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Working Paper

M&As, innovation and superstar firms

JRC Working Papers on Corporate R&D and Innovation (CoRDI), No. 3/2025

Provided in Cooperation with:
Joint Research Centre (JRC), European Commission

Suggested Citation: Martinez Cillero, Maria; Napolitano, Lorenzo; Rentocchini, Francesco; Seri, Cecilia; Zaurino, Elena (2025) : M&As, innovation and superstar firms, JRC Working Papers on Corporate R&D and Innovation (CoRDI), No. 3/2025, European Commission, Joint Research Centre (JRC), Seville

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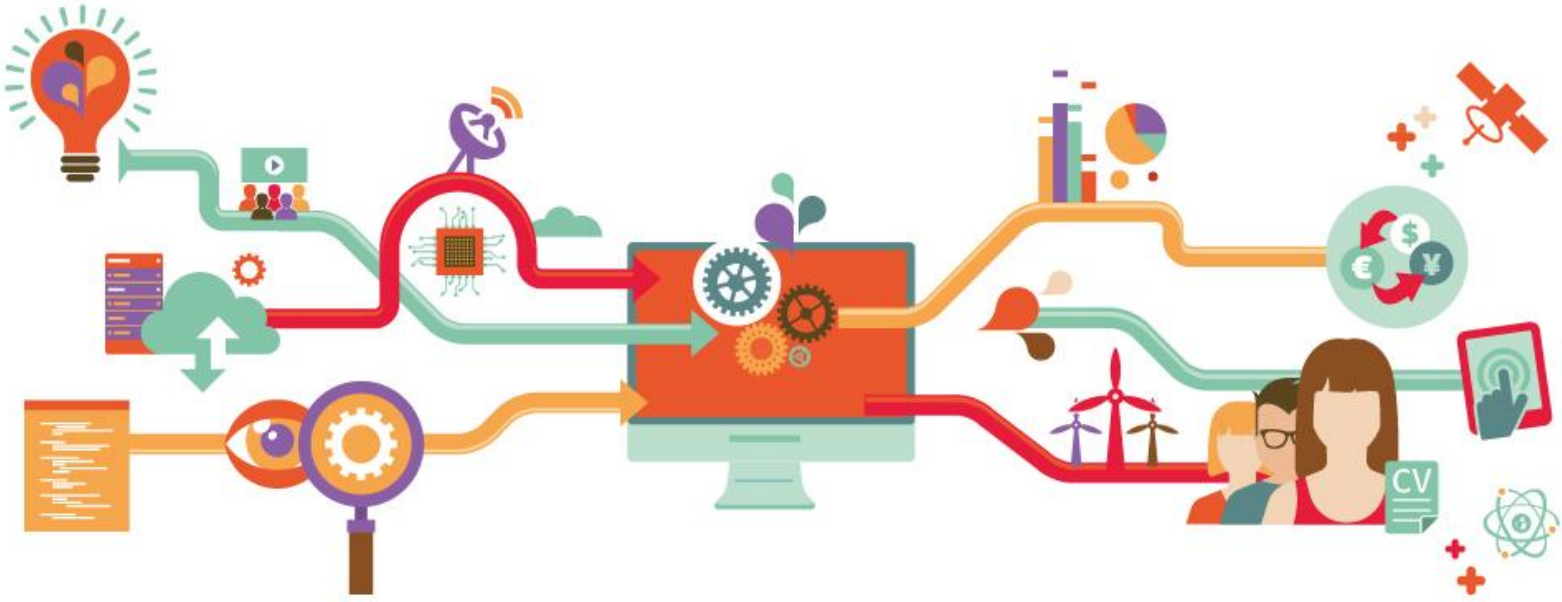
European Commission

M&As, Innovation and Superstar Firms

JRC Working Papers on Corporate R&D and Innovation (CoRDI)

No 3/2025

Martinez Cillero, M., Napolitano, L., Rentocchini, F., Seri, C., Zaurino, E.



Joint Research Centre

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Editorial Board: The JRC Working Papers on Corporate R&D and Innovation are published under the editorial supervision of Pietro Moncada-Paternò-Castello (Solvay Brussels School of Economics and Management, Université Libre de Bruxelles, Belgium) and Alexander Tübke in collaboration with Fernando Hervás, Koen Jonkers, Francesco Rentocchini at the European Commission – Joint Research Centre, and in cooperation with Sara Amoroso (German Institute for Economic Research, Germany), Michele Cincera (Solvay Brussels School of Economics and Management, Université Libre de Bruxelles, Belgium), Alex Coad (Waseda University, Tokyo, Japan), Enrico Santarelli (University of Bologna, Italy), Daniel Vertesy (International Telecommunication Union, Switzerland – and UNU-MERIT, The Netherlands), Antonio Vezzani (UNCTAD, Switzerland); Marco Vivarelli (Università Cattolica del Sacro Cuore, Italy) and Zoltan Csefalvay (Mathias Corvinus Collegium, Hungary).

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How to cite this report: Martinez Cillero, M., Napolitano, L., Rentocchini, F., Seri, C. and Zaurino, E., M&As, Innovation and Superstar Firms - JRC Working Papers on Corporate R&D and Innovation No 3/2025, European Commission, Seville, 2025, JRC143

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M&As, Innovation and Superstar Firms

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Abstract

Rising market concentration and the dominance of 'superstar' firms have sparked concerns about declining competition and innovation. While technological change and globalisation are key drivers, mergers and acquisitions (M&As) may also play a role. This paper investigates whether firms use technological M&As — acquisitions of innovative subsidiaries with patent portfolios — to enhance market power. Using a global panel of 8,314 publicly listed firms from 2008 to 2020 and a staggered difference-in-differences approach, we find that such acquisitions increase acquiring firms' markups by 2% on average. Effects are stronger among top R&D investors, US-based firms, and those in high-tech manufacturing. The main mechanism appears to be greater insulation from competitors via acquired patents, which limit knowledge spillovers and raise entry barriers. These findings highlight the need for antitrust policies that balance innovation incentives with the risks of growing market power.

Executive summary

Corporate concentration and the rise of "superstar" firms have increased concerns about market power and its detrimental effects on investment, productivity, wages and business dynamism. Mergers and acquisitions (M&As) are widely discussed as a potential driver of these trends, yet causal evidence from the acquirer's perspective — especially for deals that transfer strategic technologies — remains limited. This paper examines whether technological M&As — acquisitions where the target holds patent assets — raise the market power of acquiring firms, and through which channels.

