Rising Markups, Common Ownership, and Technological Capacities*

Alexandra J. Gibbon† Jan Philip Schain†

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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 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 3.3% on average 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 9.6% in high-spillover industries on average. Both findings are consistent with recent theoretical findings in López and Vives (2019).

JEL codes: *L13, L41, L60, G23, G32, O31*

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

1 Introduction

The recently observed pattern of a long term rise in market power accompanied by increasing industry concentration (De Loecker et al., 2020; 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.

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[1]. 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, 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[2]. 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., 2022).

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-

[1]Considerable volumes of common ownership can be found in publicly listed companies, for instance in the airline, banking, or pharmacy sector in the USA (Azar et al., 2018), as well as in the chemical sector and car industry in Germany (Seldeslachts et al., 2017).

[2]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 (2022).

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. (2022) 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 beneficial effect. Depending on technological spillovers in a given industry, common ownership can spur innovation by increasing the marginal benefit of investment in research and development (R&D). They conclude that in markets with high technological spillovers, firms internalise 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 (2022). On the contrary, Gutiérrez and Philippon (2017) show empirically 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 (O'Brien and Waehrer, 2017; Rock and Rubinfeld, 2018; Patel, 2018; Lambert and Sykuta, 2019; Koch et al., 2021 and Lewellen and Lowry, 2021)[3]. 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

[3]Discussions by Kennedy et al. (2017) and Dennis et al. (2022), specifically targeted at the empirical strategy by Azar et al. (2018), have been refuted in Azar et al. (2021) and Azar et al. (2022a). The latter shows that original estimates were in fact biased towards zero and that even higher anti-competitive price effects can be found. Elhauge (2020) provides further insights in how addressing these methodological critiques may actually reveal larger anti-competitive effects.

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, relying on 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 reaches 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 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 the measure of common ownership, regression and production function specifications, as well as a one-to-one propensity score matching approach combined with a difference-in-differences setup.

Although there are some empirical industry-specific studies that analyse anti-competitive effects of common ownership on prices[4] in the airline and banking industry (Azar et al., 2018, 2022b), there is less work on a wider firm panel containing multiple industries. Backus et al. (2021) perform a calibration exercise on firms in the S&P500 index with initial markup estimates taken from De Loecker and Eeckhout (2021). In our analysis we abstract from general equilibrium effects as in Azar and Vives (2021a,b); Ederer and Pellegrino (2022). Kini et al. (2022) 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

[4]Apart from prices, markups, and innovation, researchers have also dealt with managerial incentives (Antón et al., 2022), market entry and exit (Xie, 2020; Newham et al., 2022), and mergers and acquisitions (Antón et al., 2021b) that are influenced by common ownership structures in industries. Schmalz (2021); Elhauge (2021) provide comprehensive overviews of the literature on competitive effects of common ownership.

with our findings on innovation, but our results differ in terms of markups. Antón et al. (2021a) 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 (2020) 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. 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. (2022), 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.

The rest of this article proceeds as follows. Section 2 gives an overview of the data set and markup estimation. The identification strategy and the measure for common ownership are 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 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 markup distribution has developed over time.

2.1 Data Description

Manufacturing Firms' Financial Data

The Amadeus data base by Bureau van Dijk provides a comprehensive collection of financial data and information on corporate structure of European companies, which also covers non-listed firms. Our analyses are conducted using a rich firm-level panel of the manufacturing sector (NACE two-digit codes 10 to 32) for the observation period 2005 to 2016. 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, with a total of 7229 unique firms. 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.

Markets are defined using the Statistical Classification of Economic Activities in the European Community (NACE) at the three-digit level in the product dimension and for geographical differentiation at the country level, such that each NACE three-digit and country combination in the European manufacturing sector defines a separate market. Each firm is assigned its main three-digit industry in the dataset Amadeus by Bureau van Dijk, such that a firm occurs only once per time period and not in several markets. The market definition implies that for example, a German company assigned to a specific German three-digit industry[5] neither competes with firms in another three-digit industry in Germany nor with firms in the same or other three-digit industries in another country. Our raw sample incorporates 35 European countries and 1398 markets, i.e. NACE three-digit code and country combinations, over the complete sample period. Not all three-digit codes are prevalent in each country, and on average, there are 1217 markets per year and around 8 firms per market per year.

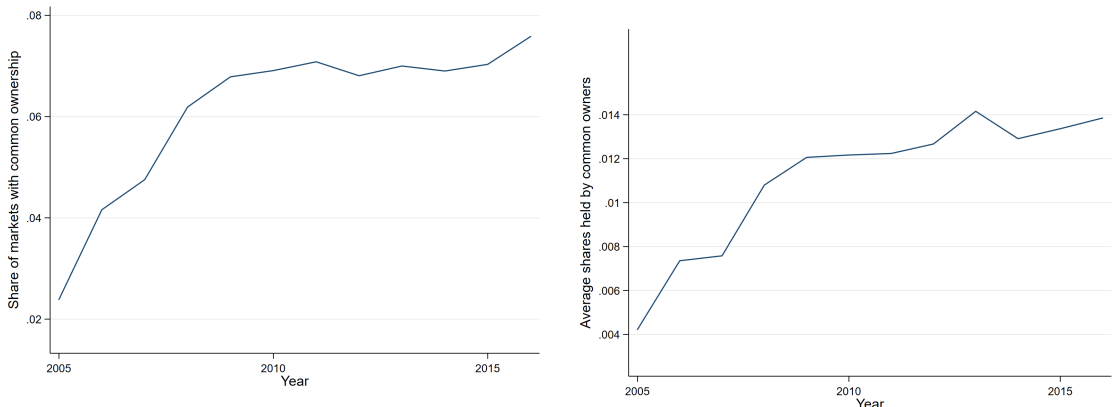
Common ownership arises when any institutional investor holds any equity share in two or more companies within the same market. We assume proportionate control, where the percentages held in equity are proportional to control rights, as there is no distinction between ownership and control shares in the data[6]. In order to acknowledge holding structures, different subsidiaries of some of the largest investors are 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). On the full sample, there are on average 2.3% firms affected by common ownership. In a market exposed to common ownership, around 27.7% of firms are directly affected by common ownership, on average. In our dataset, common ownership becomes more prevalent over time. The percentage of markets with

[5]One example for a NACE three-digit code: 106 *"Manufacture of grain mill products, starches and starch products: This group includes the milling of flour or meal from grains or vegetables, the milling, cleaning and polishing of rice, as well as the manufacture of flour mixes or doughs from these products. Also included in this group are the wet milling of corn and vegetables and the manufacture of starch and starch products"* Source: Statistical Classification of Economic Activities in the European Community (NACE Rev. 2, 2008).

[6]For example, in the US, around 90% of publicly listed companies issue shares with equal voting rights with a single class of stock. Council of Institutional Investors (13.02.2022). Dual-class stock. Available at https://www.cii.org/dualclass_stock.

common ownership increases from roughly 2.5% to almost 8% from 2005 to 2016 as shown in Figure 1a. During the same period, the average share held by common owners increases from 0.4% to 1.4%, as shown in Figure 1b. This rising pattern of common ownership is consistent with findings in other studies, such as Backus et al. (2021) for the S&P500 and Boot et al. (2022) for the S&P Europe 350. Figures C.1a and C.1b show the percentage of markets and the share of firms with common ownership per NACE two-digit industry, respectively. In the graphs, we distinguish between the industries in high, medium-high, medium-low, and low-technology classes.

Figure 1: Market-level and firm-level evolution of common ownership



a) Markets with common ownership

b) Shares held by common owners

Note: The figure on the left shows the percentage of affected markets, defined as NACE three-digit and country combinations. The figure on the right shows the average share held by common owners over the whole sample. 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.

For structural estimation of production functions, it is common practice to use accounting data proxies as information on produced quantities are not widely available. 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 annual producer price indices per two-digit industry and country for the years 2005 to 2016 from Eurostat[7].

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.

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.

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

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 each NACE three-digit industry.

As an additional measure, we obtain a classification of technology intensity of the manufacturing industries. According to the definition by the European Commission (2019), each 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 (see Table A.2).

2.2 Productivity and Markup Estimation

Estimation of markups relies on preceding estimation of a production function and respective output elasticities using the standard procedure proposed by Ackerberg et al. (2015). We assume a logarithmic Cobb-Douglas production function to account for substitutability of inputs. The production function of firm j in year t (note that each firm only operates in one market p, their main line of business) for output q_{jt} includes the inputs capital k_{jt}, labour l_{jt}, materials m_{jt}, unobserved productivity ω_{jt}, and a measurement error ϵ_{jt}, such that $q_{jt} = \beta^0 + \beta^k k_{jt} + \beta^l l_{jt} + \beta^m m_{jt} + \omega_{jt} + \epsilon_{jt}$. The estimation consists of a two-step procedure. In the first stage, we correct for measurement error without identifying any of the input coefficients by predicting output using inverted material input demand that consists of a third order polynomial in input factors labour, capital, and materials, as well as country fixed effects. In the second step following Ackerberg et al. (2015), the serial correlation of productivity is modelled as a controlled first order Markov process, in which we allow for common ownership to endogenously impact future productivity. The exogenous part of this process is used for the identification of the coefficients of the production function. We estimate output elasticities for nine subsets of the manufacturing industry. A more detailed description of the estimation procedure, information on the pooled industry subsets, and the results of the production function estimation can be found in the Appendix B[8].

Using the elasticity of output with respect to materials and the revenue share of material expenditures following De Loecker and Warzynski (2012), we compute markups as

$$\mu_{jt} = \frac{\beta^m}{\hat{\alpha}^m_{jt}} = \left(\frac{P_{jt}Q_{jt}}{w^m_{jt}m_{jt}}\right) \frac{\partial Q_{jt}(\cdot)}{\partial m_{jt}} \frac{m_{jt}}{Q_{jt}}, \tag{1}$$

where μ_{jt} is the markup of firm j in year t. The product of output prices and quantities $P_{jt}Q_{jt}$ is given as sales, and the product of the price and quantities of materials $w^m_{jt}m_{jt}$ is given as material expenditures in the data. The second term, $\frac{\partial Q_{jt}(\cdot)}{\partial m_{jt}} \frac{m_{jt}}{Q_{jt}}$, denotes the elasticity of output with respect to material inputs, obtained by the previous estimation of the production function and the respective input coefficients. An error correction is applied to deflated sales in the calculation of the revenue share of the costs of materials, such that $\hat{\alpha}^m_{jt} = \frac{w^m_{jt}m_{jt}}{\frac{P_{jt}Q_{jt}}{exp(\hat{\epsilon}_{jt})}}$. Markups are calculated for each firm from the estimated material elasticities,

[8] In a robustness check we also estimate a Translog production function. In another robustness check we control for wages in the first stage to mitigate potential endogeneity concerns resulting from unobserved price data as described in De Loecker (2021).

starting in 2006[9].

Figure 2 shows the evolution of markups weighted with labour input costs. The construction of the percentiles follows the same methodology as in De Loecker et al. (2020), in order to make the percentiles comparable to the weighted average. We see that the 90th percentile of markups show a rising pattern[10], similar to the results in De Loecker et al. (2020) for the USA, and globally in De Loecker and Eeckhout (2021). The authors also show weighted average markups specifically for Europe, which are relatively flat, similar to our results in the respective time period. However, their sample displays a sharp rise in the last periods, where our sample remains flat. Another study with similar markup patterns on a global sample is Calligaris et al. (2022). A recent working paper (Ciapanna et al., 2022) analyses markup evolution with Italian data. The manufacturing sample shows very similar dynamics as in this article. The weighted average is relatively flat and only the upper ten percent of markups show a rising pattern. Flat average markups in Europe for the periods of our sample are also reported in Cavalleri et al. (2020); De Loecker et al. (2018); Gradzewicz and Mućk (2019).

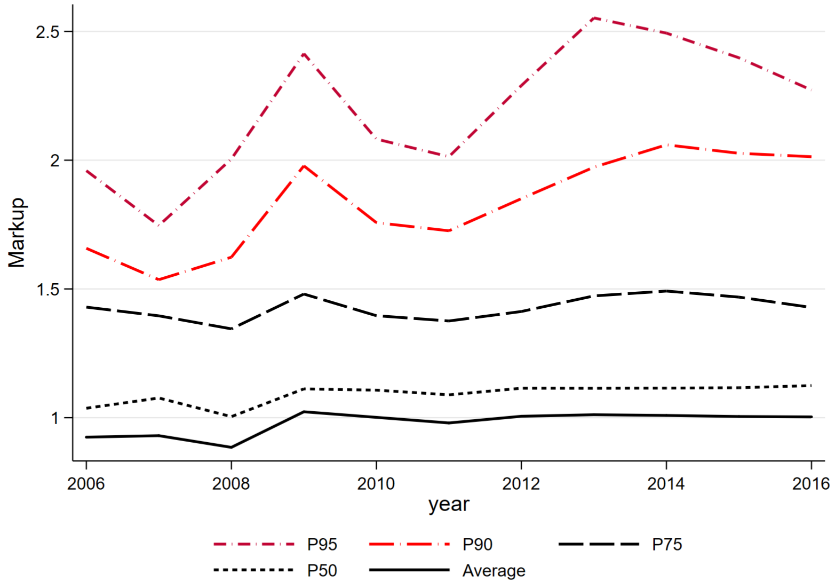
3 Empirical Strategy

This section presents the identification strategy employed to determine the effect of common ownership on markups and citation-weighted patents. The propensity score reweighting procedure following Guadalupe et al. (2012) including the construction of inverse probability weights is detailed in Subsection 3.1, and a discussion of reweighted regressions follows in Subsection 3.2.

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

[10]Using alternative weighting variables (see Figures B.1a and B.1b in the Appendix) does not change markup patterns.

Figure 2: Evolution of markups, weighted with labour input costs



Note: The figure illustrates the evolution of the weighted distribution of firm markups from 2006 to 2016. Labour input costs are used as weights. 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. For the construction of the percentiles we follow the methodology of De Loecker et al. (2020).

3.1 Propensity Score Reweighting

The investment strategies of asset managers are clearly not independent of the performance or profitability of their potential portfolio firms. 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.

We apply a propensity score reweighting approach following Guadalupe et al. (2012) using weighted panel fixed-effects regressions to account for these potential biases. 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)[11]. The aim of this method is to construct a sample with a control group that can approximate the counterfactual outcome of the treated group absent treatment by assigning weights corresponding to the inverse probability of treatment to observations (Hirano and Imbens, 2001; Hirano et al., 2003; Imbens, 2004). Fixed-effects models control for time-constant characteristics and identify the effects using only within-firm variation.

