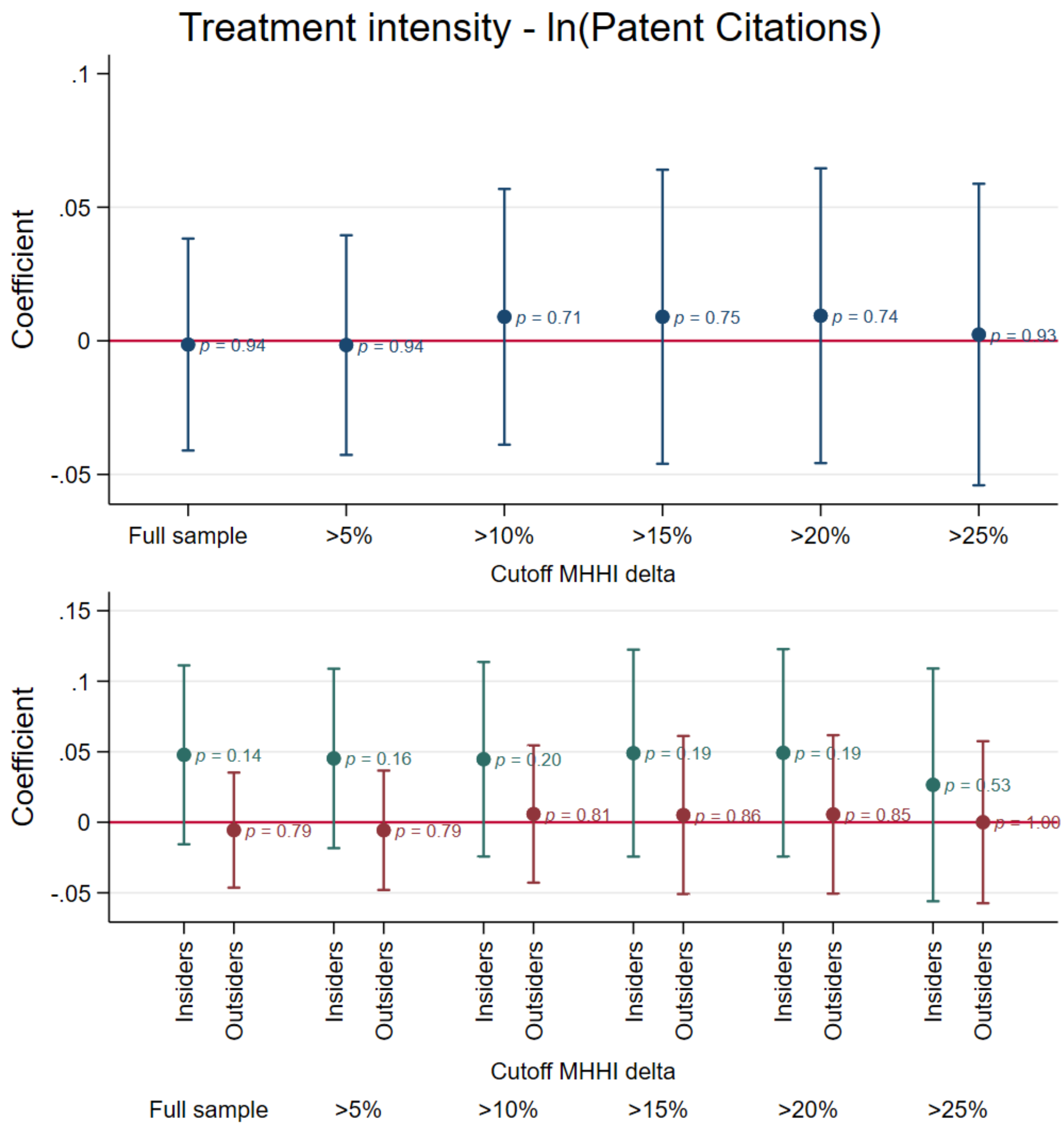
In addition to estimating the treatment effect for different percentiles of the MHHI distribution, we estimate a model on the full sample including dummy variables for MHHI delta below 15%, between 15% and 25%, and above 25% of the distribution of positive MHHI delta. Table C.6 shows the result of this regression of the logarithm of markups including additional time-heterogeneous country and three-digit NACE industry fixed effects. The average treatment effect is increasing in in treatment intensity as measured by the percentile indicator variables. For a small MHHI delta below the 15^{th} percentile the effect is negative, but becomes statistically significant and amounts to around 1.4% increase in markups for MHHI delta above the 25^{th} percentile.

Innovation

We are interested in whether also the innovation output of the firms changes with common ownership. The same propensity score reweighting procedure is performed using a linear count data model with the logarithm of patent citations as the outcome variable. Propensity score weights are assigned as in Subsection 3.2. Pooling directly held firms and indirectly affected competitors together, the treatment effect is not statistically significant. Distinguishing between inside and outside firms in Figure 5 reveals that the first occurrence of common ownership only affects the innovation output of directly commonly held firms. The average treatment effect on inside firms is positive in all subsamples, and remains stable with increasing treatment intensity. The magnitude of the effect for insiders ranges between 2.7 to 5.0%. Coefficients of the outside firms are first slightly negative, then slightly positive and insignificant. The corresponding regression results are reported in Tables C.4 and C.5.

For innovation we perform the same exercise as for markups and estimate a model on the full sample containing dummy variables for MHHI delta below 15%, between 15% and 25%, and above 25% of the distribution of positive MHHI delta. In Table C.7, we show the effects on innovation output accounting for different time-heterogeneous fixed effects. Here, the largest positive and highly statistically significant average effect is found in firms

Figure 5: Reweighting estimator: Coefficients of treatment indicator by cutoffs, ln(Patent Citations)



Note: The graph plots the estimated coefficients of the treatment indicator and respective confidence intervals and p-values. The different coefficients are estimated in subsamples where we keep control observations with MHHI delta equal to 0 and treated observations with positive MHHI delta above the indicated percentile of the distribution of MHHI delta. Treatment is defined as the first occurrence of common ownership, i.e. a non-zero MHHI delta. Insiders are defined as directly commonly owned firms. Outsiders are non-commonly owned competitors in the same market. We control for HHI at the three-digit industry country level, share of institutional holdings, a dummy for zero citations, firm and year-fixed effects and cluster standard errors at the three-digit industry-country level. Zero patent citations are set to one. The red line indicates zero.

with MHHI delta between the 15^{th} and 25^{th} percentile, implying an average increase of 8.8% percent in patent citations.

4.2 Heterogeneous Effects

This section further explores the driving factors of the effects of common ownership on markups and innovation activity. Following López and Vives (2019), technological market characteristics play a major role in determining the effects of common ownership on strategic variables. First, we briefly discuss the main model by López and Vives (2019). Second, the results regarding the effects of common ownership for varying levels of technological spillovers are presented. Third, the results of splitting the sample according to different technological capacities are shown.

Theoretical Background

A very recent article by López and Vives (2019) presents an integrated theoretical framework to analyse competitive effects of common ownership. Their main model is a symmetric Cournot oligopoly with a symmetric overlapping ownership structure. Firms have two strategic variables: output and marginal cost-reducing research and development (R&D) spending. Innovation of a given firm spills over to a certain degree to other firms operating in the same market. The authors characterise an equilibrium under some regularity conditions and perform a comparative static exercise regarding how equilibrium output and innovation activity is impacted by an increase in common ownership for varying degrees of technological spillovers. They find three different regions along the spillover dimension, characterised by low, intermediate and high spillovers.

The mechanism described by López and Vives (2019) shows how an increase in common ownership impacts innovation through two distinct channels. Possible internalisation of R&D efforts in the presence of spillovers increases the incentives to innovate. The strength of this positive incentive depends on the degree of spillovers. The second channel is rather indirect. The cartelisation effect has a negative effect on output, which in turn leads to lower marginal incentives to innovate as now the overall gain of innovation is lower with fewer units of output.

In the first region, categorised by low-spillover markets, common ownership has a negative effect on output, thus a positive effect on prices, and a negative or no effect on innovation. The non-positive impact on innovation in this region stems from the low spillovers that lead to relatively small internalisation effects of common ownership on innovation, such that the negative impact of the reduced output on innovation outweighs the positive effects due to internalisation. In this region, we would expect to find a positive effect on firm markups if innovation is not impacted by common ownership.

For increasing spillovers in the second region, we would expect to find an increasing effect on markups, because in the adjacent region with higher spillovers the effect of common ownership on output is still negative, and thus positive on prices, and also positive on equilibrium innovation, such that marginal costs are decreasing in common ownership. Here, the spillovers are sufficiently large for the positive internalisation effects of common ownership on innovation to outweigh the reduced incentives to innovate due to lower output.

In the third region, characterised by very high spillovers, common ownership has a positive effect on output and innovation, thus the effect on markups is ambiguous. Here, the positive spillover effect on innovation is expected to be the largest, such that the increased incentives to innovate let marginal costs decrease, even resulting in increased output. However, this region is not guaranteed to exist by the assumptions of the model by López and Vives (2019).