Data and approach. We assemble a global firm-level panel by linking Orbis financials and ownership data with Zephyr M&A transactions and Orbis IP patents for 8,314 publicly listed firms worldwide over 2008–2020. Firm-level markups (price over marginal cost) are estimated using the De Loecker–Warzynski production-function method from accounting data. Identification relies on a staggered difference-in-differences/event-study design; we report the robustness of the results to recent heterogeneous-treatment estimators.

Main findings

- Technological M&As increase acquirer markups by 2% on average, with effects that are persistent, economically meaningful and robust across specifications and estimators. This impact is incremental to the average effects associated with general M&A activity.
- Heterogeneity. Effects are stronger for top R&D investors, US-headquartered firms, and high-tech manufacturing. In sectoral splits, significant effects also appear in low-tech manufacturing, driven by beverages and leather products — industries with global brands, large patent portfolios and active M&A histories. For EU firms, the point estimate is positive (+3%) but weaker.

Mechanisms. We test two non-exclusive channels: (i) innovation-enhancing synergies (post-deal patenting by the merged entity) and (ii) innovation-shielding via acquired patents (insulating technology to curb spillovers). The evidence points squarely to the innovation-shielding mechanism: the stock of patents acquired with the target has a persistent, positive effect on markups. By contrast, we do not find that higher post-M&A patent flows translate into higher markups, suggesting limited productivity-enhancement synergies in the short run. In plain terms, IP consolidation appears more relevant than IP creation for the observed markup effects.

Interpretation. Technological M&As enable incumbents to internalise innovation rents and restrict knowledge diffusion, raising barriers to entry and cushioning competitive pressure. This mechanism aligns with broader evidence on

rising markups associated with intangible assets and contributes to the concentration dynamics consistent with the "superstar firm" narrative. The result is not a critique of technology-motivated acquisitions as such; rather, it highlights a systematic risk of market-power amplification when patent portfolios are absorbed without adequate safeguards.

Policy implications. Our results support targeted adjustments in merger control and industrial policy to balance innovation incentives with market contestability:

1. *Bring innovation explicitly into merger review.* Alongside conventional concentration screens, assess technology-centric indicators (e.g., patent quality/citations, technology-overlap and blocking potential, R&D intensity, expected spillover suppression). Where parties rely on an "innovation defence", require verifiable, ex-ante commitments with ex-post monitoring to ensure promised dynamic efficiencies materialise rather than merely increase market power. This is coherent with the policy direction advocated in recent EU strategic competitiveness work (e.g., Draghi report) to integrate innovation potential and systematic post-merger evaluations.

2. *Use tailored remedies when clearing tech deals.* Consider licensing obligations (including FRAND-like terms) on specific acquired patent families, limited hold-separate or divestiture of patent bundles, data-access remedies where relevant. Prioritise remedies that preserve knowledge diffusion without nullifying legitimate efficiency gains.

3. *Align state aid and industrial policy with competition goals.* In strategic areas (clean energy, advanced manufacturing, digital), condition support for scaling on open standards, patent-pool participation, and collaborative R&D to reduce reliance on consolidation as a growth model. Coordinate state-aid approvals with merger remedies to avoid publicly supported foreclosure.

4. *Strengthen EU economic-security screening for critical technologies.* Deploy early-warning mechanisms for cross-border acquisitions involving sensitive patent assets and develop a unified disclosure/monitoring platform combining R&D reports and M&A intentions to flag consolidation risks in strategic technologies at an early stage.

Bottom line. Technological M&As do raise market power on average —- primarily by consolidating and defending patent assets —- with the largest effects among big R&D investors and high-tech incumbents. A case-by-case, innovation-aware merger regime, coupled with targeted remedies and industrial-policy alignment, can preserve true dynamic efficiencies while curbing the drift toward extant market dominance.

1 Introduction

Over the past few decades, concerns about rising corporate concentration and market power have become increasingly prominent in both academic and policy debates. Rising concentration has been largely documented for the US (Crouzet and Eberly, 2018; Grullon et al., 2019), and although with more conflicting results, similar dynamics have also been observed in other regions (De Loecker and Eeckhout, 2018; Diez et al., 2018). A central aspect of this phenomenon is the role of so-called "superstar firms" — dominant companies with growing market shares that are driving the rise in concentration, while also exhibiting increasing levels of productivity and profits (Autor et al., 2020).

This increase in market power has been linked to several important economic consequences. Notably, it has been associated with declining investment patterns, slower productivity growth and widening productivity gaps, stagnant wages, a falling labor share of GDP, and reduced business dynamism (Autor et al., 2020; Akcigit and Ates, 2021, 2023; Barkai, 2020; Döttling et al., 2017).

Yet, despite the extensive literature documenting trends in market power and their economic consequences, the drivers behind these trends remain less well understood. Among the potential explanations, globalization and technological advancements may have played a major role, making competition tougher and rewarding the most productive firms, solidifying their already dominant positions (De Loecker et al., 2021). Moreover, firms' strategic behaviour, and in particular mergers and acquisitions (M&As), have attracted attention as a key mechanism through which firms consolidate their dominance and acquire control over strategically valuable intangible assets (Cunningham et al., 2021; Ederer and Pellegrino, 2023; Jin et al., 2023).

While the role of M&As has often been discussed, few empirical studies have formally tested their causal impact on market power, especially from the perspective of acquiring firms. This is a crucial gap in the literature, given that M&A activity has increased markedly in recent decades and has the potential to reshape both the structure of markets and the pace of innovation. In fact, M&As are also likely to have relevant but mixed effects on innovation activities and firms' intangible assets, which in turn are found to be related to market power. Historically, firms have used "fundamental patents" to gain dominant positions and control competition, thus creating monopoly or cartel positions (Scott and Spadavecchia, 2019, 2023). More recently, Calligaris et al. (2024) show that the intangible components of the digital transformation are the main drivers of the rise in firms' markups, while Akcigit and Ates (2023) present new evidence that corroborates a declining knowledge diffusion in the economy as the reason behind the reduction in business dynamism and the increase in market power. Despite the clear

relevance of the interplay of business strategies and technology appropriation to increase market power, a considerable gap remains in understanding the strategic use of M&As to concentrate technology and sediment dominant positions. This study aims to provide empirical evidence in this regard, examining the strategic use of M&As — specifically those targeting innovative firms — as a channel through which acquiring firms accumulate intangible assets and increase their market power. We focus our analysis on "technological M&As", which we define as acquisitions in which the target firm owns at least one patent at the time of the deal. By acquiring patented technologies through M&As, firms may not only internalize innovation gains but also reduce competition and limit knowledge spillovers to rivals.