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).

In our application, firms in markets where we observe new occurrences of common ownership links are considered to be in the treatment group. For each NACE three-digit industry and country combination, we construct the common ownership measure MHHI delta to denote treated markets (i.e. there is common ownership when MHHI delta > 0)[12]. The MHHI delta reflects common ownership concentration in a market and is calculated as the difference between the MHHI and the classical HHI (Salop and O'Brien, 2000). For each market at a given point in time, $\text{MHHI} = \sum_j s_j^2 + \sum_j \sum_{f \neq j} s_j s_f \frac{\sum_i \beta_{ij} \beta_{if}}{\sum_i \beta_{ij}^2}$, where subscripts j and f denote firms and competitors, i indexes the investors, and β_{ij} are ownership shares assuming proportionate control, such that ownership shares equal control shares. Individual profit weights between each pair of commonly owned firms are weighted with the product

[11] There are numerous other studies relying on estimates under selection on observables that have applied propensity score procedures. Examples include firm-level studies (Alfaro and Chen, 2012; Aghion et al., 2013; Smeets and Warzynski, 2013; Bena and Li, 2014; Geurts and Van Biesebroeck, 2019; Cunningham et al., 2021), notably also regarding common ownership (He and Huang, 2017), and applications within other contexts (Heckman et al., 1997; Acemoglu et al., 2019).

[12] 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. For a more detailed description, see Appendix C.1. More information on the MHHI delta can be found in Appendix C.2.

of market shares s_j and s_f of the firm and respective rival. The average change in MHHI delta around treatment is 0.01 which constitutes $\frac{1}{4}$ standard deviation of the MHHI delta distribution.

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. The following firm-level variables are included to estimate the propensity score, using only pre-treatment covariates for the treated firms: the logarithm of markups and 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 D.2 shows that the majority of covariates significantly determine treatment.

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 and calculate the 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 D.1 in the Appendix 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 D.2, D.3 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 D.1 shows yearly averages[13] of markups and patent citations in logarithms, using only pre-treatment observations for the treatment group. 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.

3.2 Regression Specification

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. Our main variable of interest is the binary variable indicating the first occurrence of common ownership in a market. The main specification with firm j's logarithm of markups in market p[14] and period t as the outcome variable includes year and firm-fixed effects τ_t and ν_j, such that

$$ln(\mu)_{jt} = \beta_1 \mathbf{1}[\text{MHHI delta} > 0]_{pt} + \beta_2 \text{HHI}_{pt} + \beta_3 \text{Inst}_{jt} + \tau_t + \nu_j + \epsilon_{jt}. \tag{2}$$

$\mathbf{1}[\text{MHHI delta} > 0]_{pt}$ is the common ownership treatment indicator variable, taking the value of one for MHHI $\text{delta}_{pt} > 0$, i.e. a market with common ownership, and zero for a market without common ownership, where MHHI $\text{delta}_{pt} = 0$. Firm-fixed effects rather than market-

[13]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.

[14]In the data, firms are only assigned to a single market, therefore $ln(\mu)_{jpt} = ln(\mu)_{jt}$ and $\nu_{jp} = \nu_j$.

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 and year-level and the variable $Inst$ at the firm-year level, capturing institutional holdings in each firm, measured by the percentage of shares held by institutional investors. By including additional control variables, the precision of the weighted least squares model is enhanced (Imbens, 2004). Standard errors are clustered at the market level, as the treatment indicator varies at the aggregated market level and unobserved shocks might lead to correlation of errors of firms in the same market. There are a total of 468 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[15]. Additionally, 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%. As a robustness check, we also employ alternative firm-specific continuous measures of common ownership.

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 $\mathbf{X}_{jt}$ 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

[15]Balancing for each of the subsamples is shown in Table D.3.

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

$$ln(cites)_{jt} = \beta_1 \mathbf{1}[\text{MHHI delta} > 0]_{pt} + \beta_2 \text{HHI}_{pt} + \beta_3 \text{Inst}_{jt} + \mathbf{X}_{jt}\theta + \tau_t + \nu_j + \epsilon_{jt}. \quad (3)$$

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 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 show results for the full sample and varying treatment intensity as described above, and examine 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

Figure 3 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 3.1. 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 zero and treated observations with positive MHHI delta above the indicated percentile of the distribution of

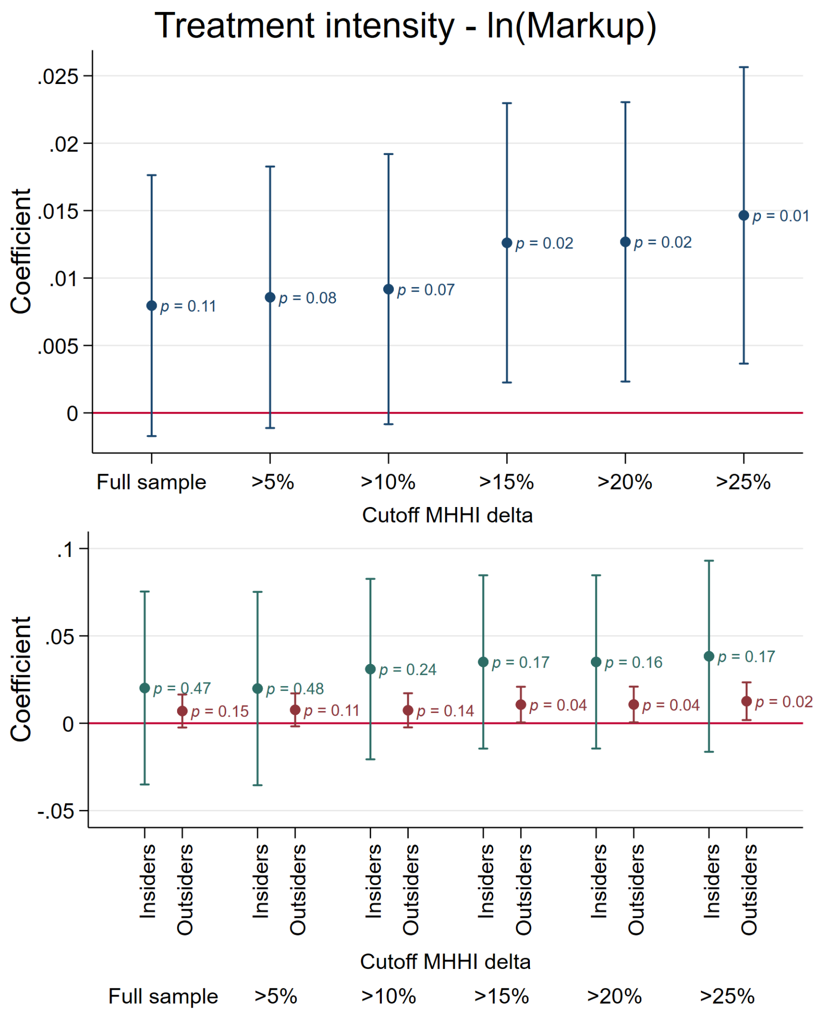
MHHI delta. In all subsets, we control for HHI at the three-digit industry-country level, share of institutional holdings, firm and year-fixed effects. By including firm-fixed effects, we account for selection based on time-invariant firm idiosyncrasies. Standard errors are clustered at the three-digit 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 0.9 to 1.5% 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. 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 the direct effect of common ownership on markups to be more pronounced than the indirect effect[16]. 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 point estimate for inside firms is insignificant but always larger than the indirect effect for the competing firms, and ranges from 2 to 3.8%. The effect for outside firms lies between 0.7 and 1.3%. Table E.1 and E.2 in the Appendix show the corresponding weighted least squares regression results.

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

[16] There is only little known about the effects of common ownership on outsiders in the literature. Papadopoulos (2021) analyses common ownership in the form of cross-ownership as minority stakes in rivals. He finds that firms that are not part of a cross-ownership scheme always benefit from their competitors that are forming cross-ownership links and shows that outsiders increase output as a response to the change in market structure.

Figure 3: Reweighting estimator: Markups - Treatment intensity



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.

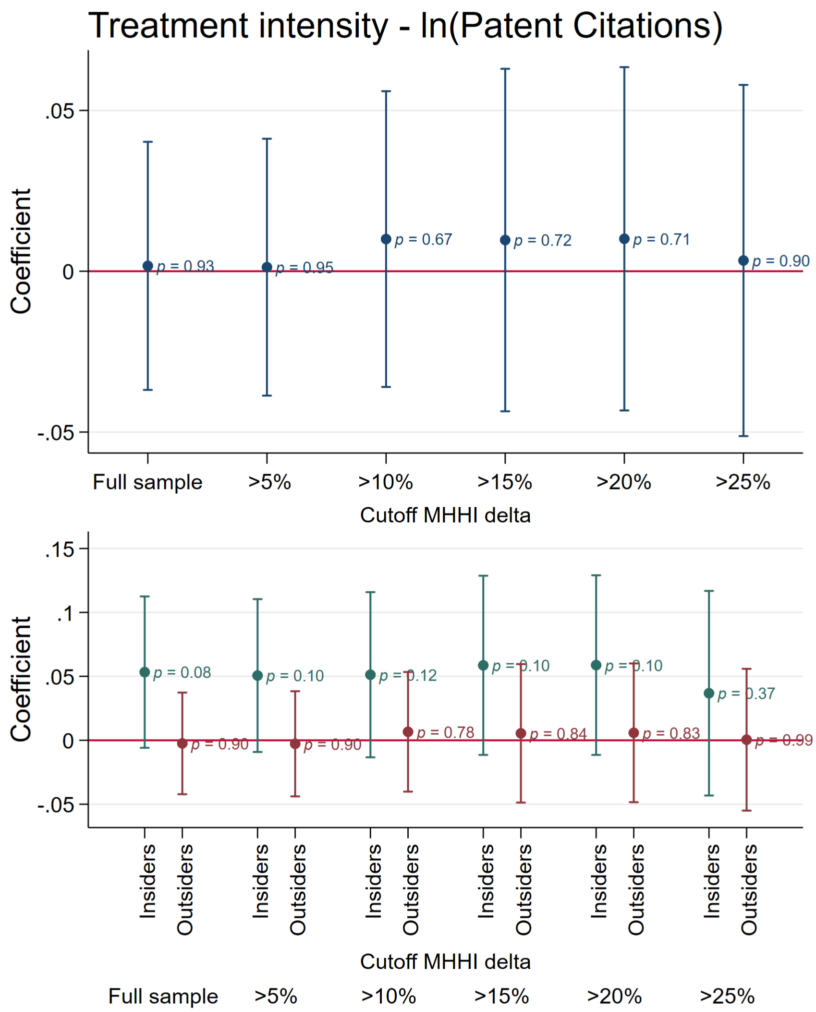
below 15%, between 15% and 25%, and above 25% of the distribution of positive MHHI delta. Table E.5 shows the result of this regression of the logarithm of markups including additional models controlling for time-heterogeneous country and three-digit NACE industry fixed effects. The average treatment effect is increasing 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 3.1. Pooling directly held firms and indirectly affected competitors together, the treatment effect is not statistically significant. Distinguishing between inside and outside firms in Figure 4 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 does not increase with increasing treatment intensity. The magnitude of the effect for insiders is weakly significant for the full sample and for the subsample discarding the lower 5^{th} percentile of the MHHI. The effect for insiders lies between 5 and 5.9%. Coefficients of the outside firms are very close to zero and insignificant. The corresponding regression results are reported in Tables E.3 and E.4.

We also 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 E.6, 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 with MHHI delta between the 15^{th} and 25^{th} percentile, implying an average increase of 8.5% percent in patent citations.

Figure 4: Reweighting estimator: Innovation - Treatment intensity



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, 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. We also include firm and year-country-fixed effects and cluster standard errors at the three-digit industry-country level. The red line indicates zero.

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[17].

Theoretical Background

A 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 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 showing how equilibrium output and innovation activity is impacted by an increase in common ownership for varying degrees of technological spillovers.

An increase in common ownership impacts innovation through two distinct channels. Possible internalisation of R&D efforts in the presence of positive spillovers increases the incentives to innovate. The strength of this positive incentive depends on the degree of spillovers. The second mechanism 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. They find three different regions along the spillover dimension, characterised by low, intermediate and high spillovers.

In the first region, categorised by low-spillover markets, common ownership has a negative

[17] We also explore heterogeneity with respect to different levels of HHI and investor concentration in the Appendix in Section E.2.

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). Federico et al. (2018) show merger effects on innovation incentives and on consumer surplus where non-merging firms increase innovation effort, but this increase does not compensate for reduction of the innovation effort by merging firms. Motta and Tarantino (2021) show that in case of mergers without or weak synergy gains insiders decrease and outsiders increase innovation effort. While insiders increase prices, outsiders may increase or decrease prices.

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 5a and 5b display the treatment effect along the spillover dimension on markups and innovation, respectively[18]. 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 reaches up to roughly 6% in high-spillover industries. A one standard deviation increase in spillovers increases the effect of common ownership on markups by 1.4 percentage points. For example, the treatment effect at the 75^{th} percentile of the spillover distribution is highly significant and 1.9%. An increase of one standard deviation in spillovers increases the effect to 3.3%. 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

[18]The treatment effect from the first columns in tables E.7 and E.8 is plotted for markups and innovation, respectively. The first columns in both tables interact the treatment effect with spillovers.

in spillovers increases the effect of common ownership on patent citations by 2 percentage points. The effect for outsiders is decreasing in spillovers, such that it is positive for lower levels of spillovers and becomes negative for high spillovers.