One aspect that is not addressed in the article by López and Vives (2019) is how the effect of common ownership changes in the presence of firms that are not directly commonly owned, but that compete with commonly owned firms in the same market. The authors only consider a symmetric setup where all firms are commonly owned. Regarding price changes of insiders and outsiders due to the cartelisation effect, neglecting innovation, one would expect the effects to go in the same direction. However, the impact of common ownership on the innovation activity of outside firms in this context is unclear. To the best of our knowledge, there is no theoretical or empirical work that analyses this aspect in terms of common ownership specifically. There are also only relatively few articles in the literature on mergers and acquisitions that focus on rivals' responses to mergers in terms of innovation activity. Theoretical predictions for rivals are ambiguous in this regard (Haucap et al., 2019).

Technological Spillovers

This section now turns to the empirical evidence on how the effects of common ownership on markups and innovation vary with different degrees of technological spillovers. We interact the treatment variable with a three-digit industry-level, pre-sample measure of technological spillovers by Bloom et al. (2013) and perform sample splits. Figures 6a and 6b display the treatment effect along the spillover dimension on markups and innovation, respectively[10]. Each graph contains, from top to bottom, effects for insiders and outsiders combined, for insiders only, and effects for outsiders only. The shaded area in each graph shows a 95% confidence interval. For markups, we see that the effect of common ownership is increasing in the degree of spillovers for insiders and outsiders. The effect only becomes statistically significant for all treated firms combined and for outsiders. The combined effect ranges up to roughly 6% in high-spillover industries. A one standard deviation increase in spillovers increases markups by 1.5%. The effect for insiders, although insignificant, is larger and reaches a magnitude of up to 12% in high-spillover industries. For innovation, we find an increasing effect in the degree of spillovers for firms that are directly commonly owned, which is statistically significant for medium-high and high-spillover industries. For insiders a one standard deviation increase in spillovers increases patent citations by 2.1%. The effect for outsiders is decreasing in spillovers, such that it is positive for lower levels of spillovers and becomes negative for high spillovers.

We also perform sample splits with respect to spillovers in columns 2 to 5 of Tables

[10]The treatment effect from the first columns in tables C.8 and C.9 is plotted for markups and innovation, respectively. The first columns in both tables interact the treatment effect with spillovers.

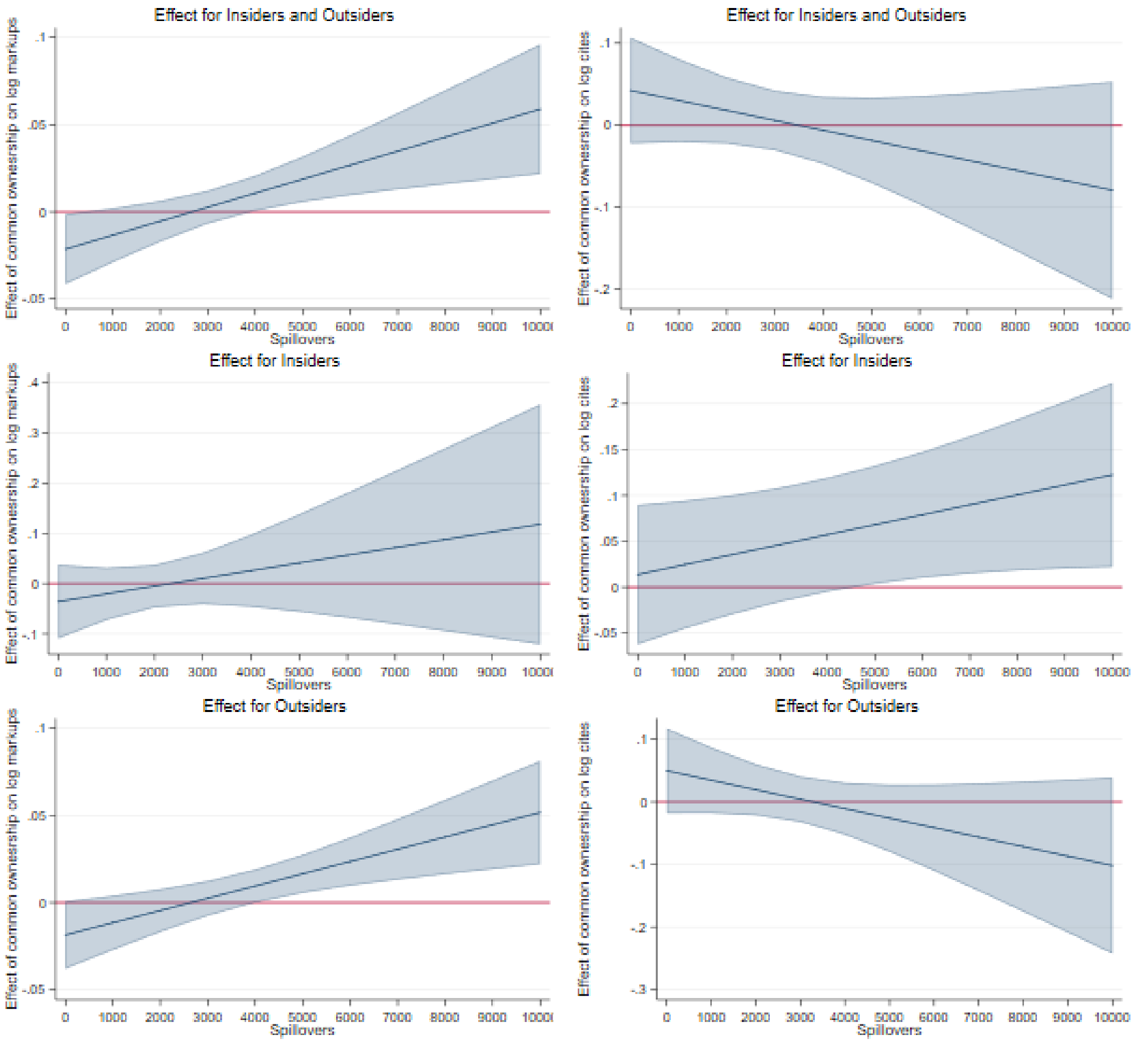
C.8 and C.9 for markups and innovation, respectively. Columns 2 in both tables show the effects for the lower 25^{th} percentile of spillovers. Columns 3 and 4 show the effects for observations below and above the median value of technological spillovers. Columns 5 in both tables show the effects for the upper 25^{th} percentile. The results of the sample splits are consistent with the interaction results shown in Figures 6a and 6b. In the sample splits, we see that the effect on markups is increasing with the levels of spillovers and reaches up to 3.4% for observations above the 75^{th} percentile of the spillover distribution. For the innovation activity of inside firms, we also see an increase of the effects with the degree of spillovers, where observations above the 75^{th} percentile experience an increase of 9.5% in patent citations. However, compared to the interaction models, the sample splits provide additional information with respect to the effect in low-spillover industries, where we see a positive effect on markups in column 2 of Table C.8. According to López and Vives (2019), we would expect a positive effect on markups in this region if there are non-negative effects of common ownership on innovation. Column 2 of Table C.9 shows that for insiders and outsiders, there is a positive insignificant effect of common ownership on innovation. Column 1 of the same table also shows insignificant positive baseline effects on innovation for insiders and outsiders when spillovers are zero.

The observed increase of the effects of common ownership on markups and innovation with the degree of spillovers, and also the positive effect on markups and non-negative effects on innovation in low-spillover regions, are consistent with theoretical predictions in López and Vives (2019).

Technological Capacities

As shown in López and Vives (2019), the effects of common ownership highly depend on the industry structure the companies are operating in. This implies the necessity of developing reliable readily available heuristics regarding industry classifications for policy and decision-makers to assess the impact of common ownership, similar to what has been done

Figure 6: Treatment effect for varying spillovers



a) ln(Markup) **b)** ln(Patent Citations)

Note: Treatment is defined as the first occurrence of common ownership, i.e. a non-zero MHHI delta. Insiders are defined as directly commonly owned firms. Outsiders are non-commonly owned competitors in the same market. We control for HHI at the three-digit industry country level, share of institutional holdings, firm and year-fixed effects and cluster standard errors at the three-digit industry-country level. Additionally for patent citations we control for ln(TFP), market size measured by average sales at the market level, capital intensity, 1-Lerner index, age, and a dummy for zero citations. Zero patent citations are set to one. The red line indicates zero. The blue shaded area is a 95% CI.

for mergers and acquisitions (European Commission, 2004). This section exploits an industry classification by the European Commission based on technological capabilities to further explore the heterogeneity of the effect of common ownership on markups and innovation.

This classification could be used as first guidance to policy and decision-makers as to which effects of common ownership are likely to matter in the industry under consideration.