In light of the aforementioned gaps in the literature, our contribution is twofold. First, we provide a novel and comprehensive empirical assessment of how technological M&As affect the markups of acquiring firms. While most existing studies focus on the targets of M&A deals or on rival firms, we focus our analysis on acquirers. Second, we look at post-acquisition dynamics by analysing two mechanisms suggested by the literature: (i) the innovation-enhancing effect of M&As, where the integration of new intangible assets boosts productivity and markups; and (ii) the innovation-shielding effect, where acquired technologies are used to limit competition, reduce spillovers, and strengthen the firm's dominant position. These channels have been discussed in separate literatures — the M&A literature on innovation outcomes and the industrial organisation (IO) literature on market power — but have not been tested together using firm-level data across several countries and sectors.

To empirically investigate these questions, we construct a novel panel dataset by linking multiple firm-level sources over the period 2008–2020. Our primary data include information on firms' financials, ownership structures, patenting activity, and M&A transactions from Orbis. A key aspect of our empirical design is the classification of M&A events as "technological", in our case if the acquired firm holds at least one patent at the time of acquisition. This definition is meant to capture deals that involve the acquisition of innovation-relevant intangible assets. Using a staggered difference-in-differences approach, we then compare the post-deal evolution of markups[1], our measure of market power, between firms conducting technological M&As and those involved in non-technological deals.

As suggested by the literature, two main channels through which technological M&As may affect market power are explored. First, we investigate how technological M&As are used to increase the acquirer's intangible assets portfolio and whether this leads to higher markup. Indeed, the synergy generated by the

[1]Firm-level markups are estimated using a production function-based approach following De Loecker and Warzynski (2012), which allows us to control for input demand elasticities and firm heterogeneity in production.

merging entities (patent portfolios, R&D labs, etc.) yields more than the sum of the parts, and increasing returns to scale from intangible assets could lead to higher markups. We proxy this channel by looking at the patent flow of the acquirer post-acquisition and its effect on the firm's markup. Secondly, we explore whether technological M&As are effective in insulating proprietary technology from rival or competing firms, reducing knowledge spillovers and increasing market power of the acquirers. We proxy this mechanism looking at the effect of the stock of patents from acquired companies on the acquirers' markups.

We show that technological M&As are associated with a significant increase in the acquiring firm's markup relative to firms undertaking non-technological M&As. This effect is robust across specifications and is especially pronounced for top R&D investors, US-based firms, and firms active in high-tech manufacturing. Moreover, we find evidence consistent with the innovation-shielding effects. The stock of patents acquired through M&As has a persistent positive effect on acquirer markups, even when controlling for post-deal R&D and patenting. This highlights the strategic use of technology appropriation: by internalizing innovative assets and restricting their diffusion, firms can strengthen their competitive moat and raise barriers to entry. Taken together, our findings suggest that technological M&As are a powerful strategic tool for increasing market power, and they highlight the importance of considering jointly the innovation effects of M&As and also their implications for market structure and competition policy.

Literature Review. Our paper contributes to three main strands of the literature: (i) the determinants behind the rise in market power; (ii) the impact of M&A activity on competition and innovation; and (iii) the strategic use of intangible assets — particularly patents — in consolidating market dominance.

A large body of work has documented the rise in concentration and market power, particularly in advanced economies. Markups, the percentage difference of what companies are able to charge in prices over their marginal costs, have become in the past decade a common measure of market power in the industrial organization literature and beyond. In fact, the trends in firms' markups have been paralleled by increasing profit margins signalling an increase in market power, especially of superstar firms [2]. However, important heterogeneities are found across global regions and sectors. In the US, which have been explored by the earlier and majority of studies, clear trends of markup increase have been documented, with a rise from 21 percent above marginal cost in 1980 to 61 percent in 2016 (De Loecker et al., 2020; Diez et al., 2018). The aggregate increase is

[2]While in the past concentration ratios such as the HHI have prevailed in the study of market power and concentration, it has been argued that these become problematic when analyzing market power across different industries with differentiated products and over long time periods, due to their sensitivity to the market definition (Bresnahan, 1989; Syverson, 2019). Moreover, additional caution is required when using data that are not comprehensive of the universe of firms, such as when limiting the sample to publicly traded firms.

mainly due to increasing markups for firms at the top of the distribution as well as to the reallocation of market shares towards these firms, providing support to the "superstar firm" phenomenon. For Europe and other regions, results on markup trends are more conflicting. While in Canada trends have been found to be similar to those encountered for the United States, markups have increased less and later - since the 2000s - in Europe (Diez et al., 2018; De Loecker and Eeckhout, 2018). Across different European countries results are mixed. For example, for the UK, Aquilante et al. (2019) and De Loecker et al. (2024) have found increasing markups, but for the Netherlands van Heuvelen et al. (2019) have not found evidence of such increase. In Asia markups have been lower in level and have increased more moderately, and particularly in Japan they have been substantially lower than in other developed countries. For emerging markets and developing economies, there is less evidence of a rise in markups (Diez et al., 2018; De Loecker and Eeckhout, 2018). In terms of sectoral heterogeneity, the average markup is found to be higher in services than in other sectors. Despite the aforementioned heterogeneities, it can be argued that there is overall support for increasing concentration and market power in advanced economies and, given the implications that these entail, this is a matter deserving academic and policy attention.

The second strand of the literature we contribute to looks at the effects of M&As on competition and innovation, although results are often mixed and depend on the industry and type of acquisition. Recent papers have highlighted the potential negative effects on competition, including the suppression of nascent rivals through so-called "killer acquisitions" (Cunningham et al., 2021), and defensive consolidations aimed at eliminating innovation threats (Ederer and Pellegrino, 2023; Jin et al., 2023). When exploring the effects of M&As on markups, most empirical analyses focus on the targets rather than acquirers. For example, Blonigen and Pierce (2015) find that target firms in US manufacturing increase their markups by about 12 percentage points relative to non-acquired peers. Similarly, Stiebale and Vencappa (2018) report post-acquisition markup increases in India, although they attribute these gains to improvements in efficiency and quality. Stiebale and Szücs (2022) shift the focus to non-merging rivals of acquiring firms, showing that mergers in already concentrated markets can also lead to higher markups among competitors, due to reduced competitive pressure.

Particular interest has been devoted to M&A activity in the Big Tech sector focusing on major firms known as GAFAM — Google, Amazon, Facebook, Apple and Microsoft.[3] While GAFAM firms certainly play a key role in market dynam-

[3]Several studies have examined Big Tech (GAFAM) M&A activity, finding that such acquisitions can reduce venture capital investment and, in many cases, lead to the discontinuation of acquired products —particularly from younger firms — although they do not necessarily eliminate competitive threats from other major players. The impact on innovation appears mixed and

ics, and case studies allow for the close investigation of specific factors, they also fail to account for the overall impact of increased M&A activity on the broader economy. And when it comes to the effects on market power and concentration, these impacts could be non negligible. In a recent study, Cao and Zhu (2025) build a dynamic general equilibrium model calibrated with data for the US economy and suggest that surging M&As could account for about 60 percent of the 9.75 percentage points of increase in aggregate markups observed from 1980s to 2010s.