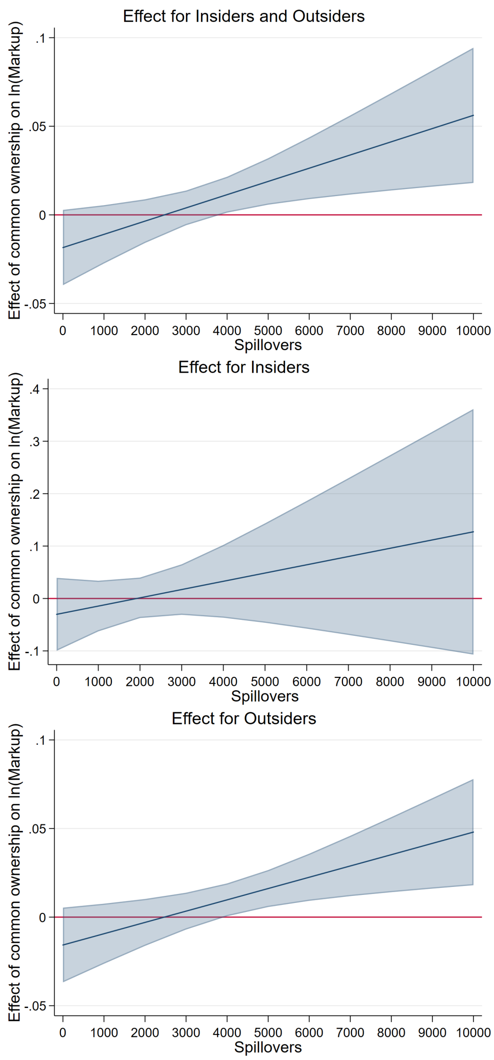
We also perform sample splits with respect to spillovers in columns 2 to 5 of Tables E.7 and E.8 for markups and innovation, respectively. Columns 2 in both tables show the effects for the lower 25% of the spillover distribution. Columns 3 and 4 show the effects for observations below and above the median value of technological spillovers. Columns 5 in both tables show the effects for the upper 25% of the spillover distribution. The results of the sample splits are consistent with the interaction results shown in Figures 5a and 5b. In the sample splits, we see that the effect on markups is increasing with the levels of spillovers and reaches up to 3.3% 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 9.6% in patent citations.

Technological Capacities

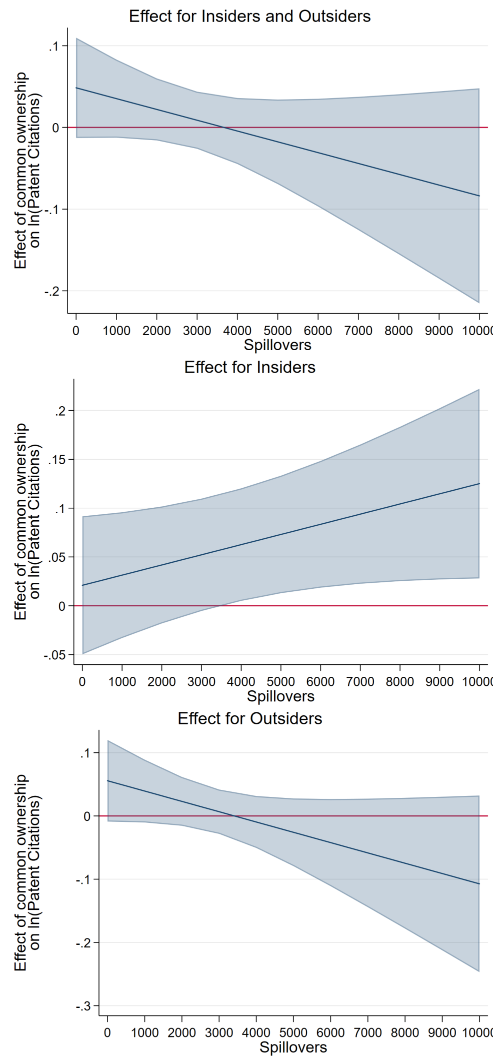
As shown in López and Vives (2019), the effects of common ownership highly depend on the industry structure the companies are operating in. This implies the necessity of developing reliable readily available heuristics regarding industry classifications for policy and decision-makers to assess the impact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

Figure 5: Reweighting estimator: Spillover interaction effect



a) Markups - Spillover interaction effect



b) Innovation - Spillover interaction effect

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.

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 2 and 3, 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 3 show the largest and statistically significant results on patent citations for firms directly commonly owned. Here, treatment increases patent citations for insiders by 16.6% and 20.2%, respectively. For markups, we find the largest effect in high-tech industries in column 4 of Table 2, where treatment increases markups by 2.2%. We also find a significant effect of 2.1% in low-tech industries in column 1. 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 manufacturing 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 2: Reweighting estimator: Markups - Technology classes split

Dep. Variable:	**ln(Markup)**			
	(1)	(2)	(3)	(4)
Technology	Low	Medium-Low	Medium-High	High
$1_{(MHHIdelta>0)}$	0.021**	0.004	-0.006	0.022**
	(0.009)	(0.011)	(0.009)	(0.009)
HHI	0.069	0.041	0.041	-0.030
	(0.066)	(0.047)	(0.039)	(0.052)
Inst. Holdings	-0.036**	0.046***	0.006	-0.027
	(0.016)	(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	3654	4975	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 3: Reweighting estimator: Innovation - Technology classes split

Dep. Variable:	**ln(Patent Citations)**			
	(1)	(2)	(3)	(4)
Technology	Low	Medium-Low	Medium-High	High
$1_{(MHHIdelta>0)} \times$ Insider	0.000	-0.010	0.166**	0.202***
	(0.021)	(0.056)	(0.073)	(0.069)
$1_{(MHHIdelta>0)} \times$ Outsider	-0.013	-0.004	0.038	-0.016
	(0.015)	(0.027)	(0.053)	(0.060)
HHI	-0.050	-0.123	0.053	-0.425*
	(0.069)	(0.136)	(0.149)	(0.218)
Inst. Holdings	-0.031	0.316**	0.018	-0.065
	(0.041)	(0.145)	(0.068)	(0.142)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.59	0.77	0.79	0.87
N	3654	4975	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 with regard to the common ownership measure in Subsection 5.1 and different regression and production function specifications in Subsection 5.2. In Subsection 5.3 we further investigate industry balance, and apply propensity score matching combined with a difference-in-differences estimator. Neither robustness check changes our conclusion regarding the effect of common ownership on markups and innovation.

5.1 Firm-level Common Ownership

Our main specification uses a binary treatment indicator for common ownership. Even though we show treatment intensity by leveraging different percentiles of the MHHI delta distribution and we differentiate between insiders and outsiders, the measure estimates an average effect for affected firms. One might be concerned how robust the findings are with respect to other measures for common ownership. To mitigate this issue, we use two different continuous firm-level measures of common ownership on the weighted sample as a robustness check.

First, we follow Azar et al. (2018) and use a firm-level average of the weights placed on competitors' profits, reflecting the degree of rival profit internalisation. Their *carrier-route common ownership variable* (CRCO) is calculated for each combination of airline carrier and route. As each firm is only assigned to one market in our data, the corresponding measure is defined at the firm level and termed *firm common ownership* (FCO)[19]. This measure represents by how much a given firm internalises its competitors' profits. For each firm j in year t, using the profit weights relative to all firms $f \neq j$, the market-share weighted average FCO can be specified as

$$FCO_{jt} = \sum_{f \neq j} \frac{\sum_i \beta_{ij}\beta_{if}}{\sum_i \beta_{ij}^2} \frac{s_{ft}}{1 - s_{jt}}.$$

We replicate the main results using this firm-level measure for markups in Table E.9 and Figure E.3a, and for innovation in Table E.10 and Figure E.3b.

Second, we use the aggregate holdings of common owners at the firm level. This measure has the advantage that it does not include any market shares. It is known that common ownership measures that utilise market shares suffer from endogeneity (Azar et al., 2018). The results of this robustness check for markups are reported in Table E.11 and Figure E.4a, and for innovation in Table E.12 and Figure E.4b. All models for both measures of common ownership include the respective firm-specific measure of common ownership for directly impacted firms (insiders), and a dummy variable for indirectly affected firms (outsiders). The conclusions regarding the effect of common ownership for insiders and outsiders on both

[19]Figure C.2 shows the sample average of this measure over time.

outcome variables do not change.

5.2 Regression and Production Function Specification

Using a propensity score reweighting estimator as before, we additionally control for changes in marginal costs when regressing markups on the binary 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 E.5a and E.5b. 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 E.6a, E.6b display the results for markups, and Figures E.7a, E.7b show the results for citation-weighted patents of these specifications.

Furthermore, we present results for markups under different assumptions of the production function estimation. First, we use a translog specification which produces more variation in markups. Figure E.8a shows the treatment effect in this setup for different degrees of treatment intensity. Figure E.8b shows how the treatment effect on markups varies with spillovers in the translog specification. 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 reported in Figure E.9a and Figure E.9b.

The results are robust with respect to controlling for TFP and including country-time and industry-time-fixed effects in the regression specifications as well as different assumptions of the production function estimation.

5.3 Further Robustness Checks

While the propensity score does take into account industry characteristics, such as HHI, technology dispersion and technology ranking, and probit regressions are estimated separately for low and high-technological capacity industries, the question remains if the industries in the treatment and control group are balanced. To address this question we proceed as follows. First, Figure E.10 shows the distributions of two-digit NACE industries for treatment and control group in the weighted sample. Visual inspection suggests that the distributions do not differ much. Second, we perform a balancing test for each two-digit NACE industry. The result of this exercise is presented in Table E.13, showing that all but three industries are balanced. In order to ensure that this does not influence our results, we drop these three industries and show that the main results remain unchanged. The results for markups are shown in Figures E.11a and E.11b and the results for innovation are shown in Figures E.12a and E.12b.

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. We assign treated and control observations based on a one-to-one matching, and only use firms on common support. After matching, we use difference-in-differences estimation to determine the average treatment effect on the treated of common ownership on markups and innovation output[20]. Table E.14 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. Tables E.15 and E.16 show how the effect varies with technological spillovers for markups and innovation, respectively. The conclusion regarding the effect of common ownership on markups and innovation remains unchanged.

[20]For a more detailed description of the estimation see Section E.3.6

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 comprehensive firm ownership information. As an additional outcome variable, citation-weighted patents measure the innovation output of firms. A propensity reweighting estimator corrects for observational biases. We define treatment as the first exposure of a market to common ownership and 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 the measure of common ownership, production function and regression 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 together with an increase in markups. 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 effects of common ownership. This article delivers reduced form evidence that industry structure, prices, and innovation output play a major role for assessing competitive effects of common ownership. A full structural model taking into account multiple strategic variables, such as prices and innovation could be promising for future research, in order to help to disentangle the multiple effects of common ownership and to develop guidelines on how to approach this issue.

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 Appendix

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 p (note that each firm only operates in one market $p(j)$, their main line of business) and year t for output q_{jt} is designed with the inputs capital k_{jt}, labour l_{jt}, materials m_{jt}, unobserved productivity ω_{jt}, and a measurement error ϵ_{jt}, such that

$$q_{jt} = \beta^0 + \beta^k k_{jt} + \beta^l l_{jt} + \beta^m m_{jt} + \omega_{jt} + \epsilon_{jt}. \tag{4}$$

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 to proxy productivity. Therefore a third order polynomial in input factors labour, capital, and materials is included as well as 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

$$\omega_{jt} = g(\omega_{jt-1}, \mathrm{MHHIdelta}_{pt-1}, \mathrm{HHI}_{pt-1}) + \xi_{jt} \tag{5}$$

where $g(\omega_{jt-1}, \mathrm{MHHIdelta}_{pt-1}, \mathrm{HHI}_{pt-1})$ 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_{jt} 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. We follow Collard-Wexler and De Loecker (2021) and correct for measurement error in capital, using lagged investment as an instrument for capital[21]. Constructed with the innovation to productivity $\xi_{jt} = \omega_{jt} - E[\omega_{jt}|\omega_{jt-1}, \text{MHHIdelta}_{pt-1}, \text{HHI}_{pt-1}]$ from the law of motion, the objective function minimises the moment conditions

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

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_{jt} and $\boldsymbol{Z}$ as a stacked matrix containing instruments for the input factors (Collard-Wexler and De Loecker, 2021).

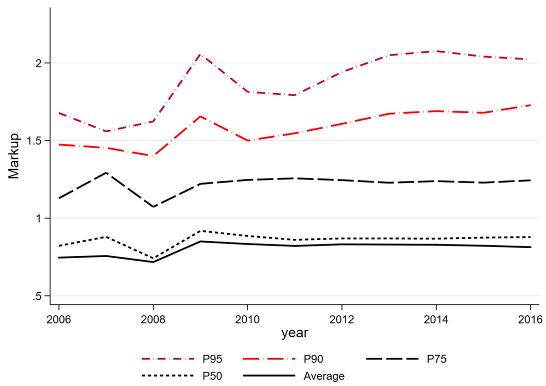
Table B.1: Production function estimates

NACE code	**Industries**	β_k	β_l	β_m	N	μ_{jt}	TFP_{jt}
10, 11, 12	Food, beverages, tobacco	0.106	0.442	0.300	2585	0.592	2.483
13, 14, 15	Textiles, wearing apparel, leather	0.015	0.407	0.614	637	1.397	0.549
16, 17	Wood, paper	0.150	0.404	0.412	962	0.850	0.121
19, 20, 21	Coke, chemicals, pharmaceuticals	0.134	0.538	0.314	2239	0.817	3.220
22, 23	Rubber, plastic, minerals	0.117	0.170	0.568	2060	1.391	6.590
24, 25	Basic, fabricated metals	0.048	0.376	0.596	2612	1.316	1.170
26, 27	Computer, electronic, electrical eq.	0.076	0.437	0.478	2149	1.153	0.927
28, 29, 30	Machinery, motor, transport	0.125	0.341	0.448	4941	1.005	2.930
31, 32	Furniture, other manufacturing	0.012	0.361	0.660	452	1.586	0.344

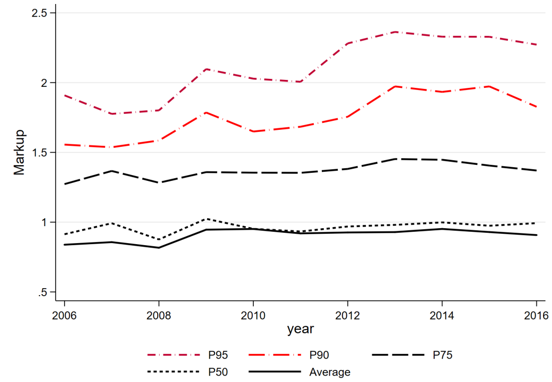
Note: This table presents output elasticities obtained from production function estimation (Cobb-Douglas) following the method of Ackerberg et al. (2015). For estimation of output elasticities, nine subsets of the data were regarded separately, pooling these NACE two-digit codes. μ_{jt} and TFP_{jt}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

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

Figure B.1: Evolution of markups



a) Sales weighted



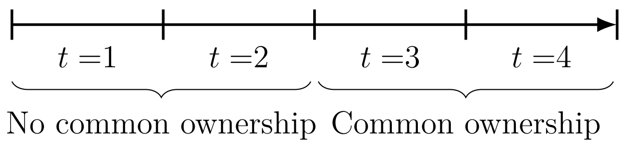
b) Tangible fixed assets weighted

Note: The figures illustrate the evolution of the weighted distribution of firm markups from 2006 to 2016. The left figure uses sales as weights and the right figure uses tangible fixed assets as weights. 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. For the construction of the percentiles we follow the methodology of De Loecker et al. (2020).