We apply the classification of NACE two-digit and some three-digit industries by means of technological capacities by the European Commission (2019), as described in Subsection 2.1, to our data. We estimate the treatment effect separately for each technological class. The results for markups and patent citations are presented in Tables 3 and 4, respectively. In both tables, columns 1 to 4 show the results in ascending order from low-technology to high-technology industries. Following our results regarding spillovers and considering theoretical predictions by López and Vives (2019), we would expect to find a positive effect on markups and innovation in high-tech industries and a positive effect for markups in low-tech industries. This is exactly what we find, as the medium-high-tech and high-tech models in columns 3 and 4 in Table 4 show the largest and statistically significant results on patent citations for firms directly commonly owned. Here, treatment increases patent citations for insiders by 17% and 20%, respectively. For markups, we find the largest effect in high-tech industries in column 4 of Table 3, where treatment increases markups by 2.1%. We also find a significant effect of 1.7% in low-tech industries in column 1. As mentioned, we would only expect to find a positive effect in these low-tech-low-spillover industries if innovation is not an important strategic variable. As shown in Table A.1, low-technology industries include of food, beverages, tobacco, different kinds of textile industries, wood and paper, furniture and other manufacturing industries, which are arguably industries where innovation does not play a major role. High-technology industries comprise the pharmaceutical industry, computer and optical products, and the air and spacecraft industry. For innovation, we also find a positive effect in the medium-high-tech industries consisting of chemicals, weapons, electrical equipment, machinery, motor vehicles and other transport equipment, and medical instruments and supplies.

Table 3: Technology Classes, Markup

Dep. Variable:	**ln(Markup)**			
	(1)	(2)	(3)	(4)
Technology	Low	Medium-Low	Medium-High	High
$1_{(MHHIdelta>0)}$	0.017**	0.005	-0.006	0.021**
	(0.008)	(0.011)	(0.009)	(0.009)
HHI	0.114**	0.037	0.041	-0.029
	(0.057)	(0.047)	(0.039)	(0.051)
Inst. Holdings	-0.033**	0.048***	0.006	-0.028
	(0.014)	(0.017)	(0.023)	(0.047)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.98	0.92	0.95	0.94
N	3633	4978	5117	1664
Market clusters	120	138	158	52

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.

Table 4: Technology Classes, Innovation

Dep. Variable:	**ln(Patent Citations)**			
	(1)	(2)	(3)	(4)
Technology	Low	Medium-Low	Medium-High	High
$1_{(MHHIdelta>0)} \times$ Insider	-0.008	-0.016	0.169**	0.201***
	(0.025)	(0.058)	(0.073)	(0.069)
$1_{(MHHIdelta>0)} \times$ Outsider	-0.014	-0.009	0.040	-0.016
	(0.018)	(0.027)	(0.054)	(0.060)
HHI	-0.012	-0.117	0.054	-0.425*
	(0.065)	(0.138)	(0.150)	(0.219)
Inst. Holdings	-0.025	0.334**	0.018	-0.065
	(0.040)	(0.158)	(0.068)	(0.142)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.58	0.77	0.79	0.87
N	3633	4978	5117	1664
Market clusters	120	138	158	52

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. Insiders are defined as directly commonly owned firms. Outsiders are non-commonly owned competitors in the same market. We control for HHI at the three-digit industry country level, ln(TFP), market size measured by average sales at the market level, capital intensity, 1-Lerner index, and age, share of institutional holdings, a dummy for zero citations, firm and year-fixed effects. Zero patent citations are set to one. HHI and MHHI delta are rescaled by division by 10,000, such that the HHI ranges from 0 to 1.

5 Robustness Checks

This section reports the results of a variety of robustness checks. We perform robustness checks with regard to the markup and innovation regression specifications in Subsection 5.1. Subsection 5.2 implements some additional production function specifications under different assumptions. We further apply propensity score matching combined with a difference-in-differences setup in Subsection 5.3 to support our results using an additional identification strategy. Neither of the robustness checks changes our conclusion regarding the effect of common ownership on markups and innovation.

5.1 Regression specification

Using a propensity score reweighting estimator as before, we additionally control for changes in marginal costs when regressing markups on our variable of interest, the common ownership treatment indicator. We add a polynomial function of TFP as regressors to reflect changes in marginal costs. The results of this exercise are reported in Figures C.3b and C.3a.

Furthermore, as our sample consists of many different countries that are subject to different governmental policy shocks, we include country-specific time-fixed effects in the markup and patent citation models. We also include broad two-digit industry-time-fixed effects to absorb industry-specific cost shocks. Figures C.4a, C.4b, C.5a, and C.5b show the results of these specifications. In both models, the average effect on markups becomes insignificant because of the slightly lower size of estimated treatment effects, but the effects with respect to spillovers do not change.

5.2 Production function specifications

In the following, we show the results for markups under different assumptions of the production function estimation. First, we use a translog specification which produces more variation in markups. Figure C.6a shows the treatment effect in this setup for different degrees of treatment intensity. The results do not change qualitatively, as we still observe a positive significant treatment effect of 0.4%, which is three times smaller compared to a Cobb Douglas production function specification. Figure C.6b shows how the treatment effect on markups varies with spillovers in the translog specification. Again, the results do not change qualitatively as the effect is increasing for insiders and outsiders and is also significant for high spillovers.

Second, as a further robustness check on the production function specification, we follow De Loecker and Scott (2017) by including the logarithm of wages in the first stage of predicting output in response to the critique by Gandhi et al. (2020), who illustrate identification problems of gross output production functions. Results are shown in Figure C.7a and Figure

C.7b. This specification does not change the interpretation of the results either.

5.3 Propensity Score Matching and Difference-in-Differences

As a further robustness check on our identification strategy, we combine a propensity score matching approach with a difference-in-differences design. As before, firms in markets where we observe entry of common ownership are considered to be in the treatment group.

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. In the first step, a probit model is estimated to determine the treatment probabilities, or balancing score, from covariates for all observations. In the second step, pair matching on the balancing score is performed, such that the distribution of covariates is similar in treatment and control group (Rosenbaum and Rubin, 1983).

We perform the matching procedure for each year individually with separate probit regressions. The outcome variable is one if the market experiences entry of common ownership in the next year, and zero otherwise. We use the same pre-treatment variables for matching as in the propensity score reweighting approach[11] and include 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. We match treated and control observations based on a one-to-one matching, and only use firms on common support. After successful matching of propensity scores, treatment and control group do not differ systematically in observables.

After matching, we use difference-in-differences estimation to determine the average treat-

[11] We use the following pre-treatment firm-level variables: markups, log TFP, age, number of patent citations, labour, capital, and output in logarithms, and share of institutional holdings. As 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 such as the HHI, technological spillovers, the technological gap between firms, and the high-tech industry dummy. For some years, we use additional functional forms of the firm-level variables TFP, age, and capital to ensure balancing of the samples.

ment effect on the treated of common ownership on markups and innovation output.

$$y_{jmt} = \delta_1 \text{Treat}_m \times \text{Post}_{mt} + \delta_2 \text{Post}_{mt} + \tau_t + \nu_{jm} + \epsilon_{jmt}. \tag{6}$$

The outcome variable y_{jmt} is either the logarithm of markups or the logarithm of patent citations. In addition to the difference-in-differences coefficient $\text{Treat}_m \times \text{Post}_{mt}$ and the post period with Post_{mt}, we control for firm and year-fixed effects ν_{jm} and τ_t, as time of treatment varies across markets and therefore individual firms. The indicator variable Treat_m for the treatment group is subsumed by the firm-fixed effects. We cluster standard errors at the market level.

Table C.10 shows the results of the difference-in-differences estimator on the matched sample. Columns 1 and 2 show results with markups and columns 3 and 4 results with patent citations as the outcome variables. For markups, we find a statistically significant, positive average effect in column 1. When firms are first exposed to common ownership in the market, average markups increase by 2.3%, supporting our main results employing propensity score reweighting. In column 2, we disentangle direct and indirect effects of common ownership on markups. Both effects are positive. As expected, the effect is even larger for inside firms that are commonly held. For innovation, we find results of the same notion as before in column 3: On average, the effect is negative. The direct effect on commonly owned firms in column 4 is positive, increasing patent citation by approximately 10.5%.

Analysing how the treatment effect on the treated changes with the level of spillovers in an industry, we are able to draw the same conclusions as in the propensity score reweighting analysis. The median splits show that the effect of common ownership on markups is larger for all firms in the high-spillover sample (Table C.11). Both the direct and the indirect effect are increasing in spillovers. The effect on patent citations in Table C.12 is larger for the commonly held firms in the high-spillover sample.

6 Conclusion

This article analyses the relationship between common ownership and markups and innovation using a broad European manufacturing sample. 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 variable, citation-weighted patents measure the innovation output of firms. We use a propensity reweighting estimator to correct for observational biases. 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 explore detailed heterogeneous treatment effects in various ways.

We find a positive effect of common ownership on markups that is increasing in technological spillovers. Using an industry classification by the European Commission (2019), we distinguish between effects in industries characterised by different technological capabilities. We find positive effects of common ownership on markups for high-tech industries that consist of highly innovative and high-spillover industries. We also find a positive effect for low-tech industries which are characterised by little innovation activity and low technological spillovers. Our findings also help to shed light on the ambiguous effects of common ownership on markups and innovation. Whereas 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. We find that common ownership increases innovation output measured as patent citations in high-spillover industries for firms directly commonly owned. Our results are robust with respect to production function specifications and the identification strategy.

This article 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 have direct policy implications for competition authorities. First, common ownership may have economically meaningful anti-competitive effects for the entire industry. In particular, in low-tech industries with low technological spillovers, where there is no positive effect on innovation by common ownership, decision makers should be concerned about a rise in markups. We provide evidence that in high-tech industries, common ownership can also lead to more innovation activity, which could in turn be pro-competitive. 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, which could then lead to the described effects. In the future, regulations on the degree of common ownership may be required to tackle these issues. Further empirical research is needed on the net welfare effects of common ownership. Especially in high-tech and high-spillover industries, where we find a positive effect on markups as well as on innovation, more evidence to help develop guidelines on how to approach the issue of common ownership is required.