A third strand of literature focuses on the role of intangible assets — especially technology-related ones — in shaping market power. In models of firm heterogeneity, intangibles tend to reduce marginal costs while raising fixed costs, thereby reinforcing returns to scale and increasing entry barriers (Calligaris et al., 2024; Akcigit and Ates, 2023). Patents, in particular, provide exclusion rights that can be strategically used to limit imitation and restrict competition. Recent contributions highlight how digital and proprietary technologies — such as data, algorithms, and software — are increasingly important drivers of firm markups (Bessen, 2020; De Ridder, 2024). These assets are not only a source of productivity but also a defensive tool to insulate firms from rivals and reduce knowledge spillovers. Although the innovation literature has extensively examined the effects of M&As on R&D inputs and patenting outcomes (Ahuja and Katila, 2001; Berger et al., 2025; Cloodt et al., 2006; Desyllas and Hughes, 2010), few studies have connected these two dimensions to assess how firms may strategically use technological M&As —- that is, acquisitions of innovative firms holding intangible assets — to expand their market power. Our study addresses this gap by focusing on the acquirer's perspective and empirically analysing whether technological M&As lead to sustained increases in markup through intangible accumulation and reduced technological diffusion.

The remainder of the paper is structured as follows. In Section 2, we describe the construction and main characteristics of our dataset, and present the empirical strategy. In Section 3 we present and discuss the main results. Finally, Section 4 concludes discussing policy implications and avenues for future research.

2 Data and empirical strategy

2.1 Data

To obtain a dataset of global firms conducting M&As, including their financial characteristics and innovation activity, we combine different sources from the Orbis global database developed by Bureau van Dijk (BvD), a Moody's Analyt-

varies by acquirer and time period (Gugler et al., 2025; Jin et al., 2023; Gautier and Lamesch, 2021).

ics company. Orbis is one of the largest cross-country firm-level databases and provides information on firms' financial activities and corporate structure. It has been extensively used in economics research and, despite limitations, it "is the best publicly available database for comparing firm panels across countries" (Autor et al., 2020; Kalemli-Özcan et al., 2024). Our analysis is conducted using a rich firm-level panel[4] of 8,314 listed companies distributed worldwide for the observation period 2008 to 2020.

In addition to firms' financial statements and ownership structure, Orbis provides, through separate databases, also information on M&A deals (Zephyr)[5] and patents (Orbis IP). We use these different sources and link them through a common firm identifier to build a dataset of acquirer and target firms, their financial characteristics, and their patenting activity over 2008-2020.

Our objective is to construct, for each year, the ownership structure (i.e. the corporate group, including the mother company and its subsidiaries) of a given firm we identify as carrying out an acquisition between 2008 and 2020. To do so, we start with the Zephyr database that contains information about M&A deals from 2007 to 2020. From these deals, we are interested in identifying acquisitions of equity stakes leading to majority (or control) acquisitions. For this we use information about the initial, acquired, and final stake of the acquiring company into the target, and the information categorizing the deals in types. Based on this, we keep acquisitions and exclude internal-company deals, joint ventures, mergers or de-mergers. Moreover, within acquisitions we select only majority acquisitions (defined as those where the final stake of the investor in the target firm is above 50%[6]).

The identification of the relevant acquisitions through the aforementioned steps is the starting point for the next steps of the database construction. We extract the list of all investor firms involved in any of the selected transactions (in any year of the sample) and, using the Orbis Historical Ownership database, recover the subsidiaries of these investing firms in 2007 (the first year for which Orbis Historical Ownership data is available). We keep only the first tier subsidiaries in 2007, defined as those in which a given investor firm was the global ultimate owner or the direct majority shareholder (in both cases defined using the 50% stakes threshold).

Starting from this 2007 "original" subsidiary structure, we then sequentially incorporate the yearly data on majority acquisitions from 2008 to 2020, in order to

[4]We exclude the following NACE two-digit codes, 01 to 09, 53, 87, 95, and 97 to 99, due to the limited data availability which impairs the markup estimation.

[5]These are gathered relying on several sources: media, press releases, financial reports, and administrative filings.

[6]We also drop deals with no stake information, those implying no effective increase in the acquired stake (due to approximation) and those where the initial stake was already a controlling one (more than 50%) and the final stake is equal or below 100%.

identify and track the movement of the subsidiaries from year 2007 to 2008 (and then from subsequent t to t+1) across the investor firms in our sample[7]. Through this process, we obtain a final database in which, for every year between 2007 and 2020, we have the full list of companies owned by an acquiring company.

For the patent data, we rely on Orbis IP, which provides information on patents filed by different entities at any patent office globally. We only consider patents for which the applicant is a firm (i.e. it has a firm identifier), which allows us to merge these data with the deals and the financial data. We consider patent applications during the period 1970-2020 to account for the patent stock of both acquiring and acquired entities before the M&A. We work at the patent family level to avoid double counting when considering patent applications at all patent offices globally.

Finally, we merge the two datasets, the ownership structure with the patent information relying on the common firm identifier (the Orbis BvD ID), and we obtain a dataset spanning 2008-2020 that has information on: (i) the flow of patents applied for by each investor company (and all its subsidiaries) in each year (ii) the stock of inventive activity of the investor company (including all its subsidiaries) in each year; and (iii) the stock of patents for which the targets have applied until the year of acquisition. This information is used to characterize companies and define our treatment and control groups, as well as to capture the technology-related mechanisms through which M&As affect acquirers' markup, which constitutes our main variable of interest and whose construction is detailed in Section 2.2.

2.2 Markup estimation

A central component of our empirical analysis is selecting an appropriate indicator of firms' market power. A natural candidate is the price-to-marginal cost ratio, commonly referred to as the markup. This metric captures the deviation between the price firms actually charge and what they would charge under perfect competition with no distortions. However, despite the availability of production price data, marginal costs are rarely observable in practice.