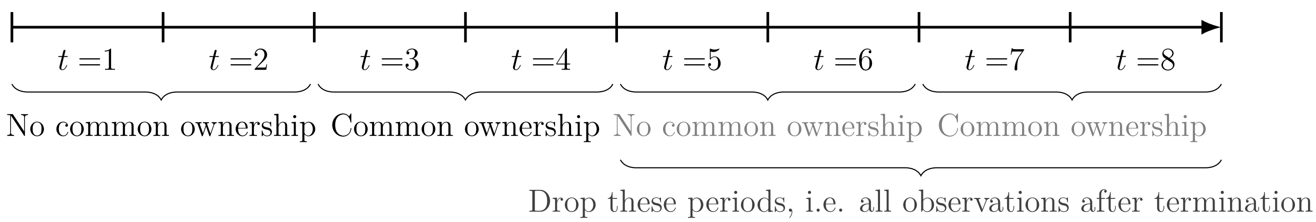
C Common Ownership Appendix

C.1 Market-level Binary Treatment Indicator

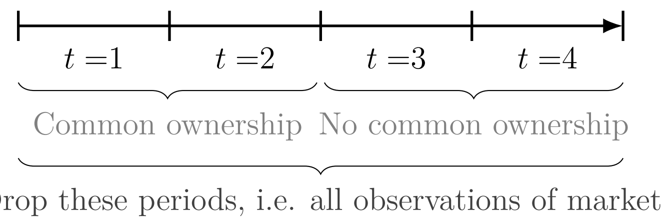
In the simple treatment case, there are periods without common ownership (treatment dummy equal to zero) followed by the first exposure to common ownership after the formation of a new horizontal ownership link between two or more firms in a market (treatment dummy equal to one), as illustrated below:



Additionally, there are two cases of intermittent common ownership. First, markets, defined at the NACE three-digit and country-level, can have multiple "entries" of common owners. The common ownership indicator starts at zero and then switches to one when the common ownership link occurs for the first time. As soon as the ownership link is terminated, we keep the markets while they experience new common ownership for the first time, but we drop the observations in all of the following periods, such that there cannot be multiple "new" occurrences of common ownership. Example of a market with intermittent common ownership:



Second, markets can have common ownership in the first period they appear in the data. It might either stay that way, with the indicator variable always being equal to one, or the common ownership link between firms within that market can be dissolved. In this case, the common ownership indicator variable switches from one to zero. It may even return to one, but we cannot be sure if this is due to new ownership links forming, or data errors. In any case, the effects of the common owners of the first periods may still be prevalent, such that the effect of a new ownership link might not be fully disentangled. Example of a market with common ownership links from the beginning of the sample, which then get dissolved in period 3:



C.2 Market-level MHHI Delta

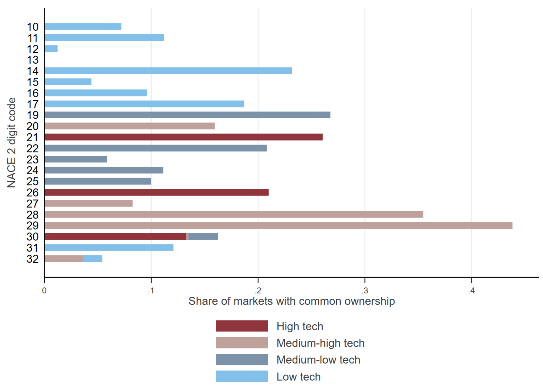
We introduce a frequently used measure for common ownership, the MHHI. The MHHI delta reflects common ownership concentration in a market and is constructed as the difference between the MHHI and the classical HHI (Salop and O'Brien, 2000), such that for a single market at a given point in time

$$\text{MHHI} = \sum_j \sum_f s_j s_f \frac{\sum_i \beta_{ij}\beta_{if}}{\sum_i \beta_{ij}^2} = \underbrace{\sum_j s_j^2}_{\text{HHI}} + \underbrace{\sum_j \sum_{f \neq j} s_j s_f \frac{\sum_i \beta_{ij}\beta_{if}}{\sum_i \beta_{ij}^2}}_{\text{MHHI delta}} .$$

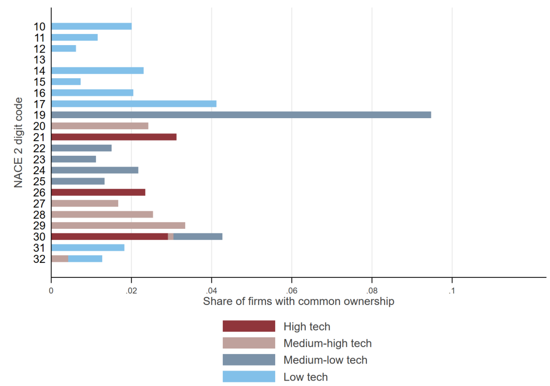
The first part of the equation is the classical HHI as sum of squared market shares s_j of all market participants j, and the second part, MHHI delta, captures the degree of common ownership networks. Subscripts j and f denote firms and competitors, i indexes the investors, and β_{ij} are ownership shares. We assume proportionate control, such that ownership shares equal control shares. 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_f 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 articles exploit exogenous variation in the MHHI due to mergers at the investor level, we use the MHHI as a measure for treatment intensity.

Figure C.1: Common ownership by NACE two-digit industry



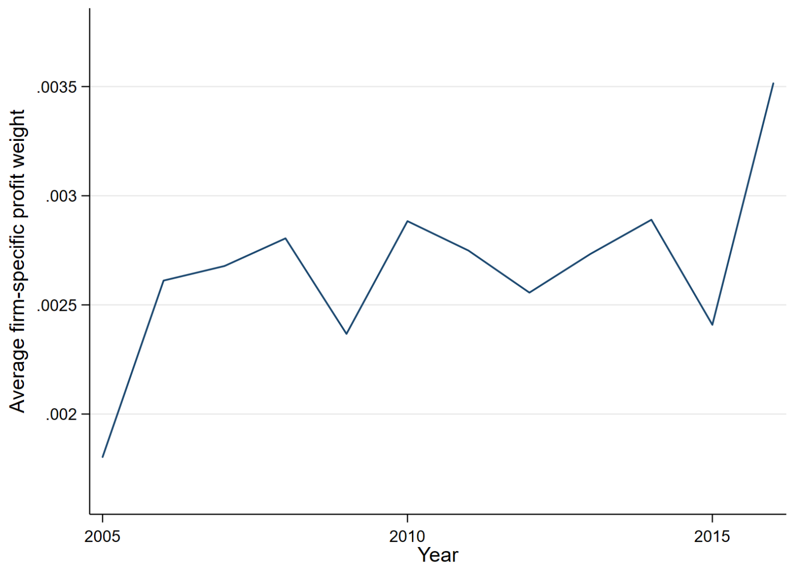
a) Share of markets with common ownership per NACE two-digit industry



b) Share of firms with common ownership per NACE two-digit industry

Note: The figure on the left shows the percentage of markets with common ownership by NACE two-digit industry code. The figure on the right 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.

Figure C.2: Common ownership profit weight

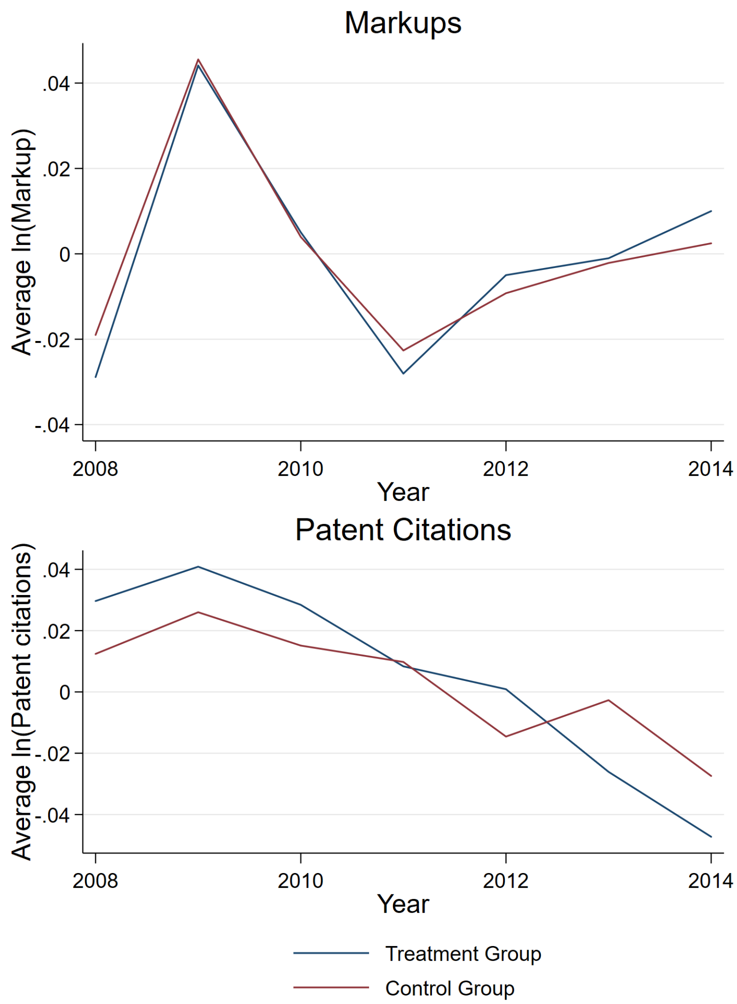


Note: The figure plots the firm-specific profit weights as in Azar et al. (2018) as an average over the whole sample. We use European ownership data from the Amadeus data base by Bureau van Dijk. Common ownership in a market is defined as two competing firms being held by overlapping sets of institutional investors.

D Propensity Score Reweighting Appendix

D.1 Parallel Trends

Figure D.1: 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.

D.2 Balancing Property

Table D.1: Balancing property - unweighted and weighted sample

	Balancing	
Sample	Unweighted	Weighted
ln(Markup)	0.138**	0.084
	(0.057)	(0.084)
ln(TFP)	-0.048	-0.145
	(0.149)	(0.168)
Age	1.481	1.469
	(2.189)	(2.698)
Patent citations	3.412**	-0.091
	(1.493)	(0.990)
ln(Capital)	-0.280***	-0.132
	(0.103)	(0.159)
ln(Labour)	0.105*	0.018
	(0.059)	(0.076)
ln(Sales)	-0.110*	-0.101
	(0.062)	(0.102)
Inst. Holdings	0.020**	0.014
	(0.010)	(0.016)
HHI	-0.071***	-0.013
	(0.025)	(0.041)
Techn. gap	0.026	0.013
	(0.027)	(0.034)
Techn. ranking	4.332	0.038
	(4.906)	(6.118)

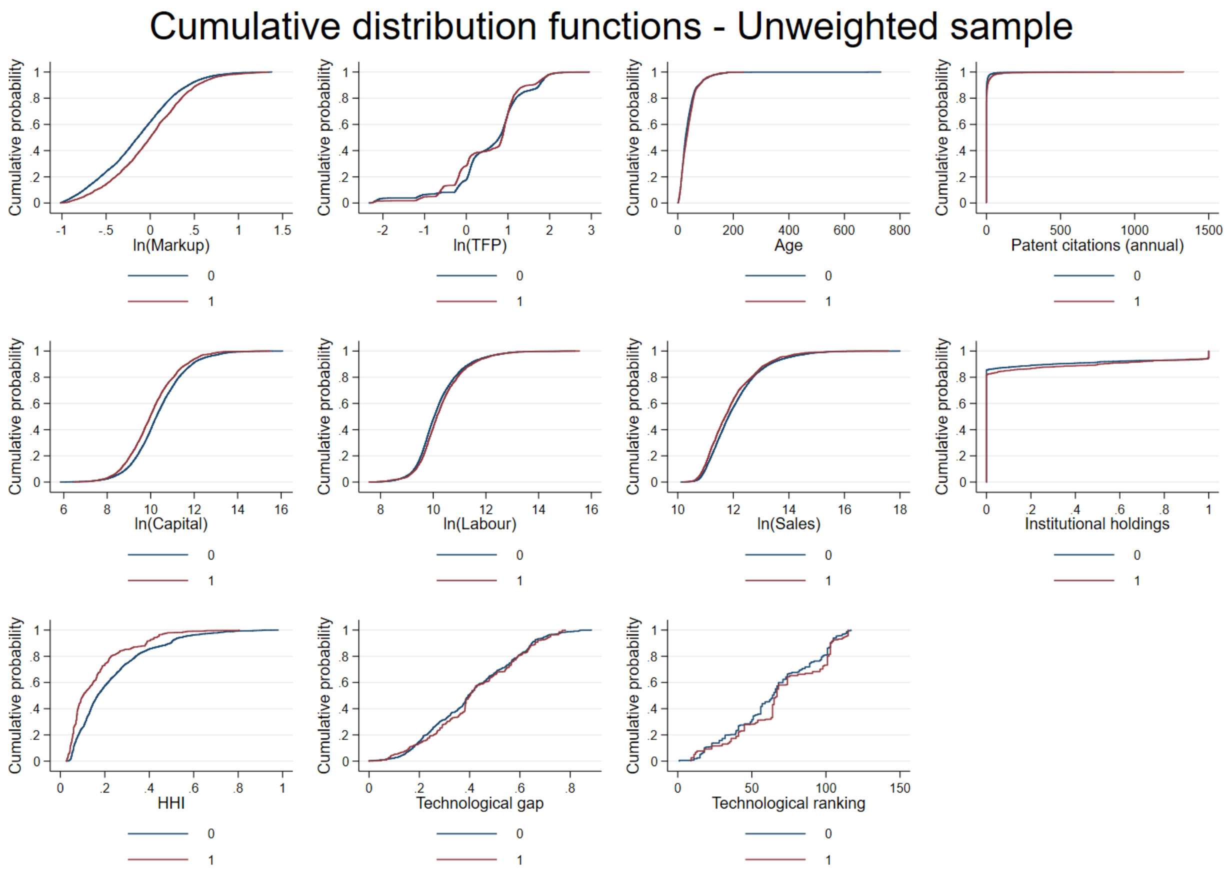
Note: Standard errors in parentheses and clustered at the market level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. The table shows the differences in pre-treatment means between treatment and control group after controlling for year fixed effects. Propensity scores are the predicted values from the Probit model in Table D.2. 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.