Appendices

A Technology Classification

According to the definition of the European Commission, NACE two-digit and three-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**
High-technology		
21		Basic pharmaceutical products and pharmaceutical preparations
26		Computer, electronic and optical products
	30.3	Air and spacecraft and related machinery
Medium-high-technology		
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
Medium-low-technology		
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
Low-technology		
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

Table A.2: Technology classification characteristics

	Patents	Patents before 2005	Percent innovating firms	Capital investment	Technological spillovers
High-tech	13.7***	7.4***	41.0***	18364.9***	6014.7***
	(0.6)	(0.4)	(0.7)	(1055.7)	(25.1)
Medium-high-tech	6.4***	3.1***	35.0***	13246.7***	4148.1***
	(0.3)	(0.2)	(0.4)	(539.2)	(12.8)
Medium-low-tech	2.1***	1.6***	24.2***	13645.6***	3231.9***
	(0.4)	(0.3)	(0.4)	(665.2)	(15.8)
Low-tech	0.8**	0.6**	11.7***	9993.5***	2037.7***
	(0.4)	(0.3)	(0.4)	(676.5)	(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. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

B Production Function Estimation

Table B.1: Production function estimates

NACE code	Industries	β_k	β_l	β_m	N	Median μ_{jt}	Median ω_{jt}
10, 11, 12	Food, beverages, tobacco	0.106	0.442	0.300	5452	0.996	1.175
13, 14, 15	Textiles, wearing apparel, leather	0.015	0.406	0.614	1405	1.166	0.620
16, 17, 18	Wood, paper, print	0.150	0.404	0.412	2024	0.888	1.666
19, 20, 21	Coke, chemicals, pharmaceuticals	0.134	0.538	0.314	4568	1.146	1.123
22, 23	Rubber, plastic, minerals	0.117	0.170	0.568	4293	1.172	1.864
24, 25	Basic, fabricated metals	0.048	0.376	0.596	5319	1.176	1.278
26, 27	Computer, electronic, electrical eq.	0.076	0.437	0.478	4443	1.182	1.256
28, 29, 30	Machinery, motor, transport	0.124	0.342	0.448	10058	1.167	0.947
31, 32, 33	Furniture, other manufacturing	0.012	0.361	0.660	1004	1.242	1.661

Note: This table presents output elasticities obtained from production function estimation (Cobb-Douglas) following the method of Ackerberg et al. (2015). For estimation of output elasticities, nine subsets of the data were regarded separately, pooling these NACE two-digit codes. μ_{jt} and ω_{jt} denote the firm-level estimated markup and logarithm of estimated productivity, respectively.

C Further Results

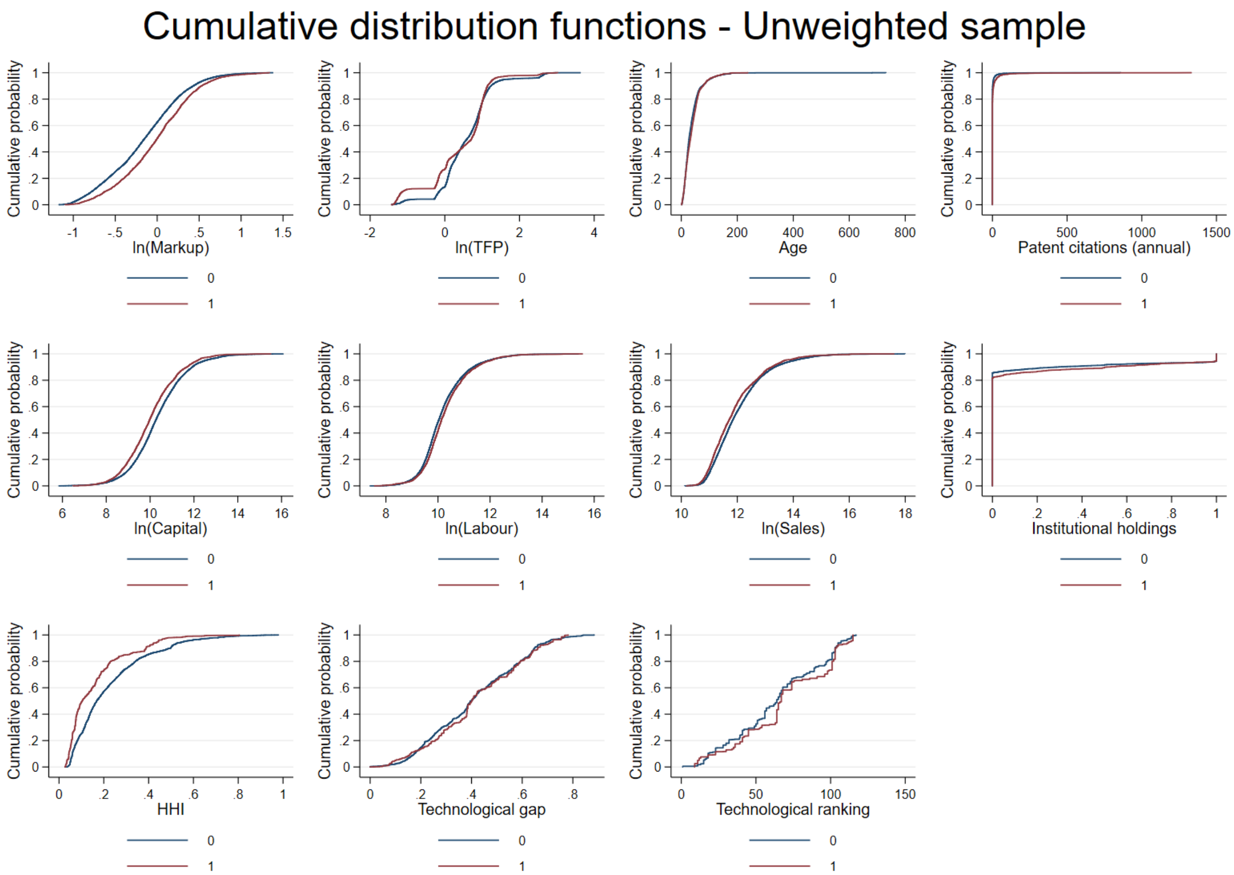
C.1 Balancing Appendix

Table C.1: Probit regressions: Propensity scores

	Dependent Variable: Treatment	
Technology	LOW	HIGH
Markup	0.248*	0.608***
	(0.130)	(0.143)
ln(TFP)	-0.207***	0.199***
	(0.066)	(0.073)
Age	0.000	-0.001
	(0.001)	(0.001)
Patent citations	0.002	0.001*
	(0.003)	(0.001)
ln(Capital)	-0.085*	-0.163***
	(0.044)	(0.038)
ln(Labour)	0.218*	0.142
	(0.113)	(0.101)
ln(Sales)	-0.068	-0.004
	(0.111)	(0.100)
Inst. Holdings	0.216*	0.161
	(0.119)	(0.140)
HHI	-1.721***	-1.313***
	(0.309)	(0.256)
Techn. gap	-0.435**	0.876***
	(0.199)	(0.186)
Techn. ranking	-0.001	0.005***
	(0.001)	(0.002)
Year Trend	Yes	Yes
Pseudo R^2	0.09	0.14
N	6132	4457
Firm clusters	1634	1349