To overcome this, we adopt the approach proposed by De Loecker and Warzynski (2012). This method leverages firm-level balance sheet data to infer markups indirectly. The basic principle is that in a perfectly competitive environment, a firm's cost share for a variable input should equal that input's output elasticity. Deviations from this equality suggest the presence of market power. Crucially, this technique is applicable across various market structures and does not require

[7]When a company A which is an investor of company B is also the target of an acquisition by company C, we re-assign company B to company C (and eliminate the "intermediate" step). The underlying assumption we impose on the data is that there is one layer of ownership only here, otherwise we could continue in an infinite loop of re-assignment.

specifying a demand system. We assume that each firm i at time t produces output Q_{it} according to a production function that depends on labor L_{it}, capital K_{it}, intermediate inputs M_{it}, and a firm-specific productivity shock Ω_{it}:

$$Q_{it} = F_{it}(L_{it}, K_{it}, M_{it}, \Omega_{it}) \tag{1}$$

This function is assumed to be continuous and twice differentiable. As in De Loecker and Warzynski (2012), the key identifying assumption is that firms can freely adjust at least one input, in our case, intermediate inputs, which are considered flexible. In contrast, capital and labor are treated as dynamic inputs, reflecting adjustment costs and rigidities.

From the firm's cost minimization problem, we obtain the following markup formula:

$$\mu_{it} = \frac{\theta_{it}^{M}}{\alpha_{it}^{M}} \tag{2}$$

Here, θ_{it}^{M} denotes the output elasticity of intermediate inputs (to be estimated), and α_{it}^{M} is the share of spending on intermediates relative to sales, which can be directly calculated from balance sheet data. The method's advantage lies in its reliance on just these two quantities.

Estimating θ_{it}^{M} presents a challenge because output elasticities are not directly observable and are potentially biased due to the endogeneity of input choices with respect to productivity. To address this, we use the control function approach of Ackerberg et al. (2015), which effectively corrects for the simultaneity between input decisions and productivity shocks. For structural estimation of production functions, it is common practice to use accounting data, since information on produced quantities are not available. We use balance sheet data on sales (approximating output), tangible fixed assets (capital), material expenses (physical materials)[8], and the costs of employment (labour). All of these variables are converted from nominal to real terms using country-level GDP deflators from the World Bank[9]. We perform further cleaning as detailed in the Appendix A.

We estimate production functions separately for each aggregate 2-digit NACE sector using a log-linearized translog specification:

$$q_{it} = f_{it}(l_{it}, k_{it}, m_{it}; \beta) + \omega_{it} + \varepsilon_{it} \tag{3}$$

where the production function $f_{it}(.)$ is assumed to be translog, ω_{it} is the Hicks neutral productivity level observed by the firm, potentially correlated to the level of the inputs in production, while ε_{it} is the unanticipated productivity shock as-

[8]When the material expenses are not reported, we impute them using the sector-level average of cost of sold goods, production, services (COGS). These are costs directly related to the production of the goods sold, including the depreciation of those costs, as defined by Orbis.

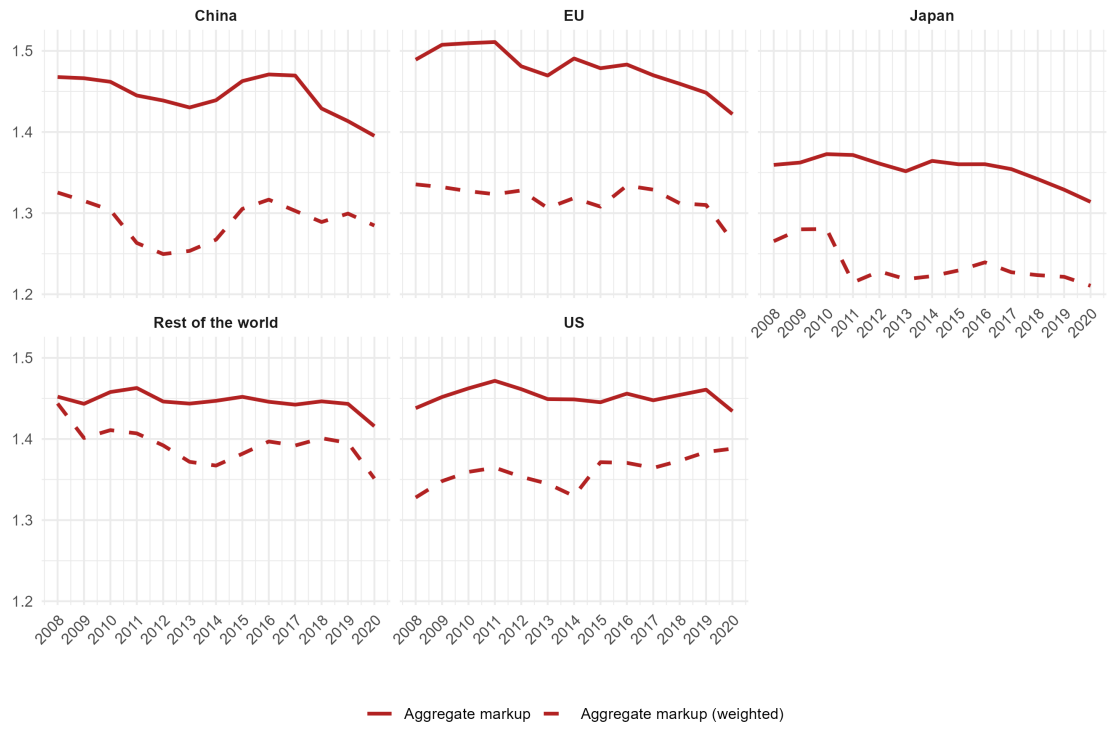
[9]A detailed description of the variables included here can be found in Appendix B.

sumed to be independent and identically distributed across firms. Although this approach relies on revenue data rather than physical quantities, which may introduce some bias in levels, prior research such as De Ridder et al. (2024) indicates that this bias is limited when focusing on changes over time, which is our primary interest. The markup is then computed as the ratio of the estimated intermediate input elasticity to its revenue share, correcting for first-stage errors. See Appendix C for more details on the theory behind this estimation procedure.

2.3 Descriptive statistics

Our sample consists of listed firms conducting at least an M&A over 2008-2020. This yields a total of 8,314 firms from 79 countries representing all global regions. Given its construction, our sample does not aspire at being representative of the overall market dynamics. However, since our main interest is investigating the effect of tech M&As on firms' market power proxied by markup, we begin by exploring the trend in aggregate markup across different regions and sectors.