Table D.2: Probit regressions: Propensity scores

	Dependent Variable: Treatment	
Technology	LOW	HIGH
Markup	0.487***	0.613***
	(0.112)	(0.145)
ln(TFP)	0.038	0.187***
	(0.036)	(0.071)
Age	0.001	-0.001
	(0.001)	(0.001)
Patent citations	0.002	0.001*
	(0.002)	(0.001)
ln(Capital)	-0.138***	-0.165***
	(0.042)	(0.038)
ln(Labour)	0.116	0.137
	(0.103)	(0.101)
ln(Sales)	0.061	0.003
	(0.104)	(0.100)
Inst. Holdings	0.206*	0.160
	(0.117)	(0.140)
HHI	-1.481***	-1.322***
	(0.284)	(0.256)
Techn. gap	-0.555***	0.876***
	(0.197)	(0.186)
Techn. ranking	-0.003**	0.005***
	(0.001)	(0.002)
Year Trend	Yes	Yes
Pseudo R^2	0.08	0.14
N	6136	4457
Firm clusters	1638	1349

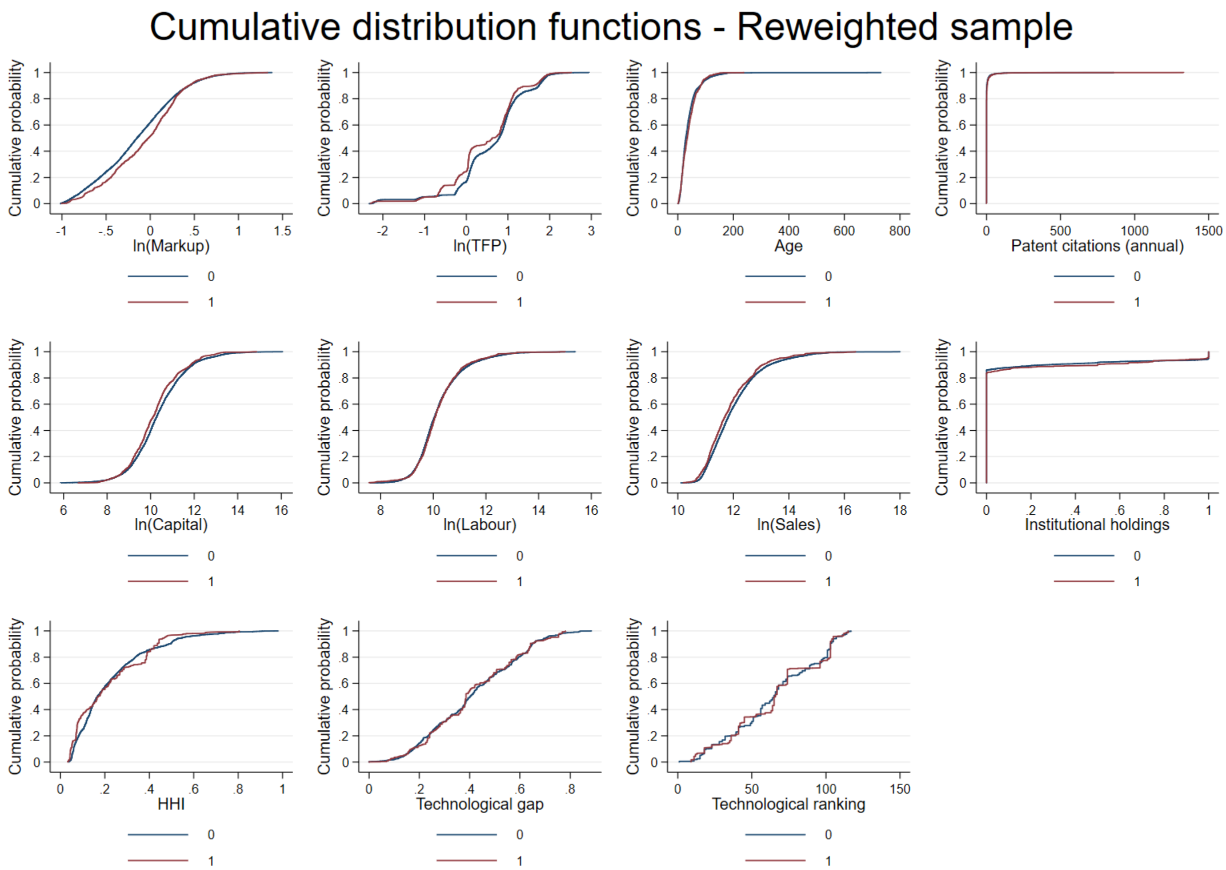
Note: Standard errors in parentheses and clustered at the firm level. * p<0.10, ** p<0.05, *** p<0.01. The table shows the results from Probit regressions. The dependent variable takes a value of one if common ownership occurs in the industry for the first time in year t+1, and zero otherwise. HIGH is 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 D.2: 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 D.3: 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.

Table D.3: Balancing: Weighted sample - MHHI delta cutoffs

	Balancing				
Sample	>5%	>10%	>15%	>20%	>25%
ln(Markup)	0.084	0.077	0.075	0.075	0.092
	(0.084)	(0.088)	(0.091)	(0.091)	(0.087)
ln(TFP)	-0.143	-0.100	-0.081	-0.082	-0.093
	(0.168)	(0.173)	(0.173)	(0.173)	(0.175)
Age	1.481	2.282	1.798	1.811	2.124
	(2.684)	(2.607)	(2.834)	(2.836)	(3.026)
Patent citations	-0.078	-0.209	0.067	0.066	0.005
	(0.995)	(1.007)	(1.068)	(1.067)	(1.008)
ln(Capital)	-0.131	-0.128	-0.104	-0.104	-0.092
	(0.159)	(0.168)	(0.173)	(0.173)	(0.181)
ln(Labour)	0.020	0.012	0.031	0.031	0.063
	(0.076)	(0.080)	(0.083)	(0.083)	(0.089)
ln(Sales)	-0.100	-0.096	-0.076	-0.076	-0.056
	(0.102)	(0.108)	(0.112)	(0.112)	(0.121)
Inst. Holdings	0.014	0.019	0.017	0.017	0.020
	(0.016)	(0.017)	(0.017)	(0.017)	(0.016)
HHI	-0.013	-0.011	-0.015	-0.015	-0.011
	(0.041)	(0.042)	(0.042)	(0.042)	(0.041)
Techn. gap	0.013	0.019	0.022	0.022	0.015
	(0.034)	(0.036)	(0.038)	(0.038)	(0.034)
Techn. ranking	0.087	0.247	1.449	1.471	0.740
	(6.113)	(6.450)	(6.696)	(6.698)	(6.205)

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 of the weighted sample between treatment and control group after controlling for year fixed effects. Each column shows a sub-sample 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. 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.

E Further Tables and Results

E.1 Main Results

E.1.1 Treatment Intensity

Table E.1: Reweighting estimator: Markups - 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	0.009*	0.009*	0.013**	0.013**	0.015***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
HHI	0.043*	0.043*	0.038	0.033	0.033	0.031
	(0.025)	(0.025)	(0.024)	(0.024)	(0.024)	(0.024)
Inst. Holdings	0.003	0.003	0.005	0.004	0.004	0.003
	(0.013)	(0.014)	(0.015)	(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	15410	15305	15339	15149	15127	14944
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 E.2: Reweighting estimator: Markups - 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	0.020	0.020	0.031	0.035	0.035	0.038
	(0.028)	(0.028)	(0.026)	(0.025)	(0.025)	(0.028)
$1_{(MHHIdelta>0)} \times$ Outsider	0.007	0.008	0.007	0.011**	0.011**	0.013**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
HHI	0.043*	0.043*	0.037	0.033	0.033	0.031
	(0.025)	(0.025)	(0.024)	(0.024)	(0.024)	(0.024)
Inst. Holdings	0.002	0.002	0.001	0.001	0.001	-0.000
	(0.014)	(0.014)	(0.015)	(0.016)	(0.016)	(0.017)
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	15410	15305	15339	15149	15127	14944
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 E.3: Reweighting estimator: Innovation - Treatment intensity

Dep. Variable:	**ln(Patent Citations)**					
	(1)	(2)	(3)	(4)	(5)	(6)
Cutoff MHHI delta	>0	>5%	>10%	>15%	>20%	>25%
$1_{(MHHIdelta>0)}$	0.002	0.001	0.010	0.010	0.010	0.003
	(0.020)	(0.020)	(0.023)	(0.027)	(0.027)	(0.028)
HHI	-0.144	-0.142	-0.137	-0.129	-0.129	-0.118
	(0.104)	(0.105)	(0.107)	(0.111)	(0.111)	(0.105)
Inst. Holdings	0.100	0.113	0.089	0.086	0.085	0.090
	(0.074)	(0.075)	(0.075)	(0.072)	(0.072)	(0.072)
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	15410	15305	15339	15149	15127	14944
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 E.4: Reweighting estimator: Innovation - 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	0.053*	0.051*	0.051	0.059	0.059	0.037
	(0.030)	(0.030)	(0.033)	(0.036)	(0.036)	(0.041)
$1_{(MHHIdelta>0)}\times$ Outsider	-0.002	-0.003	0.007	0.005	0.006	0.000
	(0.020)	(0.021)	(0.024)	(0.028)	(0.028)	(0.028)
HHI	-0.144	-0.143	-0.137	-0.130	-0.130	-0.118
	(0.103)	(0.104)	(0.107)	(0.110)	(0.111)	(0.105)
Inst. Holdings	0.093	0.106	0.083	0.079	0.078	0.085
	(0.076)	(0.077)	(0.077)	(0.075)	(0.075)	(0.075)
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	15410	15305	15339	15149	15127	14944
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 E.5: Reweighting estimator: Markups - Dummy MHHI delta distribution

Dep. Variable:	**ln(Markup)**		
	(1)	(2)	(3)
MHHI 25-100%	0.014***	0.010**	0.015**
	(0.006)	(0.005)	(0.007)
MHHI 15-25%	-0.001	0.011	0.011
	(0.005)	(0.010)	(0.010)
MHHI 0-15%	-0.016***	-0.013*	-0.002
	(0.006)	(0.007)	(0.007)
HHI	0.044*	0.039	-0.002
	(0.024)	(0.031)	(0.039)
Inst. Holdings	0.002	0.005	0.001
	(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	15410	15409	15334
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 E.6: Reweighting estimator: Innovation - Dummy MHHI delta distribution

Dep. Variable:	**ln(Patent Citations)**		
	(1)	(2)	(3)
MHHI 25-100%	-0.002	0.013	-0.016
	(0.021)	(0.020)	(0.019)
MHHI 15-25%	0.085***	0.061***	0.072**
	(0.028)	(0.018)	(0.031)
MHHI 0-15%	-0.016	0.001	-0.002
	(0.016)	(0.023)	(0.031)
HHI	-0.142	-0.061	0.039
	(0.106)	(0.129)	(0.088)
Inst. Holdings	0.103	0.097	0.104
	(0.086)	(0.088)	(0.092)
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	15410	15409	15334
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.

E.1.2 Technological Spillovers Interaction Effect

Table E.7: Reweighting estimator: Markups - Spillover interaction effect

Dep. Variable:	**ln(Markup)**				
	(1)	(2)	(3)	(4)	(5)
Spillover	ALL	<25%	<50%	>50%	>75%
$1_{(MHHIdelta>0)} \times$ Spillover	0.000***				
	(0.000)				
$1_{(MHHIdelta>0)}$	-0.018*	0.016*	-0.001	0.021***	0.033***
	(0.011)	(0.008)	(0.007)	(0.007)	(0.011)
HHI	0.035	0.053	0.051	0.031	0.024
	(0.023)	(0.059)	(0.043)	(0.029)	(0.043)
Inst. Holdings	0.005	-0.017	-0.004	0.007	-0.008
	(0.013)	(0.018)	(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	0.95	0.95
N	15410	3745	7922	7488	3593
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 E.8: Reweighting estimator: Innovation - Spillover interaction effect

Dep. Variable:	**ln(Patent Citations)**				
Spillover	(1) ALL	(2) <25%	(3) <50%	(4) >50%	(5) >75%
$1_{(MHHIdelta>0)}\times$ Insider $\times$ Spillover	0.000*				
	(0.000)				
$1_{(MHHIdelta>0)}\times$ Outsider $\times$ Spillover	-0.000*				
	(0.000)				
$1_{(MHHIdelta>0)}\times$ Insider	0.021	0.021	0.063	0.043	0.096**
	(0.036)	(0.019)	(0.039)	(0.043)	(0.045)
$1_{(MHHIdelta>0)}\times$ Outsider	0.056*	0.026	0.014	-0.023	-0.026
	(0.033)	(0.018)	(0.032)	(0.031)	(0.040)
HHI	-0.131	-0.080	-0.210	-0.090	-0.169
	(0.097)	(0.131)	(0.132)	(0.144)	(0.205)
Inst. Holdings	0.096	0.024	0.046	0.137	-0.008
	(0.076)	(0.049)	(0.037)	(0.131)	(0.084)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.80	0.68	0.76	0.83	0.86
N	15410	3745	7922	7488	3593
Market clusters	468	143	272	237	125