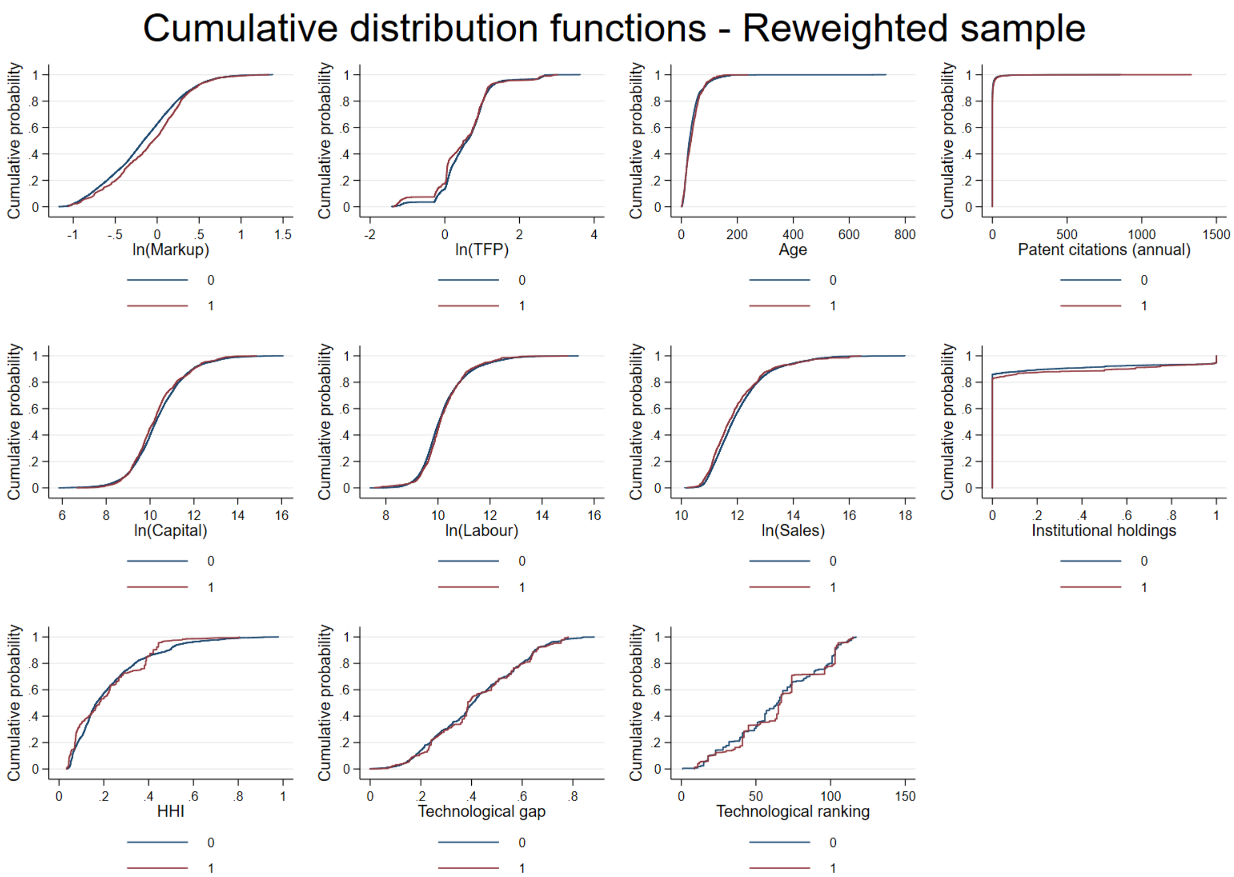
Note: Standard errors in parentheses and clustered at the firm level. * p<0.10, ** p<0.05, *** p<0.01. The table shows the results from Probit regressions. The dependent variable takes a value of one if common ownership occurs in the industry for the first time in year t+1, and zero otherwise. HIGH is 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 (LOW sample). 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.

Figure C.1: Cumulative distribution functions - Unweighted



Note: This graph shows the cumulative distribution function (cdf) of the respective variables measured as below for the unweighted regression sample. The blue line shows the cdf of the control group for firms in markets that never experience common ownership. The red line shows the cdf for the treatment group in pre-treatment periods. ln(Markup) and ln(TFP) are measured as the logarithm of markups and total factor productivity using a Cobb-Douglas production function. Additional variables are the firm age, the number of annual patent citations, the logarithm of capital, labour, and sales, the share of institutional holdings in a firm, three-digit-country level HHI, the technological gap as in Aghion et al. (2005), and the ranking in terms of technological spread.

Figure C.2: Cumulative distribution functions - Reweighted



Note: This graph shows the cumulative distribution function (cdf) of the respective variables measured as below for the reweighted regression sample using propensity score weights. The blue line shows the cdf of the control group for firms in markets that never experience common ownership. The red line shows the cdf for the treatment group in pre-treatment periods. ln(Markup) and ln(TFP) are measured as the logarithm of markups and total factor productivity using a Cobb-Douglas production function. Additional variables are the firm age, the number of annual patent citations, the logarithm of capital, labour, and sales, the share of institutional holdings in a firm, three-digit-country level HHI, the technological gap as in Aghion et al. (2005), and the ranking in terms of technological spread.

C.2 Treatment Intensity Appendix

Table C.2: Reweighting estimator: ln(Markup) - Treatment intensity

Dep. Variable:	**ln(Markup)**					
	(1)	(2)	(3)	(4)	(5)	(6)
Cutoff MHHI delta	>0	>5%	>10%	>15%	>20%	>25%
$1_{(MHHIdelta>0)}$	0.008	0.008	0.009	0.012**	0.012**	0.014**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
HHI	0.049**	0.049**	0.043*	0.039	0.038	0.037
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.025)
Inst. Holdings	0.005	0.005	0.006	0.004	0.004	0.003
	(0.013)	(0.014)	(0.014)	(0.015)	(0.015)	(0.015)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.96	0.96	0.96	0.96	0.96	0.96
N	15392	15287	15311	15128	15106	14923
Market clusters	468	468	468	468	468	468

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. The different coefficients are estimated in subsamples where we keep control observations with MHHI delta equal to 0 and treated observations with positive MHHI delta above the indicated percentile of the distribution of MHHI delta. Treatment is defined as the first occurrence of common ownership, i.e. a non-zero MHHI delta. HHI and MHHI delta are rescaled by division by 10,000, such that the HHI ranges from 0 to 1.

Table C.3: Reweighting estimator: ln(Markup) - Treatment intensity, insiders vs. outsiders

Dep. Variable:	**ln(Markup)**					
	(1)	(2)	(3)	(4)	(5)	(6)
Cutoff MHHI delta	>0	>5%	>10%	>15%	>20%	>25%
$1_{(MHHIdelta>0)} \times$ Insider	0.014	0.014	0.024	0.026	0.026	0.029
	(0.029)	(0.029)	(0.028)	(0.028)	(0.028)	(0.031)
$1_{(MHHIdelta>0)} \times$ Outsider	0.007	0.008	0.007	0.010*	0.010*	0.012**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
HHI	0.049**	0.049**	0.043*	0.038	0.038	0.036
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Inst. Holdings	0.004	0.004	0.004	0.002	0.002	0.001
	(0.014)	(0.014)	(0.015)	(0.015)	(0.015)	(0.016)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.96	0.96	0.96	0.96	0.96	0.96
N	15392	15287	15311	15128	15106	14923
Market clusters	468	468	468	468	468	468

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. The different coefficients are estimated in subsamples where we keep control observations with MHHI delta equal to 0 and treated observations with positive MHHI delta above the indicated percentile of the distribution of MHHI delta. Treatment is defined as the first occurrence of common ownership, i.e. a non-zero MHHI delta. Insiders are defined as directly commonly owned firms. Outsiders are non-commonly owned competitors in the same market. HHI and MHHI delta are rescaled by division by 10,000, such that the HHI ranges from 0 to 1.

Table C.4: Reweighting estimator: ln(Patent Citations) - Treatment intensity

Dep. Variable:	**ln(Patent Citations)**					
	(1)	(2)	(3)	(4)	(5)	(6)
Cutoff MHHI delta	>0	>5%	>10%	>15%	>20%	>25%
$1_{(MHHIdelta>0)}$	-0.001	-0.002	0.009	0.009	0.009	0.002
	(0.020)	(0.021)	(0.024)	(0.028)	(0.028)	(0.029)
HHI	-0.148	-0.146	-0.139	-0.132	-0.132	-0.120
	(0.106)	(0.107)	(0.110)	(0.113)	(0.113)	(0.107)
Inst. Holdings	0.109	0.120	0.099	0.097	0.097	0.102
	(0.080)	(0.080)	(0.081)	(0.078)	(0.078)	(0.078)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.80	0.80	0.80	0.80	0.80	0.80
N	15392	15287	15311	15128	15106	14923
Market clusters	468	468	468	468	468	468

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. The different coefficients are estimated in subsamples where we keep control observations with MHHI delta equal to 0 and treated observations with positive MHHI delta above the indicated percentile of the distribution of MHHI delta. Treatment is defined as the first occurrence of common ownership, i.e. a non-zero MHHI delta. We control for HHI at the three-digit industry country level, ln(TFP), market size measured by average sales at the market level, capital intensity, 1-Lerner index, and age, share of institutional holdings, a dummy for zero citations, firm and year-fixed effects. Zero patent citations are set to one. HHI and MHHI delta are rescaled by division by 10,000, such that the HHI ranges from 0 to 1.

Table C.5: Reweighting estimator: ln(Patent Citations) - Treatment intensity, insiders vs. outsiders

Dep. Variable:	**ln(Patent Citations)**					
	(1)	(2)	(3)	(4)	(5)	(6)
Cutoff MHHI delta	>0	>5%	>10%	>15%	>20%	>25%
$1_{(MHHIdelta>0)}\times$ Insider	0.048	0.045	0.045	0.049	0.049	0.027
	(0.032)	(0.032)	(0.035)	(0.037)	(0.037)	(0.042)
$1_{(MHHIdelta>0)}\times$ Outsider	-0.006	-0.006	0.006	0.005	0.006	0.000
	(0.021)	(0.022)	(0.025)	(0.029)	(0.029)	(0.029)
HHI	-0.148	-0.147	-0.140	-0.132	-0.132	-0.121
	(0.106)	(0.106)	(0.109)	(0.113)	(0.113)	(0.107)
Inst. Holdings	0.103	0.114	0.094	0.091	0.091	0.099
	(0.083)	(0.083)	(0.083)	(0.081)	(0.081)	(0.081)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.80	0.80	0.80	0.80	0.80	0.80
N	15392	15287	15311	15128	15106	14923
Market clusters	468	468	468	468	468	468

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. The different coefficients are estimated in subsamples where we keep control observations with MHHI delta equal to 0 and treated observations with positive MHHI delta above the indicated percentile of the distribution of MHHI delta. Treatment is defined as the first occurrence of common ownership, i.e. a non-zero MHHI delta. Insiders are defined as directly commonly owned firms. Outsiders are non-commonly owned competitors in the same market. We control for HHI at the three-digit industry country level, ln(TFP), market size measured by average sales at the market level, capital intensity, 1-Lerner index, and age, share of institutional holdings, a dummy for zero citations, firm and year-fixed effects. Zero patent citations are set to one. HHI and MHHI delta are rescaled by division by 10,000, such that the HHI ranges from 0 to 1.