Figure 1: Average Markup by Geographic Areas



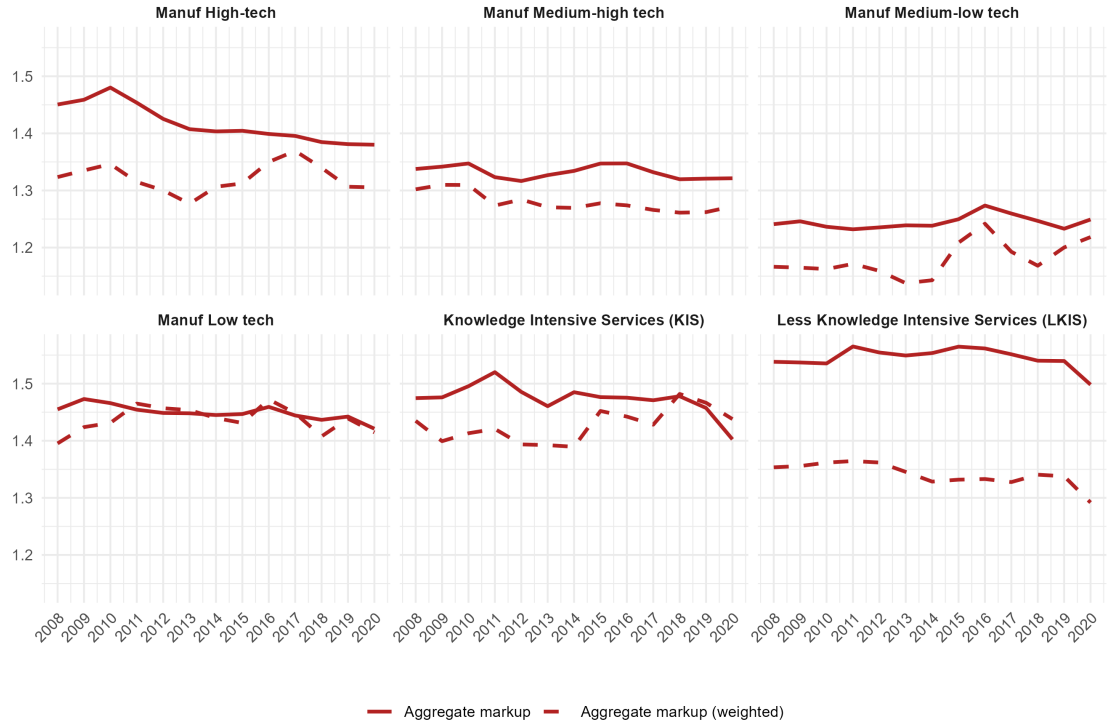
Note: The figure shows the trend in average markup over 2008-2020 calculated across the firms in our sample (listed firms conducting at least an M&A over the time span) in five geographic regions. The solid line shows the unweighted, simple average; the dashed line represents the average markup weighted by sales within each region (proxied by real operating revenues of each firm) to reflect higher contribution to aggregate regional markup of firms with larger market share.
Source: Orbis, Zephyr, Orbis IP (Moody's analytics), analysis by authors

As shown in Figure 1, among firms in our sample, those located in the EU had the highest markups at the beginning of the period, but they have been decreas-

ing after 2011, possibly related to the prolonged effects of the financial and then sovereign debt crisis. Conversely, and in line with the rest of the literature, we observe stable markups in the US, which have been steadily increasing when the aggregate markup is weighted by the firms' market share . In China and Japan markups have also been slightly decreasing, and as already observed by previous studies (De Loecker and Eeckhout, 2018; Diez et al., 2018), in Japan the average firm markup is substantially lower than in the rest of the geographic areas considered.

In terms of sectoral heterogeneity, Figure 2 shows that average markups are highest in services, which is in line with the findings in Calligaris et al. (2024) and van Heuvelen et al. (2019). In terms of trends, when looking at weighted series reflecting a larger contribution to the average of firms with larger market shares, markups have been rising the most in high-tech manufacturing and, particularly after 2014, in knowledge-intensive services.

Figure 2: Average Markup by Industry



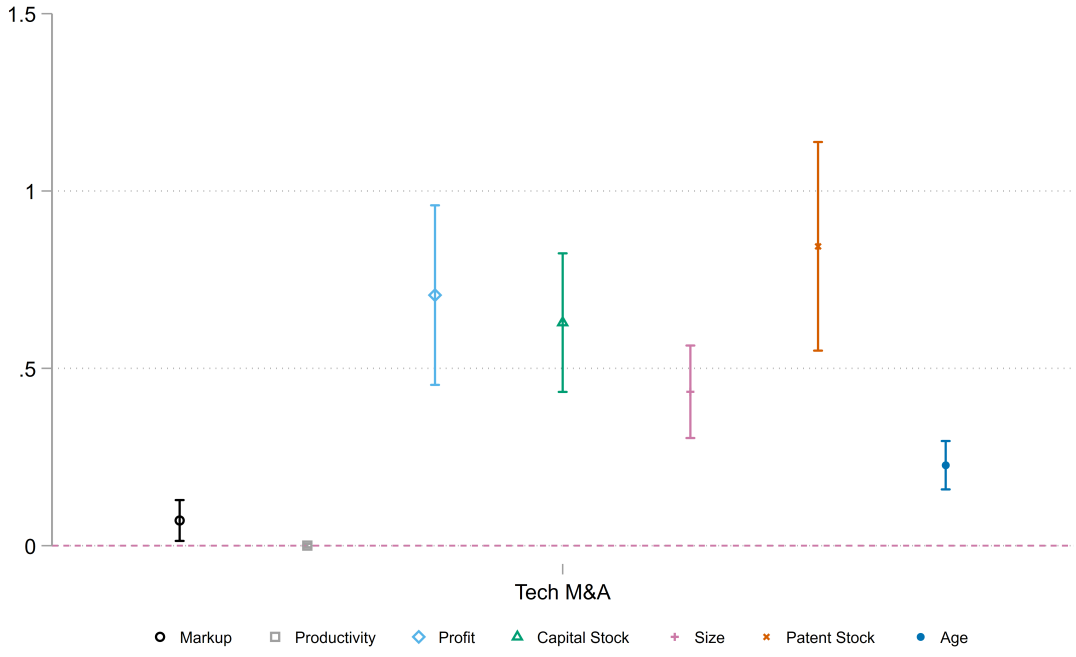
Note: The figure shows the trend in average markup over 2008-2020 calculated across the firms in our sample (listed firms conducting at least an M&A over the time span) in five geographic regions. The solid line shows the unweighted, simple average; the dashed line represents the average markup weighted by sales within each industry (proxied by real operating revenues of each firm) to reflect higher contribution to aggregate regional markup of firms with larger market share.
Source: Orbis, Zephyr, Orbis IP (Moody's analytics), analysis by authors.

Our sample comprises firms performing M&As over 2008-2020, out of which 7,515 companies acquire targets with no patents, while each year around 100 firms perform at least one technological M&A (Table D.1 in the Appendix). Figure 3 documents the heterogeneity in terms of performance and baseline character-

istics between the group of firms conducting technological M&A and those who do not. Specifically, we investigate whether firms performing a tech M&A differ significantly in terms of markup, productivity, profitability, capital and patent stocks, size and age.