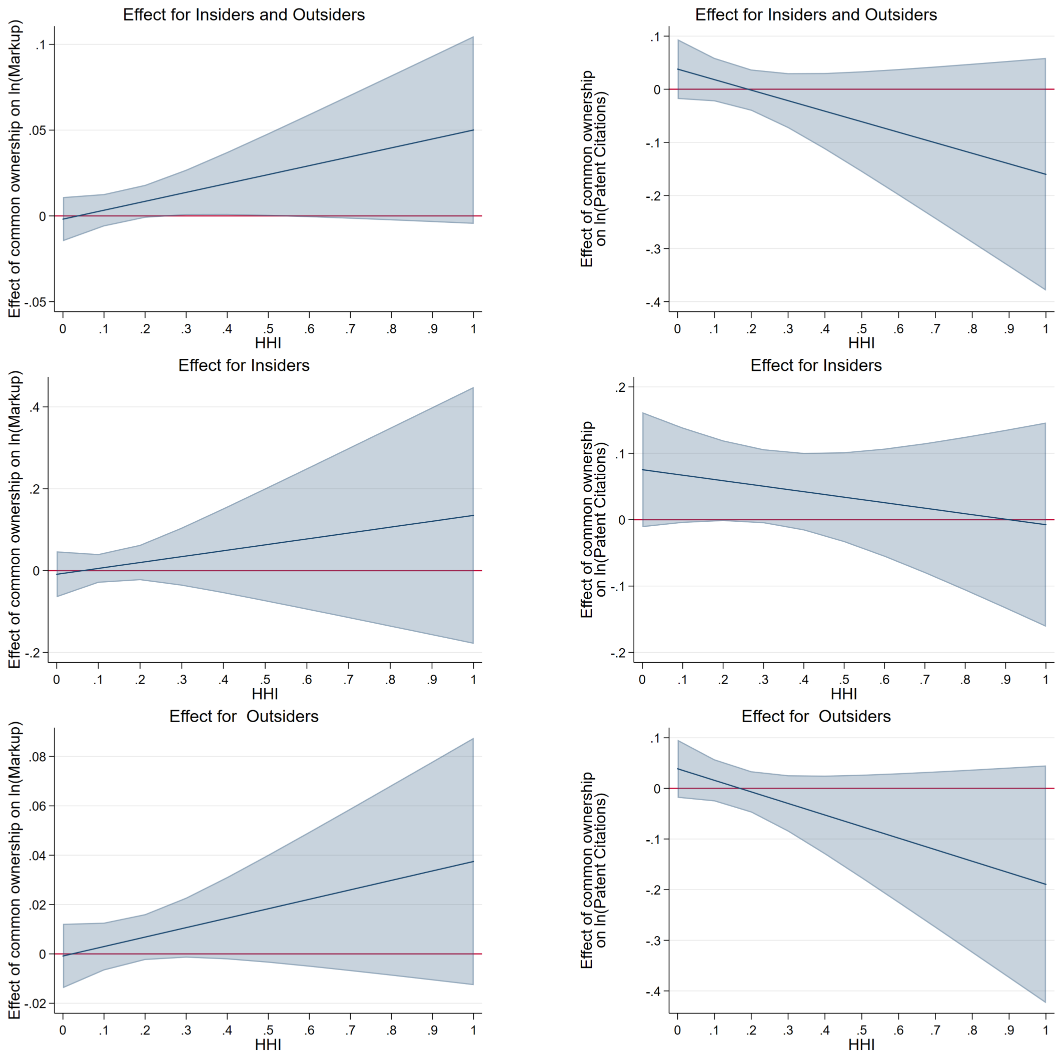
Note: Standard errors in parentheses and clustered at the three-digit industry-country level. * p<0.10, ** p<0.05, *** p<0.01 Market definition: HHI and MHHI delta calculated at the three-digit industry-country level. Insiders are defined as directly commonly owned firms. Outsiders are non-commonly owned 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.

E.2 Heterogeneity

E.2.1 HHI

Here, we analyse how the effect of common ownership varies with levels of HHI. This heterogeneity captures how the effect of common ownership varies with competition as measured by the HHI. Figures E.1a and E.1b below show the results of this exercise for markups and innovation, respectively. The combined effect on markups is increasing with HHI and significant or weakly significant for most levels of HHI. The effect for insiders and outsiders go in the same direction as the combined effect. The impact of common ownership on innovation is lower for higher levels of HHI but insignificant.

Figure E.1: Reweighting estimator: HHI interaction effect



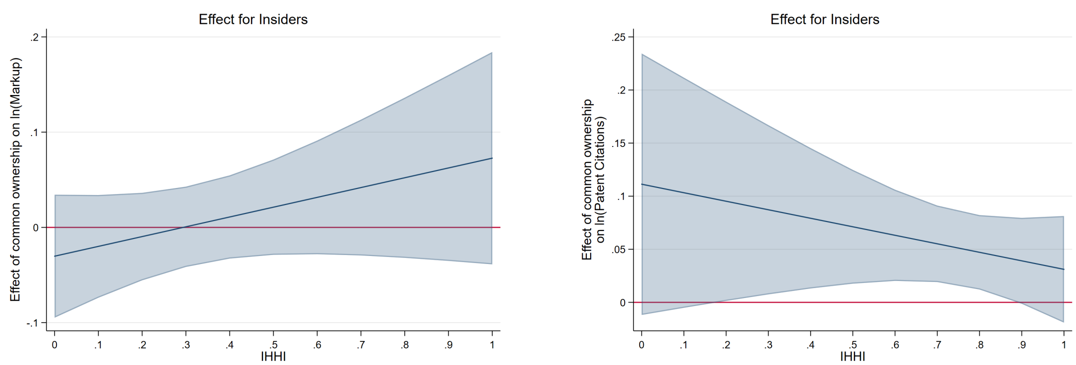
a) Markups **b)** Innovation

Note: Both graphs plot the treatment effect for varying degrees of HHI. 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 institutional holdings and firm and year-fixed effects in all models. The combined models include an interaction term of treatment group and HHI. The models with insiders and outsiders include interaction terms of insider and outsider with HHI. The innovation models further control for ln(TFP), market size measured by average sales at the market level, capital intensity, 1-Lerner index, and age, a dummy for zero citations. Zero patent citations are set to one. HHI is calculated at the three-digit industry-country level and rescaled by division by 10,000, such that it ranges from 0 to 1. The red line indicates zero.

E.2.2 Investor HHI

Here, we analyse how the effect of common ownership varies with levels of Investor HHI (IHHI) (also used in e.g. Backus et al., 2021), which is the sum of squared investor holdings similar to the classical HHI, but is calculated at the firm level using ownership shares instead of market shares. The effect of common ownership on inside firms may vary with the concentration of the investors, as investors with larger shares may exert more monitoring or indirect control in a firm. However, we do not find that common ownership varies significantly with the IHHI. Figures E.2a and E.2b below show the results for markups and innovation, respectively. Effects are not statistically significant for most of the IHHI region.

Figure E.2: Reweighting estimator: Investor HHI interaction effect



a) Markups **b)** Innovation

Note: Both graphs plot the treatment effect for varying degrees of Investor-HHI (IHHI). 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 institutional holdings and firm and year-fixed effects in all models. The models include an interaction term of insiders and IHHI. The innovation model further control for ln(TFP), market size measured by average sales at the market level, capital intensity, 1-Lerner index, and age, a dummy for zero citations. Zero patent citations are set to one. IHHI is calculated firm specific and rescaled by division by 10,000, such that it ranges from 0 to 1. The red line indicates zero.

E.3 Robustness Checks

E.3.1 Firm-level Common Ownership Measure

Table E.9: Reweighting estimator: Markups - Firm-level profit weight

ln(Markup)	**Average effect**	**Spillovers**		
	(1) ALL	(2) Interaction	(3) <50%	(4) >50%
FCO	0.211*	-0.033	0.183***	0.255
	(0.112)	(0.239)	(0.032)	(0.252)
Outsider	0.007	-0.016	-0.003	0.021***
	(0.006)	(0.011)	(0.007)	(0.006)
FCO × Spillover		0.000		
		(0.000)		
Outsider × Spillover		0.000***		
		(0.000)		
Adj. R^2	0.96	0.96	0.97	0.94
N	15404	15404	7918	7486
Market clusters	2983	467	272	236

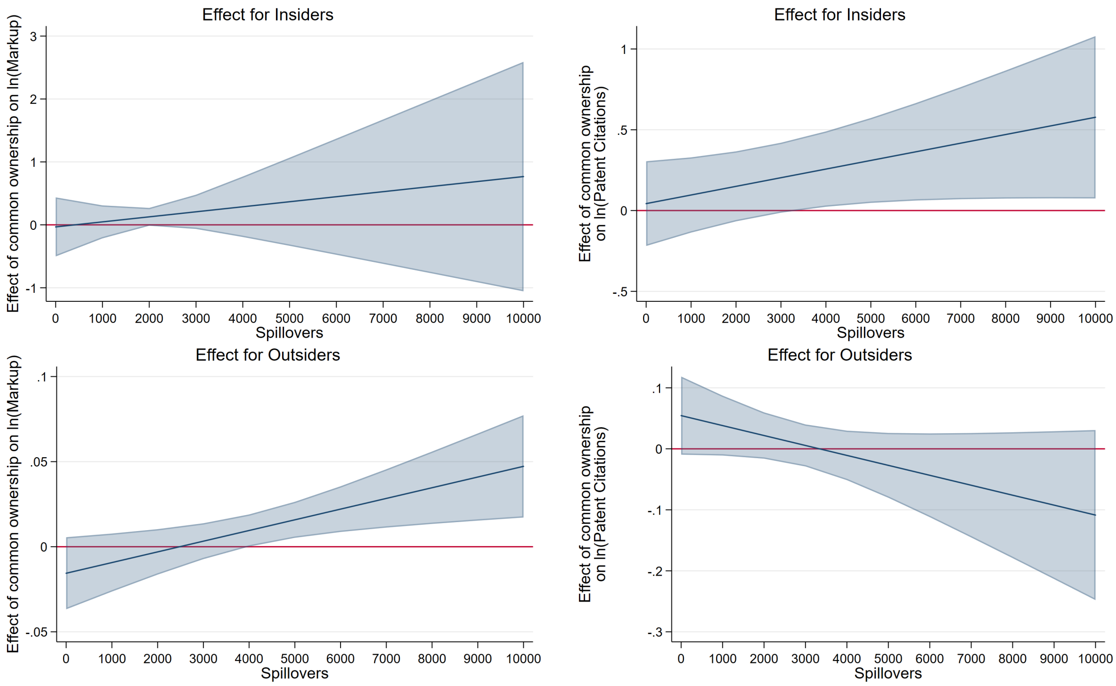
Note: Standard errors in parentheses and clustered at the market level. * p<0.10, ** p<0.05, *** p<0.01. Market definition: HHI and MHHI delta calculated at the three-digit industry-country level. We control for HHI at the three-digit industry country level, share of institutional holdings, firm and year-fixed effects. HHI and MHHI delta are rescaled by division by 10,000, such that the HHI ranges from 0 to 1.

Table E.10: Reweighting estimator: Innovation - Firm-level profit weight

ln(Patent Citations)	**Average effect**	**Spillovers**		
	(1) ALL	(2) Interaction	(3) <50%	(4) >50%
FCO	0.206*	0.043	0.216*	0.200
	(0.112)	(0.134)	(0.127)	(0.223)
Outsider	-0.004	0.054*	0.013	-0.024
	(0.022)	(0.033)	(0.031)	(0.031)
FCO × Spillover		0.000*		
		(0.000)		
Outsider × Spillover		-0.000*		
		(0.000)		
Adj. R^2	0.80	0.80	0.76	0.83
N	15404	15404	7918	7486
Market clusters	2983	467	272	236

Note: Standard errors in parentheses and clustered at the market 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, age, share of institutional holdings less commonly owned shares, 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.

Figure E.3: Reweighting estimator: Spillover interaction effect with firm-level profit weight



a) Markups - Spillover interaction effect **b)** Innovation - Spillover interaction effect

Note: The graph plots the treatment effect for varying degrees of spillovers for the outcome markups in the left graph and innovation in the right graph. Common ownership is measured as the firm-level profit weight in Azar et al. (2018). 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 less commonly owned shares, firm and year-fixed effects. For innovation, we additionally control for ln(TFP), market size measured by average sales at the market level, capital intensity, 1-Lerner index, age, a dummy for zero citations. 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. The red line indicates zero.

Table E.11: Reweighting estimator: Markups - Commonly held shares

ln(Markup)	**Average effect**	**Spillovers**		
	(1) ALL	(2) Interaction	(3) <50%	(4) >50%
CO share	0.067	-0.015	0.005	0.127
	(0.049)	(0.022)	(0.020)	(0.078)
Outsider	0.007	-0.015	-0.003	0.022***
	(0.006)	(0.011)	(0.008)	(0.008)
CO share × Spillover		0.000*		
		(0.000)		
Outsider × Spillover		0.000**		
		(0.000)		
Adj. R^2	0.96	0.96	0.97	0.95
N	15410	15410	7922	7488
Market clusters	2985	468	1567	1418

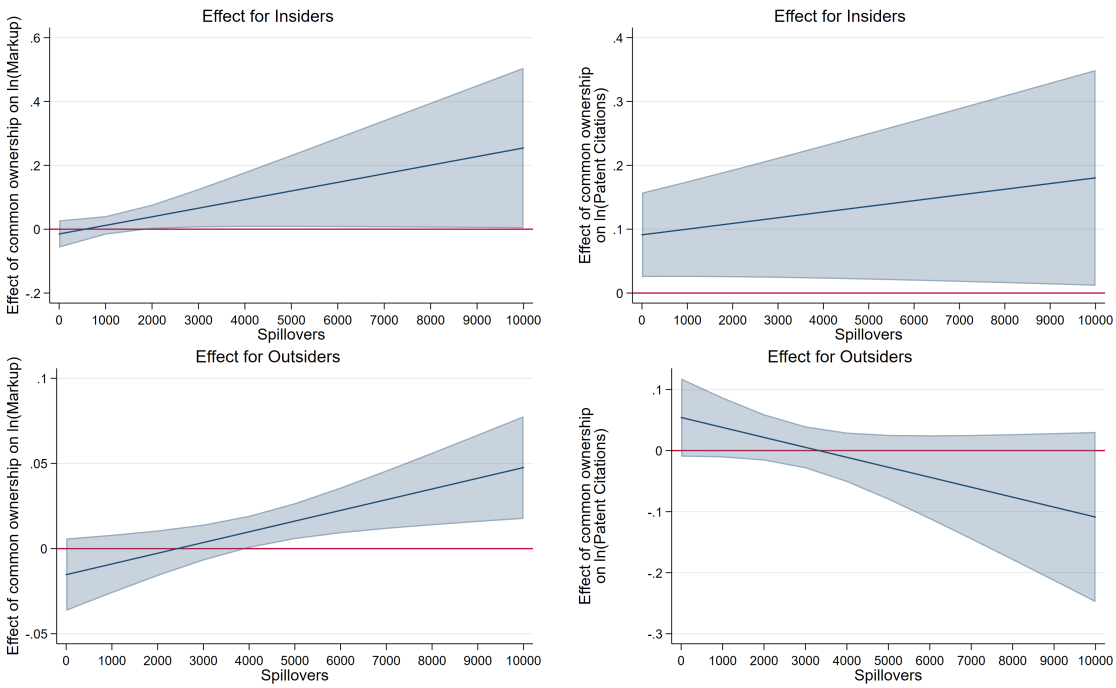
Note: Standard errors in parentheses and clustered at the market level. * p<0.10, ** p<0.05, *** p<0.01. Market definition: HHI and MHHI delta calculated at the three-digit industry-country level. We control for HHI at the three-digit industry country level, share of institutional holdings less commonly owned shares, firm and year-fixed effects. HHI and MHHI delta are rescaled by division by 10,000, such that the HHI ranges from 0 to 1.