Table C.6: Reweighting estimator: Markups - Dummy

Dep. Variable:	**ln(Markup)**		
	(1)	(2)	(3)
MHHI 25-100%	0.014**	0.010*	0.014**
	(0.006)	(0.005)	(0.007)
MHHI 15-25%	-0.001	0.011	0.011
	(0.005)	(0.010)	(0.010)
MHHI 0-15%	-0.015**	-0.012	-0.001
	(0.006)	(0.007)	(0.007)
HHI	0.049**	0.045	0.001
	(0.024)	(0.031)	(0.040)
Inst. Holdings	0.004	0.007	0.003
	(0.013)	(0.014)	(0.013)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Year×Country FE	No	Yes	Yes
Year×NACE3 FE	No	No	Yes
Adj. R^2	0.96	0.96	0.96
N	15392	15391	15316
Market clusters	468	468	463

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.

Table C.7: Reweighting estimator: Patent citations - Dummy

Dep. Variable:	**ln(Patent Citations)**		
	(1)	(2)	(3)
MHHI 25-100%	-0.006	0.008	-0.020
	(0.022)	(0.020)	(0.019)
MHHI 15-25%	0.084***	0.061***	0.071**
	(0.029)	(0.018)	(0.032)
MHHI 0-15%	-0.019	-0.003	-0.003
	(0.016)	(0.024)	(0.032)
HHI	-0.147	-0.068	0.048
	(0.108)	(0.130)	(0.089)
Inst. Holdings	0.112	0.106	0.112
	(0.092)	(0.093)	(0.098)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Year×Country FE	No	Yes	Yes
Year×NACE3 FE	No	No	Yes
Adj. R^2	0.80	0.80	0.81
N	15392	15391	15316
Market clusters	169	169	168

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. We control for HHI at the three-digit industry country level, ln(TFP), market size measured by average sales at the market level, capital intensity, 1-Lerner index, and age, share of institutional holdings, a dummy for zero citations, firm and year-fixed effects. Zero patent citations are set to one. HHI and MHHI delta are rescaled by division by 10,000, such that the HHI ranges from 0 to 1.

C.3 Spillover Appendix

Table C.8: Reweighting estimator with spillovers

Dep. Variable:	**ln(Markup)**				
Spillover	(1) ALL	(2) <25%	(3) <50%	(4) >50%	(5) >75%
$1_{(MHHIdelta>0)} \times$ Spillover	8.03e-06***				
	(0.000)				
$1_{(MHHIdelta>0)}$	-0.021**	0.015*	-0.002	0.020***	0.034***
	(0.010)	(0.008)	(0.006)	(0.007)	(0.011)
HHI	0.040*	0.090	0.070*	0.029	0.022
	(0.023)	(0.063)	(0.042)	(0.028)	(0.042)
Inst. Holdings	0.007	-0.016	-0.003	0.010	-0.011
	(0.013)	(0.017)	(0.018)	(0.018)	(0.031)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.96	0.98	0.97	0.94	0.95
N	15392	3728	7905	7487	3592
Market clusters	468	143	272	237	125

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.

Table C.9: Reweighting estimator with spillovers

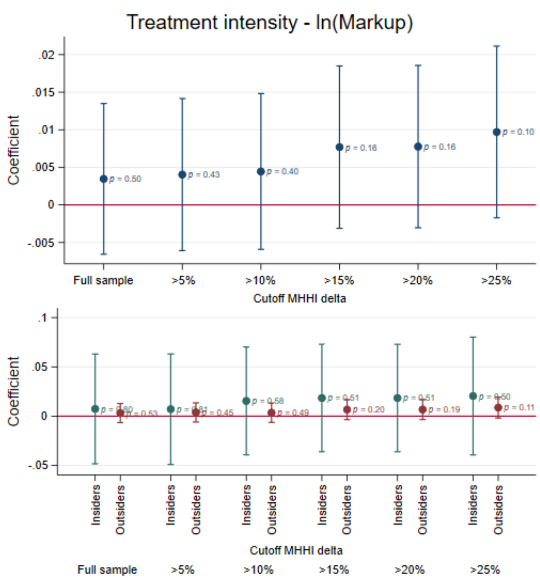
Dep. Variable:	**ln(Patent Citations)**				
	(1)	(2)	(3)	(4)	(5)
Spillover	ALL	<25%	<50%	>50%	>75%
$1_{(MHHIdelta>0)}\times$ Insider $\times$ Spillover	0.0000109*				
	(0.000)				
$1_{(MHHIdelta>0)}\times$ Outsider $\times$ Spillover	-0.0000151				
	(0.000)				
$1_{(MHHIdelta>0)}\times$ Insider	0.014	0.019	0.063	0.033	0.095**
	(0.039)	(0.021)	(0.041)	(0.046)	(0.044)
$1_{(MHHIdelta>0)}\times$ Outsider	0.050	0.025	0.012	-0.027	-0.027
	(0.035)	(0.020)	(0.033)	(0.031)	(0.040)
HHI	-0.136	-0.075	-0.222	-0.094	-0.168
	(0.099)	(0.154)	(0.143)	(0.143)	(0.206)
Inst. Holdings	0.105	0.027	0.047	0.153	-0.011
	(0.083)	(0.050)	(0.037)	(0.142)	(0.084)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.80	0.71	0.77	0.82	0.86
N	15392	3728	7905	7487	3592
Market clusters	468	143	272	237	125

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. Insiders are defined as directly commonly owned firms. Outsiders are non-commonly owned competitors in the same market. We control for HHI at the three-digit industry country level, ln(TFP), market size measured by average sales at the market level, capital intensity, 1-Lerner index, and age, share of institutional holdings, a dummy for zero citations, firm and year-fixed effects. Zero patent citations are set to one. HHI and MHHI delta are rescaled by division by 10,000, such that the HHI ranges from 0 to 1.

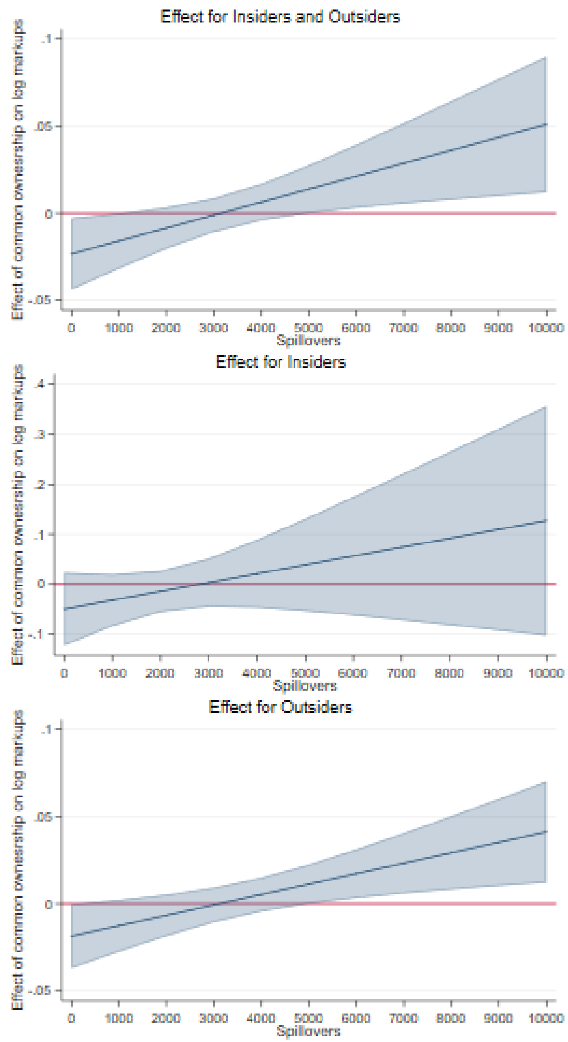
C.4 Robustness

Controlling for TFP

Figure C.3: Reweighting Estimator: Controlling for polynomial of TFP, ln(Markup)