As Figure 3 shows, within each year, region, and industry, firms engaging in technological M&As tend to have higher profits, as well as larger capital and patent stocks. They also appear to be older and larger than other firms in the sample and exhibit slightly higher markups, although they do not differ significantly in terms of productivity. This pattern holds when comparing deal versus non-deal years among firms that conduct tech M&As. However, for the subset of firms acquiring only targets without patents, there are no strong or statistically significant differences in deal years. When doing an M&A, firms tend to be slightly larger than other firms and have marginally higher profits and capital stock, but the magnitudes are much smaller than for tech M&A firms. This suggests that the observed tech M&A premia reflect characteristics or outcomes that go beyond those associated with general M&A activity.

Figure 3: Tech M&A Premia

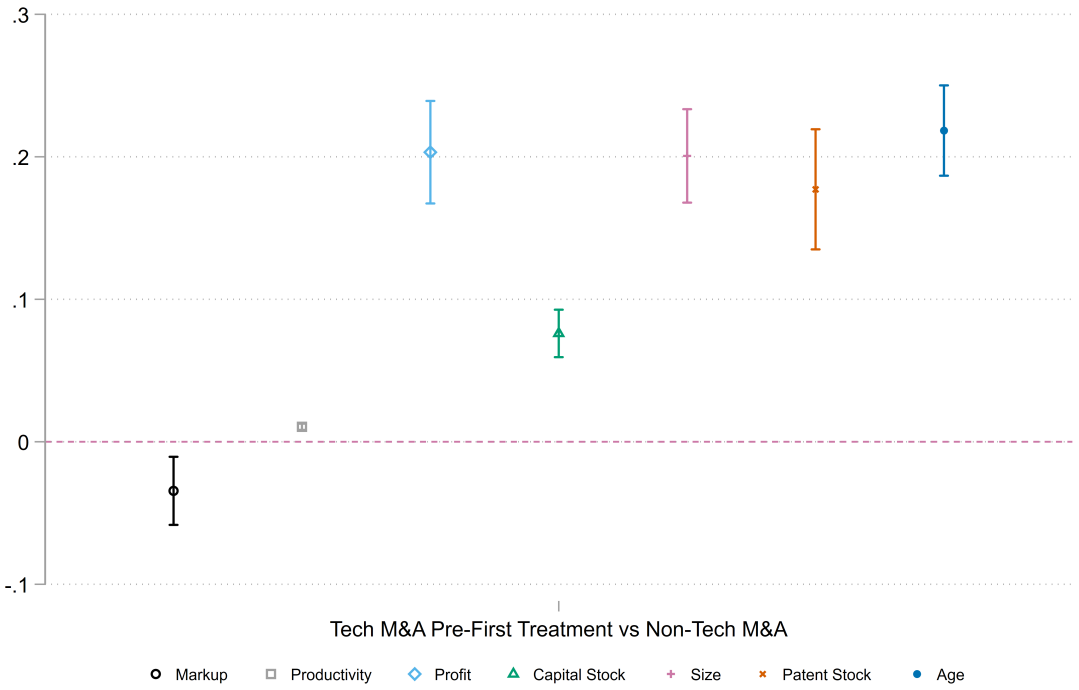


Note: The figure plots the coefficient estimates and 95% confidence intervals for a dummy indicating whether a firm conducts a tech-M&A or not in each year for OLS regressions on seven different dependent variables over 2008-2020. All variables are z-score standardized (mean-centered and scaled to unit variance). All regressions use firm-level data and include industry (NACE 2-dig), region and year fixed effects, and all standard errors are robust to heteroskedasticity. Profit is measured using EBIT, which captures earnings from operations before financing and tax effects (core profitability). Size is proxied by real operating revenues. Capital stock is derived from fixed asset changes using the Perpetual Inventory Method (PIM), accounting for depreciation. The patent stock is also PIM-depreciated. *Source:* Orbis, Zephyr, Orbis IP (Moody's analytics), analysis by authors

We further investigate whether these premia are pre-existing to any tech M&A

or they may be related and possibly consequent to the treatment. Therefore, we compare firms conducting tech M&As versus firms conducting non-tech M&As before the treatment occurs (Figure 4). We find that future-treated firms actually exhibit lower markups relative to control firms. This pattern suggests that there is indeed some selection on observables (i.e. firms that eventually do a tech M&A have lower markups pre-treatment). This, together with other relevant differences pre-treatment in terms of productivity, profitability, capital and patent stock, firm size and age, point to the need to adopt a fully fledged difference-in-differences techniques that can account for treatment timing and heterogeneity as well as pre-treatment differences.

Figure 4: Pre-treatment Tech M&A Premia



Note: The figure plots the coefficient estimates and 95% confidence intervals for a dummy distinguishing firms conducting tech M&A before the first deal and firms only conducting non-tech M&As for OLS regressions on seven different dependent variables over 2008-2020. All variables are z-score standardized (mean-centered and scaled to unit variance). All regressions use firm-level data and include industry (NACE 2-dig), region and year fixed effects, and all standard errors are robust to heteroskedasticity. Profit is measured using EBIT, which captures earnings from operations before financing and tax effects (core profitability). Size is proxied by real operating revenues. Capital stock is derived from fixed asset changes using the Perpetual Inventory Method (PIM), accounting for depreciation. The patent stock is also PIM-depreciated. *Source:* Orbis, Zephyr, Orbis IP (Moody's analytics), analysis by authors

2.4 Empirical Strategy

Does conducting a technological M&A contribute to an increase in markup at the firm level? In order to distinguish the contribution of the technological M&A event from the effects of other confounding factors, such as macroeconomic or regulatory shifts, firm-specific demand shocks and input-price fluctuations, we exploit cross-firm variation in M&A dates. Notably, we exploit a staggered difference-in-differences event-study design (which net out all time-invariant heterogeneity and common shocks), and dynamic leads and lags around the M&A to flexibly control for differential pre-trends and isolate the causal impact of the technological M&A event on markups.

$$\text{Markup}_{it} = \sum_{p=-7}^{-2} \beta_p \text{M\&A}_{it}^{p} + \sum_{p=0}^{5} \beta_p \text{M\&A}_{it}^{p} + \alpha_i + \lambda_t + \epsilon_{it} \tag{4}$$

where $Markup_{it}$ is the markup of firm i at year t where $t = 2008...2020$. α_i are the firm fixed effects which account for determinants of markup that are constant over time, while λ_t control for common shocks across firms. $M\&A_{it}^{p}$ are event-year dummies equal to 1 when the year of observation t is $p = -7, ..., 0, ...5$ years from the year in which firm i has conducted its first technological M&A. $p = -1$ is omitted, which normalizes the estimates of β_p to 0 in that year. The pre-treatment estimates of β_p can be thought of as falsification tests as their patterns and statistical significance allow us to investigate the parallel trends assumption. The control group comprises both not-yet-treated firms and firms that undertook non-technological M&A. Firms pursuing non-technological M&A offer a closer approximation to the counterfactual — that is what would have occurred had the firm not undertaken a technological M&A — in line with the fact that acquirers differ markedly from non-acquirers across multiple dimensions, including size, R&D expenditure, capital investment and profitability (Nindl et al., 2024).