Table E.12: Reweighting estimator: Innovation - Commonly held shares

ln(Patent Citations)	**Average effect**	**Spillovers**		
	(1) ALL	(2) Interaction	(3) <50%	(4) >50%
CO share	0.118***	0.091***	0.084***	0.156**
	(0.037)	(0.034)	(0.023)	(0.079)
Outsider	-0.004	0.054*	0.013	-0.024
	(0.022)	(0.033)	(0.028)	(0.033)
CO share × Spillover		0.000		
		(0.000)		
Outsider × Spillover		-0.000*		
		(0.000)		
Adj. R^2	0.80	0.80	0.76	0.83
N	15410	15410	7922	7488
Market clusters	2985	468	1567	1418

Note: Standard errors in parentheses and clustered at the market 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, age, share of institutional holdings less commonly owned shares, 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.

Figure E.4: Reweighting estimator: Spillover interaction effect with commonly held shares

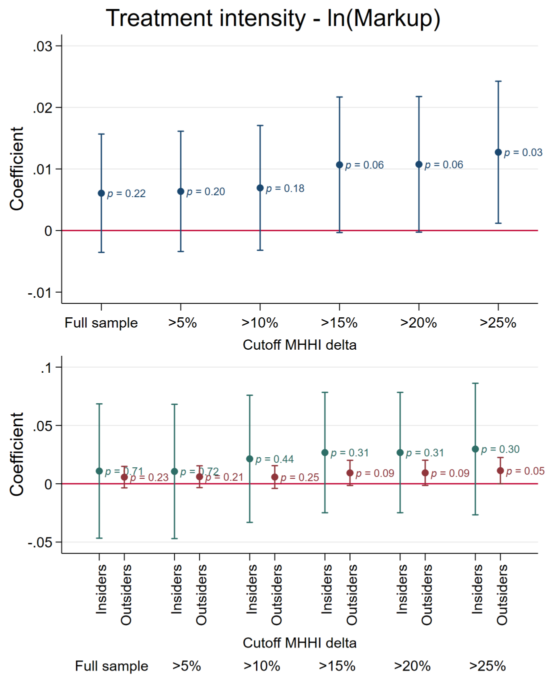


a) Markups - Spillover interaction effect **b)** Innovation - Spillover interaction effect

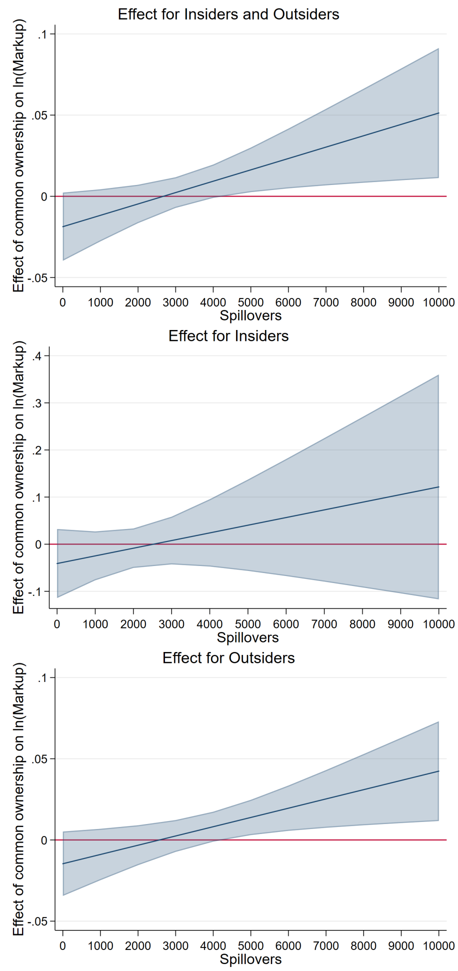
Note: The graph plots the treatment effect for varying degrees of spillovers for the outcome markups in the left graph and innovation in the right graph. Common ownership is measured as commonly held shares at the firm level. Insiders are defined as directly commonly owned firms. Outsiders are non-commonly owned competitors in the same market. We control for HHI at the three-digit industry country level, share of institutional holdings less commonly owned shares, firm and year-fixed effects. For innovation, we additionally control for ln(TFP), market size measured by average sales at the market level, capital intensity, 1-Lerner index, age, a dummy for zero citations. 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. The red line indicates zero.

E.3.2 Controlling for TFP

Figure E.5: Reweighting Estimator: Markups - Controlling for polynomial of TFP



a) Markups - Treatment intensity

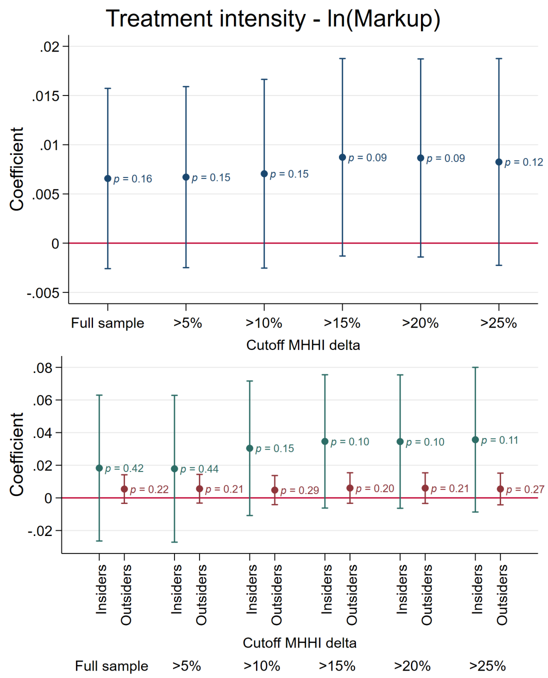


b) Markups - Spillover interaction effect

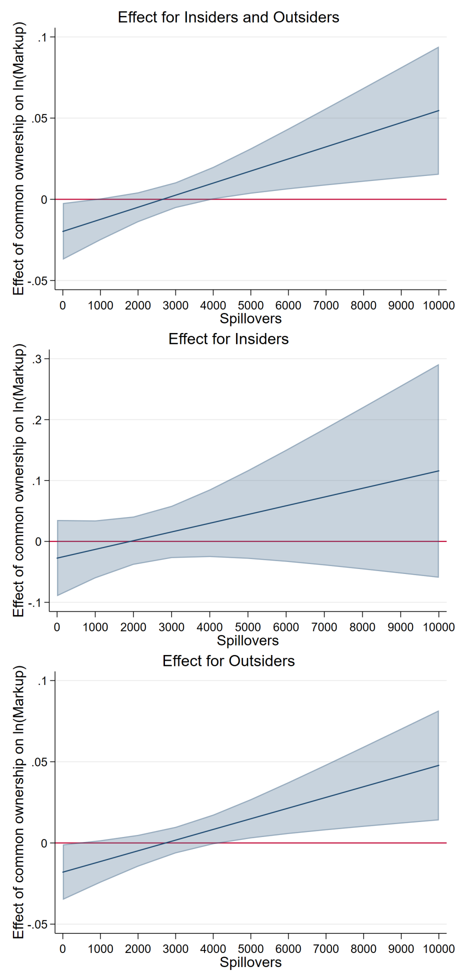
Note: The graph on the left plots the estimated coefficients of the treatment indicator and respective confidence intervals and p-values. The different coefficients are estimated in subsamples where we keep control observations with MHHI delta equal to 0 and treated observations with positive MHHI delta 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.

E.3.3 Country-specific and Industry-specific Time-fixed Effects

Figure E.6: Reweighting estimator: Markups - Country-specific and industry-specific time-fixed effects



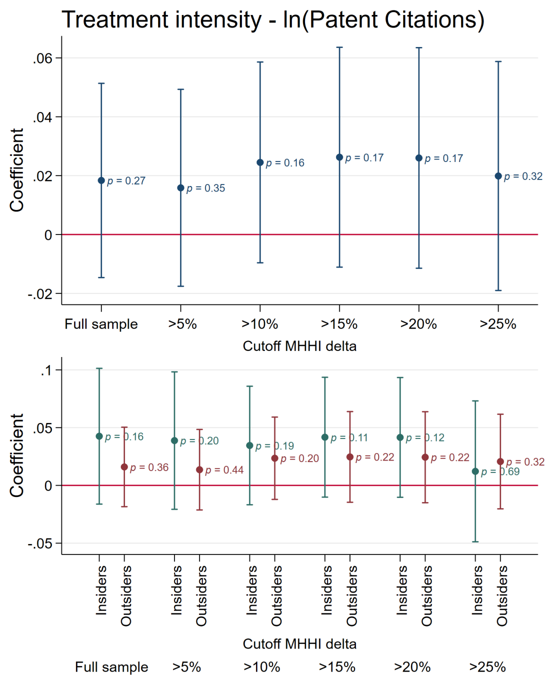
a) Markups - Treatment intensity



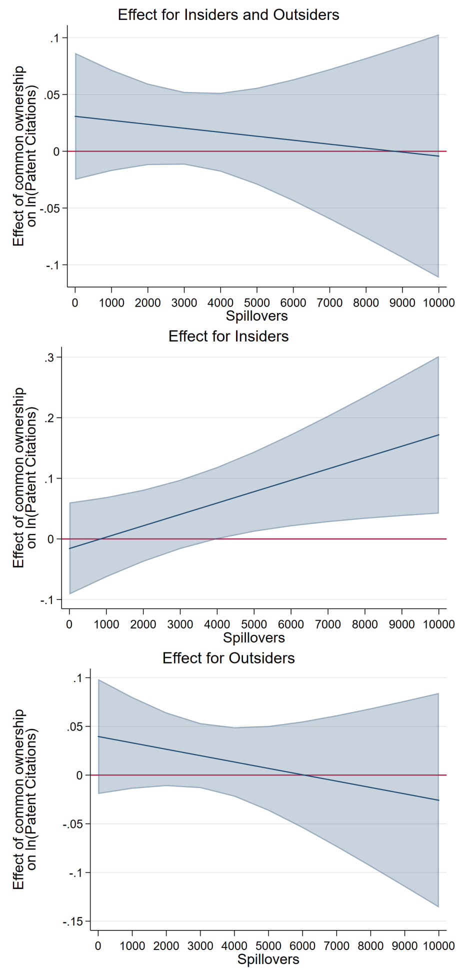
b) Markups - Spillover interaction effect

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 E.7: Reweighting estimator: Innovation - Country-specific and industry-specific time-fixed effects



a) Innovation - Treatment intensity

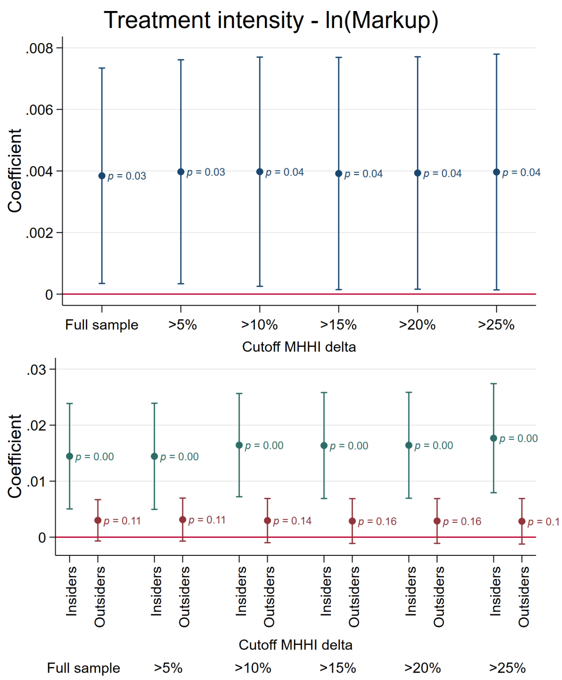


b) Innovation - Spillover interaction effect

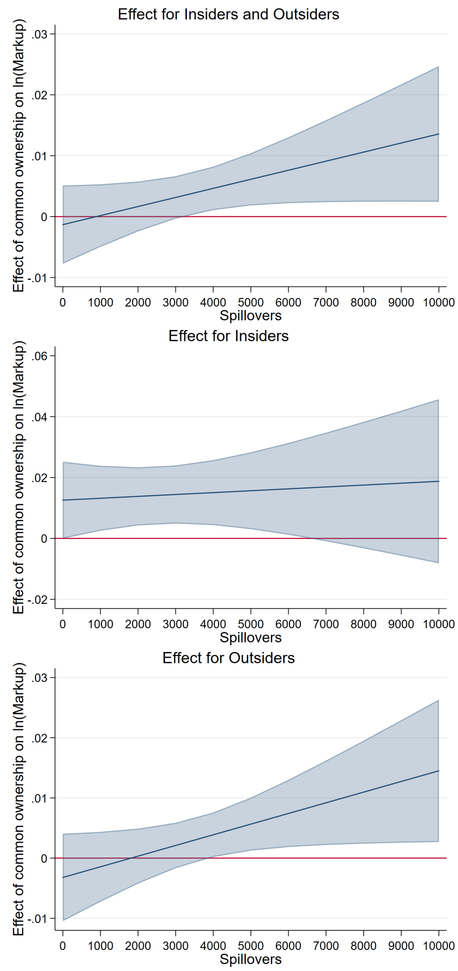
Note: The graph on the left plots the estimated coefficients of the treatment indicator and respective confidence intervals and p-values. The different coefficients are estimated in subsamples where we keep control observations with MHHI delta equal to 0 and treated observations with positive MHHI delta 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, 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. We also include firm and year-country-fixed effects and cluster standard errors at the three-digit industry-country level. The red line indicates zero. The blue shaded area is a 95% CI.