a) ln(Markup) - Intensity

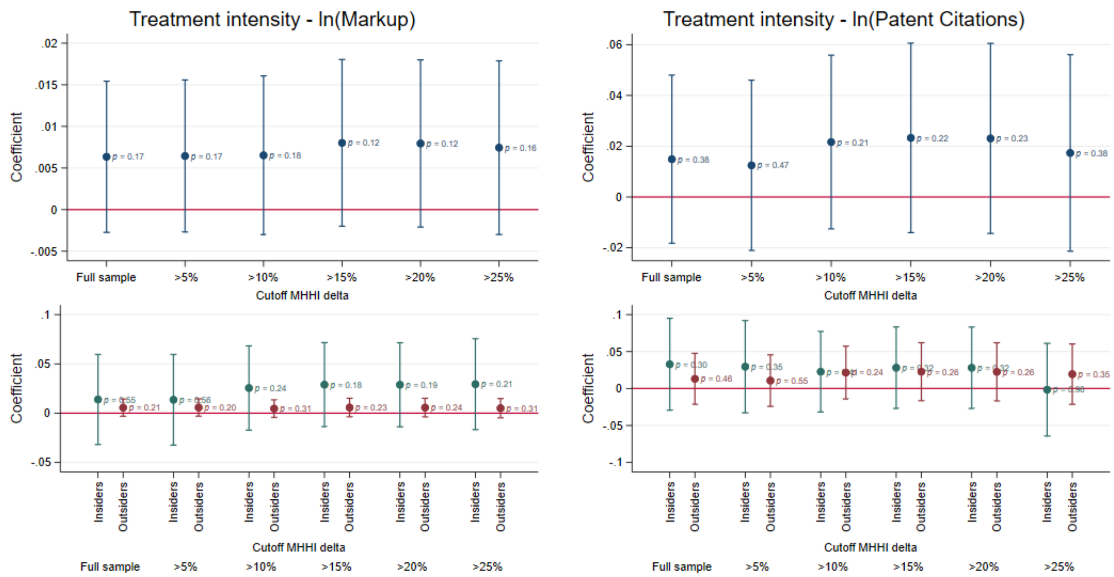


b) ln(Markup) - Spillovers

Note: The graph on the left plots the estimated coefficients of the treatment indicator and respective confidence intervals and p-values. The different coefficients are estimated in subsamples where we keep control observations with MHHI delta equal to 0 and treated observations with positive MHHI delta above the indicated percentile of the distribution of MHHI delta. The graph on the right plots the treatment effect for varying degrees of spillovers. Treatment is defined as the first occurrence of common ownership, i.e. a non-zero MHHI delta. Insiders are defined as directly commonly owned firms. Outsiders are non-commonly owned competitors in the same market. We control for HHI at the three-digit industry country level, 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.

Country-specific and industry-specific time-fixed effects

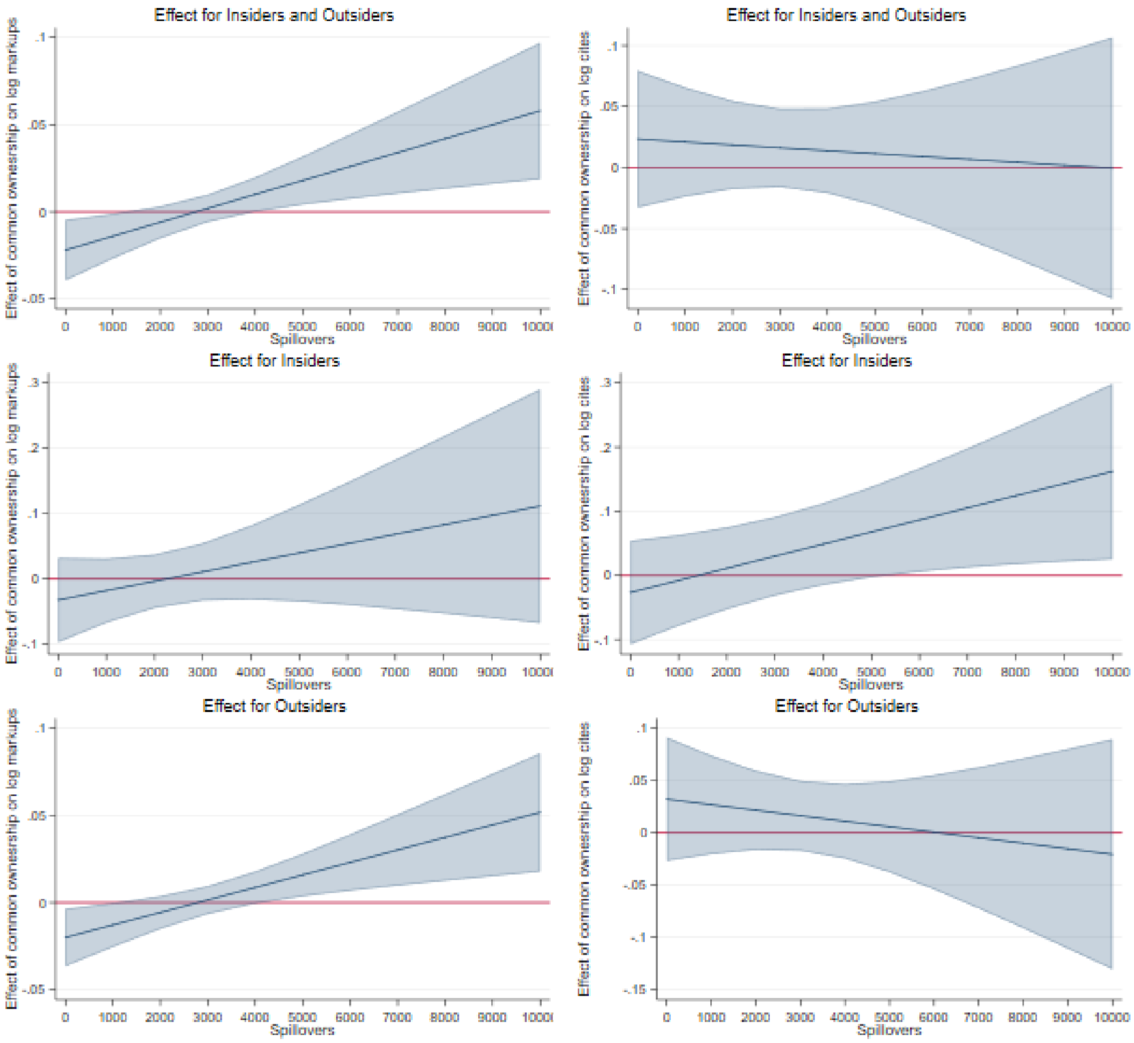
Figure C.4: Reweighting estimator: Coefficients of treatment indicator by cutoffs - country-specific and industry-specific time-fixed effects



a) ln(Markup) **b)** ln(Patent Citations)

Note: The graphs plots the estimated coefficients of the treatment indicator and respective confidence intervals and p-values. The different coefficients are estimated in subsamples where we keep control observations with MHHI delta equal to 0 and treated observations with positive MHHI delta above the indicated percentile of the distribution of MHHI delta. Treatment is defined as the first occurrence of common ownership, i.e. a non-zero MHHI delta. Insiders are defined as directly commonly owned firms. Outsiders are non-commonly owned competitors in the same market. We control for HHI at the three-digit industry country level, ln(TFP), market size measured by average sales at the market level, capital intensity, 1-Lerner index, and age, share of institutional holdings, a dummy for zero citations, firm and year-fixed effects. Zero patent citations are set to one. Standard errors clustered at the three-digit industry-country level. The red line indicates zero.

Figure C.5: Treatment effect for varying spillovers - country-specific and industry-specific time-fixed effects

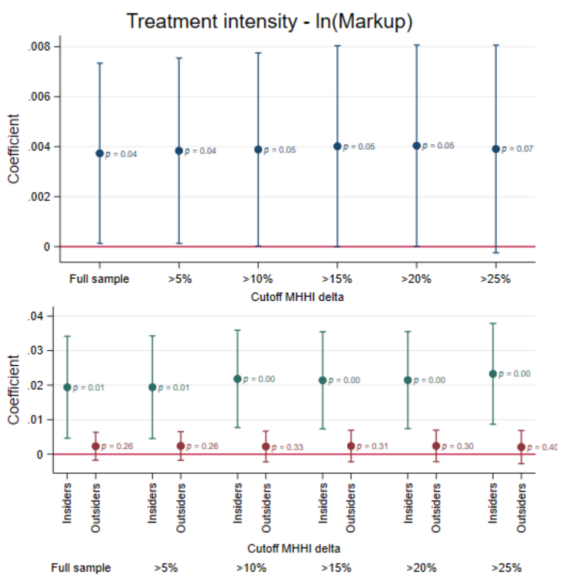


a) ln(Markup) **b)** ln(Patent Citations)

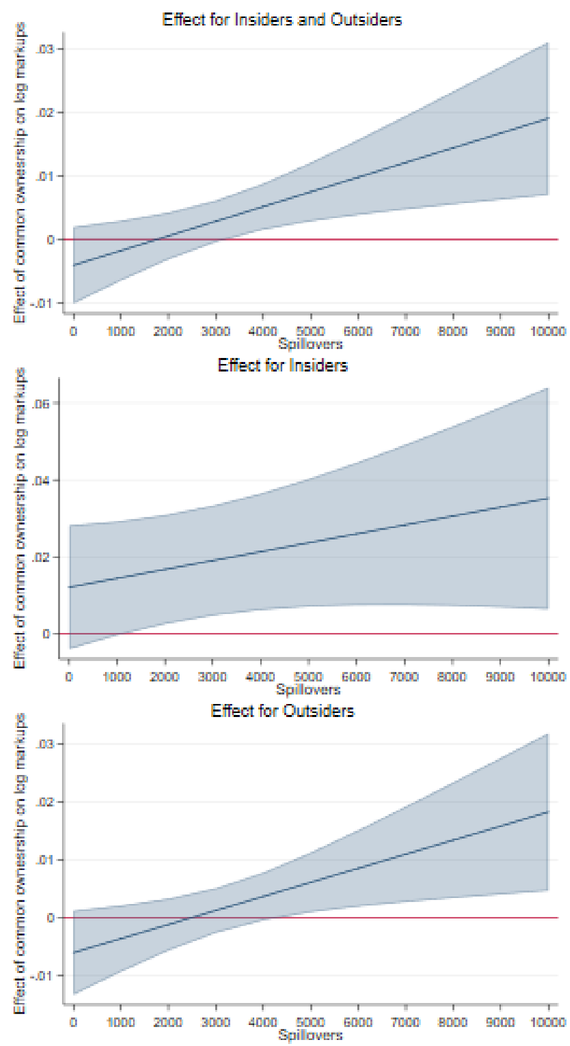
Note: Treatment is defined as the first occurrence of common ownership, i.e. a non-zero MHHI delta. Insiders are defined as directly commonly owned firms. Outsiders are non-commonly owned competitors in the same market. We control for HHI at the three-digit industry country level, share of institutional holdings, firm and year-country-fixed effects and cluster standard errors at the three-digit industry-country level. Additionally for patent citations we control for ln(TFP), market size measured by average sales at the market level, capital intensity, 1-Lerner index, age, and a dummy for zero citations. Zero patent citations are set to one. The red line indicates zero. The blue shaded area is a 95% CI.

Alternative production function specifications

Figure C.6: Reweighting estimator: ln(Markup) - Translog



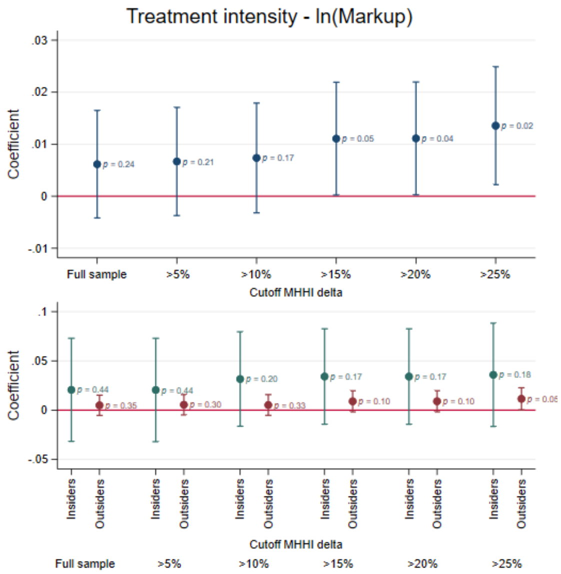
a) ln(Markup) - Intensity



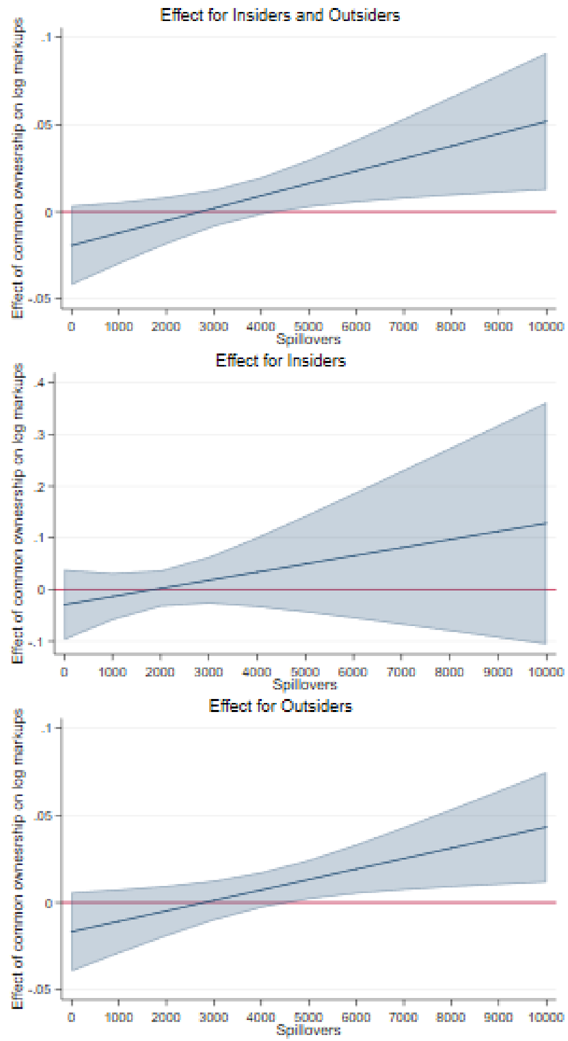
b) ln(Markup) - Spillovers

Note: The graph on the left plots the estimated coefficients of the treatment indicator and respective confidence intervals and p-values. The different coefficients are estimated in subsamples where we keep control observations with MHHI delta equal to 0 and treated observations with positive MHHI delta above the indicated percentile of the distribution of MHHI delta. The graph on the right plots the treatment effect for varying degrees of spillovers. Treatment is defined as the first occurrence of common ownership, i.e. a non-zero MHHI delta. Insiders are defined as directly commonly owned firms. Outsiders are non-commonly owned competitors in the same market. We control for HHI at the three-digit industry country level, 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 C.7: Reweighting estimator: ln(Markup) - Wage in Control Function.



a) ln(Markup) - Intensity



b) ln(Markup) - Spillovers

Note: The graph on the left plots the estimated coefficients of the treatment indicator and respective confidence intervals and p-values. The different coefficients are estimated in subsamples where we keep control observations with MHHI delta equal to 0 and treated observations with positive MHHI delta above the indicated percentile of the distribution of MHHI delta. The graph on the right plots the treatment effect for varying degrees of spillovers. Treatment is defined as the first occurrence of common ownership, i.e. a non-zero MHHI delta. Insiders are defined as directly commonly owned firms. Outsiders are non-commonly owned competitors in the same market. We control for HHI at the three-digit industry country level, 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.

C.5 Difference-in-Differences

Table C.10: Propensity score matching & difference-in-differences

Dep. Variable:	**ln(Markup)**		**ln(Patent Citations)**	
	(1)	(2)	(3)	(4)
$1_{(MHHIdelta>0)}$	0.023**		-0.044	
	(0.009)		(0.044)	
$1_{(MHHIdelta>0)}\times$ Insider		0.026		0.100**
		(0.022)		(0.045)
$1_{(MHHIdelta>0)}\times$ Outsider		0.022**		-0.053
		(0.009)		(0.044)
Post	-0.017**	-0.017**	-0.017	-0.016
	(0.008)	(0.008)	(0.033)	(0.033)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.95	0.95	0.70	0.70
N	5812	5812	5812	5812
Market clusters	252	252	252	252

Note: Standard errors in parentheses and clustered at the three-digit industry-country level. * p<0.10, ** p<0.05, *** p<0.01
Treatment is defined as the first occurrence of common ownership, i.e. a non-zero MHHI delta. Insiders are defined as directly commonly owned firms. Outsiders are non-commonly owned competitors in the same market.

Table C.11: ln(Markup) - Median split spillovers

ln(Markup)	**Average effect**		**Direct & indirect effect**	
	(1)	(2)	(3)	(4)
Spillovers	LOW	HIGH	LOW	HIGH
$1_{(MHHIdelta>0)}$	0.004	0.043***		
	(0.011)	(0.012)		
$1_{(MHHIdelta>0)}\times$ Insider			0.004	0.045
			(0.020)	(0.040)
$1_{(MHHIdelta>0)}\times$ Outsider			0.004	0.043***
			(0.011)	(0.013)
Post	-0.001	-0.031***	-0.001	-0.031***
	(0.010)	(0.010)	(0.010)	(0.010)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.96	0.94	0.96	0.94
N	2982	2830	2982	2830
Market clusters	140	137	140	137

Note: Standard errors in parentheses and clustered at the three-digit industry-country level. * p<0.10, ** p<0.05, *** p<0.01
Treatment is defined as the first occurrence of common ownership, i.e. a non-zero MHHI delta.Insiders are defined as directly commonly owned firms. Outsiders are non-commonly owned competitors in the same market.

Table C.12: ln(Patent Citations) - Median split spillovers

ln(Patent Citations)	**Average effect**		**Direct & indirect effect**	
	(1)	(2)	(3)	(4)
Spillovers	LOW	HIGH	LOW	HIGH
$1_{(MHHIdelta>0)}$	-0.073	-0.012		
	(0.064)	(0.064)		
$1_{(MHHIdelta>0)}\times$ Insider			0.055	0.137**
			(0.063)	(0.064)
$1_{(MHHIdelta>0)}\times$ Outsider			-0.082	-0.022
			(0.065)	(0.065)
Post	0.037	-0.062	0.037	-0.062
	(0.040)	(0.052)	(0.040)	(0.052)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.62	0.76	0.62	0.76
N	2982	2830	2982	2830
Market clusters	140	137	140	137

Note: Standard errors in parentheses and clustered at the three-digit industry-country level. * p<0.10, ** p<0.05, *** p<0.01
Treatment is defined as the first occurrence of common ownership, i.e. a non-zero MHHI delta.Insiders are defined as directly commonly owned firms. Outsiders are non-commonly owned competitors in the same market.

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