E.3.4 Alternative Production Function Specifications

Figure E.8: Reweighting estimator: Markups - Translog production function



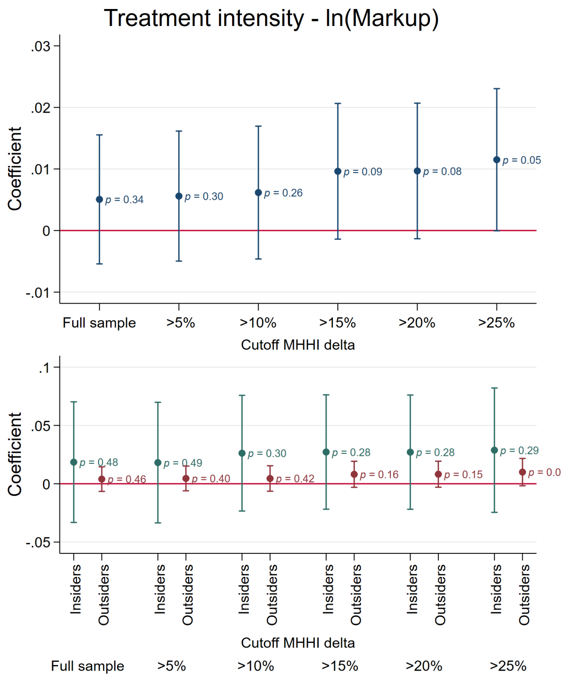
a) Markups - Treatment intensity



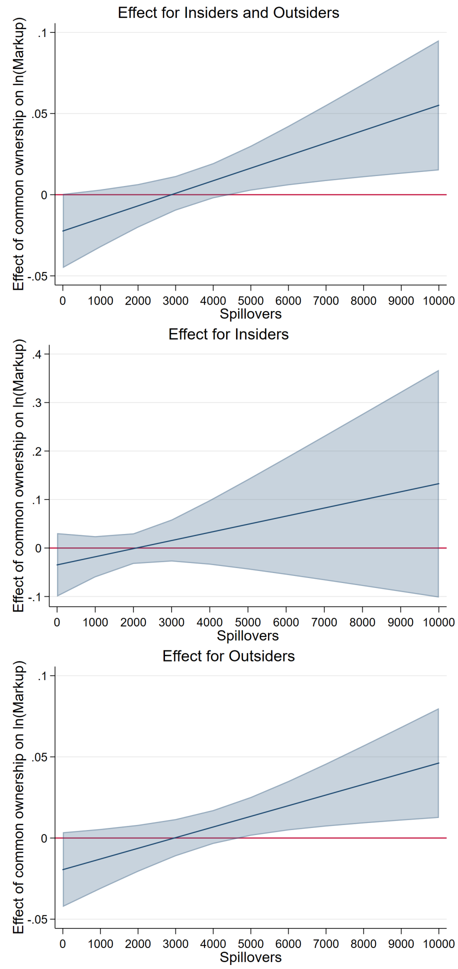
b) Markups - Spillover interaction effect

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 E.9: Reweighting estimator: Markups - Wages in control function



a) Markups - Treatment intensity

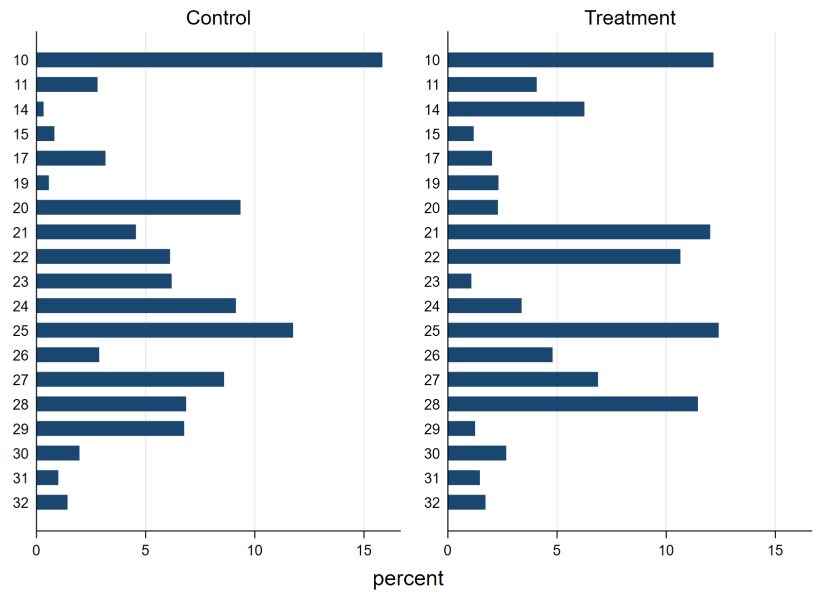


b) Markups - Spillover interaction effect

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.

E.3.5 Industry Balancing

Figure E.10: Distribution of industries for treatment and control group



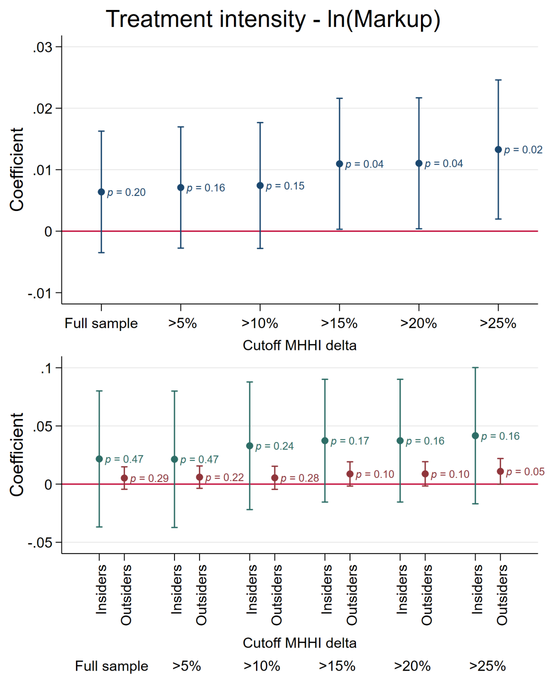
Note: This graph shows the sample probabilities of NACE two-digit industries for the reweighted regression sample using propensity score weights. Treatment is defined as the first occurrence of common ownership, i.e. a non-zero MHHI delta.

Table E.13: Balancing: Weighted sample - NACE two-digit industries

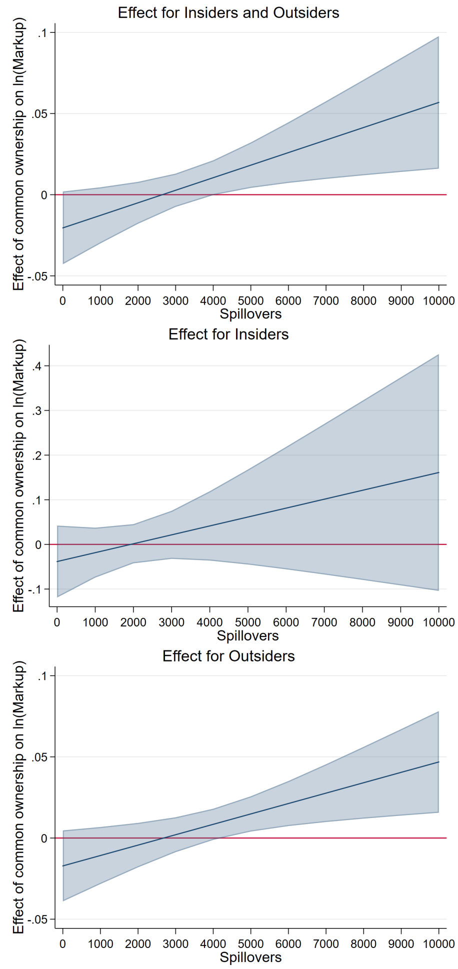
NACE two-digit	
NACE 10	-0.032
	(0.079)
NACE 11	-0.012
	(0.020)
NACE 14	0.070
	(0.048)
NACE 15	0.011
	(0.019)
NACE 17	-0.012
	(0.020)
NACE 19	0.018
	(0.024)
NACE 20	-0.083***
	(0.026)
NACE 21	0.079
	(0.087)
NACE 22	0.015
	(0.068)
NACE 23	-0.050***
	(0.019)
NACE 24	-0.057
	(0.037)
NACE 25	0.052
	(0.140)
NACE 26	0.003
	(0.022)
NACE 27	-0.016
	(0.064)
NACE 28	0.050
	(0.056)
NACE 29	-0.053**
	(0.024)
NACE 30	0.008
	(0.017)
NACE 31	0.004
	(0.013)
NACE 32	0.005
	(0.016)

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 of the weighted sample between treatment and control group after controlling for year fixed effects.

Figure E.11: Reweighting estimator: Markups - Without unbalanced NACE two-digit industries



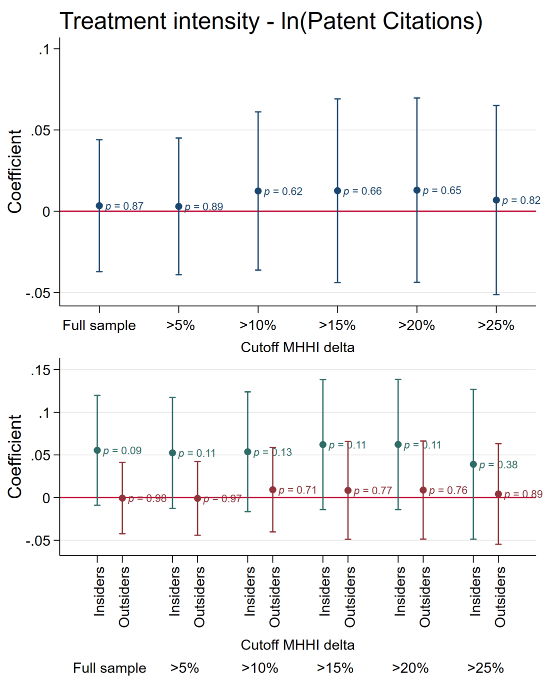
a) Markups - Treatment intensity



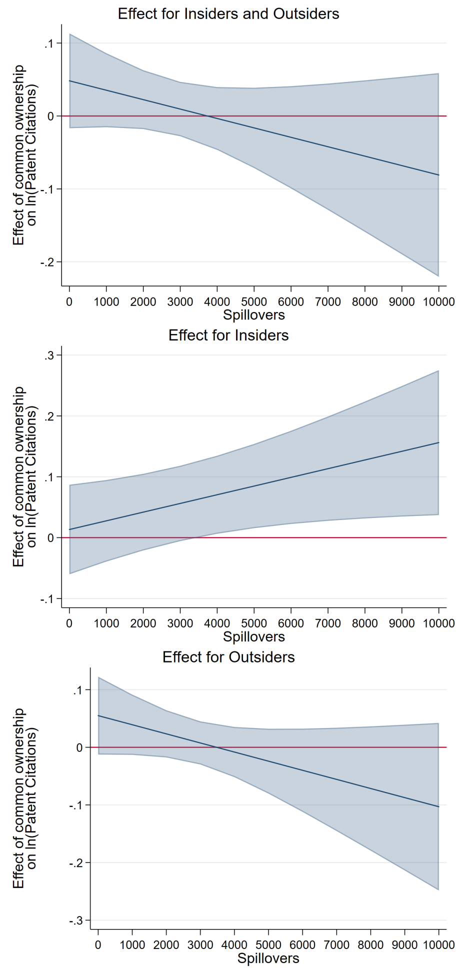
b) Markups - Spillover interaction effect

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 E.12: Reweighting estimator: Innovation - Without unbalanced NACE two-digit industries



a) Innovation - Treatment intensity



b) Innovation - Spillover interaction effect

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.

E.3.6 Difference-in-Differences

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[22] 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.

$$y_{jt} = \delta_1 \mathrm{Treat}_p \times \mathrm{Post}_{pt} + \delta_2 \mathrm{Post}_{pt} + \tau_t + \nu_j + \epsilon_{jt}. \tag{6}$$

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 $\mathrm{Treat}_p \times \mathrm{Post}_{pt}$ and the post period with Post_{pt}, we control for firm and year-fixed effects ν_j and τ_t, as time of treatment varies across markets and therefore individual firms. The indicator variable Treat_p for the treatment group is subsumed by the firm-fixed effects. We cluster standard errors at the market level.

[22] 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.

Table E.14: Difference-in-differences: Markups and Innovation

Dep. Variable:	**ln(Markup)**		**ln(Patent Citations)**	
	(1)	(2)	(3)	(4)
$1_{(MHHIdelta>0)}$	0.019*		-0.103**	
	(0.010)		(0.041)	
$1_{(MHHIdelta>0)}\times$ Insider		0.017		0.036
		(0.022)		(0.041)
$1_{(MHHIdelta>0)}\times$ Outsider		0.019*		-0.112***
		(0.010)		(0.042)
Post	-0.011	-0.011	0.088***	0.088***
	(0.008)	(0.008)	(0.030)	(0.030)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.95	0.95	0.71	0.71
N	5935	5935	5935	5935
Market clusters	258	258	258	258

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 E.15: Difference-in-differences: Markups - Median split spillovers

ln(Markup)	**Average effect**		**Direct & indirect effect**	
	(1)	(2)	(3)	(4)
Spillovers	<50%	>50%	<50%	>50%
$1_{(MHHIdelta>0)}$	0.009	0.031**		
	(0.013)	(0.014)		
$1_{(MHHIdelta>0)}\times$ Insider			-0.001	0.031
			(0.021)	(0.041)
$1_{(MHHIdelta>0)}\times$ Outsider			0.009	0.031**
			(0.013)	(0.014)
Post	0.001	-0.024*	0.001	-0.024*
	(0.012)	(0.012)	(0.012)	(0.012)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.96	0.93	0.96	0.93
N	3041	2894	3041	2894
Market clusters	150	132	150	132

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 E.16: Difference-in-differences: Innovation - Median split spillovers

ln(Patent Citations)	**Average effect**		**Direct & indirect effect**	
	(1)	(2)	(3)	(4)
Spillovers	<50%	>50%	<50%	>50%
$1_{(MHHIdelta>0)}$	-0.133**	-0.063		
	(0.057)	(0.061)		
$1_{(MHHIdelta>0)} \times$ Insider			-0.016	0.085
			(0.054)	(0.058)
$1_{(MHHIdelta>0)} \times$ Outsider			-0.140**	-0.074
			(0.058)	(0.063)
Post	0.143***	0.038	0.143***	0.038
	(0.048)	(0.038)	(0.048)	(0.037)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.62	0.77	0.62	0.77
N	3041	2894	3041	2894
Market clusters	150	132	150	132

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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