Equation 4 assumes that the technological M&A event is an absorbing treatment; that is, the indicator takes the value 1 in the year of the first technological M&A and remains 1 until the last year the firm is observed. The rationale is that, once a firm has integrated external technologies, patents and specialised R&D teams, the resultant capabilities and market position are effectively permanent, as displacement of these assets is rarely observed in practice. Furthermore, synergies from the acquisition—in particular the acquired organisational routines and technological know-how—are cumulative in nature and yield persistent shifts in competitive dynamics. By maintaining the treatment indicator at one for all post-deal years, our specification thus captures both the immediate enhancement of market power and its enduring reinforcement over time.

To address concerns of possibly biased dynamic treatment estimates in the

presence of staggered treatment and treatment effect heterogeneity, we show results for an ensemble of estimators alternative to the dynamic TWFE estimator (Sun and Abraham, 2021; Callaway and Sant'Anna, 2021). In particular, should the impact of technological M&A on firms' markups vary across M&A events, standard event study estimates may be biased (Sun and Abraham, 2021). To mitigate this concern, we estimate alternative event study estimates derived from recent contributions from the literature. Following (Sun and Abraham, 2021), we first estimate the effect of each technological M&A cohort separately and then aggregate those cohort-specific estimates to the corresponding calendar year. We also implement the approach of Callaway and Sant'Anna (2021), which initially recovers cohort-time-specific treatment effects and subsequently aggregates all possible 2 × 2 comparisons to obtain adequately weighted overall treatment effect measures.

When investigating the potential mechanisms of the technological M&A effect on markup, we instead rely on a non-absorbing (NA) treatment, where the M&A indicator takes the value 1 in the year of the event only and zero otherwise. In particular, we test whether the effect of the M&A event on markup is due to: (i) higher R&D productivity following the acquisition and/or (ii) insulation from rivals via incorporation of the target knowledge stock. In the two cases above, we consider non-absorbing treatment as we are interested in exploring how the patenting activity of the merged company reacts to the technological M&A soon after this is done.

Notably, we estimate the following two-way fixed effect models:

$$\begin{aligned} \text{Markup}_{it} = \beta_1 \, \text{M\&A_NA}_{it} + \beta_2 \, \text{PatFlow}_{it} \\ + \beta_3 \, \text{M\&A_NA}_{it} \times \text{PatFlow}_{it} + \alpha_i + \lambda_t + \epsilon_{it}. \end{aligned} \tag{5}$$

where $\text{M\&A_NA}_{it}$ takes value 1 when firm i conducts technological M&A in year t and 0 in other years. PatFlow_{it} is the average number of patents developed by the merged company in the 1, 2 or 3 years following the acquisition.[10] The coefficient β_3 of the interaction term estimates the additional contribution to firm markup of the inventive activity following the acquisition. All other variables are as in model 4.

$$\begin{aligned} \text{Markup}_{it} = \beta_1 \text{M\&A_NA}_{it} + \beta_2 \, \text{PatFlow}_{it} + \\ \beta_4 \, \text{SubPatStock}_{it} + \alpha_i + \lambda_t + \epsilon_{it} \end{aligned} \tag{6}$$

Where SubPatStock_{it} is the target's patent stock in the year of acquisition and

[10] All patent variables are transformed using the inverse hyperbolic sine (IHS) transformation. Following recent debate in the economics literature (Bellemare and Wichman, 2020; Mullahy and Norton, 2024), we also estimate specifications in which we add one to the patent count and then take its natural logarithm. These results are in line with those presented in the main text and are available from the authors upon request.

approximates the stock of knowledge acquired by the target until the year of the M&A event. [11] The coefficient β_4 estimates the contribution to firm markup of the patent knowledge stock acquired via the M&A event. All the other variables are as in model 5.

Adopting an absorbing treatment in models 5 and 6 is equivalent to recognizing the existence of reversals: firms that, during the observation period, switch into and out of treatment. Although this circumstance is relatively uncommon in our sample (only 14% of firms undertaking technological M&A), it cannot be entirely ruled out and may pose problems for standard event-study estimators. To verify that our results are not driven by the different treatment definition, we also present the event-study findings for the model 4 using the estimator proposed by De Chaisemartin and d'Haultfoeuille (2024). They develop a method for estimating treatment effects in settings with variation in treatment timing and heterogeneity of treatment effects, even when treatments may be reversible.

3 Results

3.1 Effect of Technological M&A on Firm Markup

Table 1 presents difference-in-differences estimates for different control groups. Column 1 employs the full sample, comprising both firms conducting technological M&A before and after treatment (yet-to-be-treated firms) and those engaging in general M&A before and after treatment (pre- and post-M&A). Column 2 restricts the control group to yet-to-be-treated firms and firms observed after they have conducted a general M&A. Column 3 further narrows the control group to only yet-to-be-treated firms. Therefore, given the nature of our database, we do not compare firms doing an M&A with firms that have never done such an activity.

Across all three specifications, the coefficient on conducting a technological M&A is positive and statistically significant: undertaking a technological M&A raises the firm's markup by between 1.5 per cent and 1.9 per cent. This effect is additional to the impact of a general M&A, which prior literature estimates at approximately 12 per cent (Blonigen and Pierce, 2015). Hence, the total effect of a technological M&A lies in the range of 13.68 per cent to 14.12 per cent.

[11] Target's patent stock is constructed using the perpetual-inventory method, which treats patents like depreciable capital stock. Specifically, for firm i in year t, $PS_{i,t} = (1-\delta)\, PS_{i,t-1} + P_{i,t}$ where $P_{i,t}$ is the flow of new patents in year t and δ is the annual knowledge obsolescence rate. In our application we set $\delta = 0.05$ (5%), mirroring common practice in the literature (Hall et al., 2005). The series is initialised by assuming the pre-sample stock is at its steady state $PS_{i,0} = \frac{P_{i,0}}{\delta}$ where $P_{i,0}$ is the number of patents of target firm i at the first year of observation and δ the depreciation rate (5%). The final stock variable is transformed using the inverse hyperbolic sine transformation.

For the remainder of the analysis, we adopt the specification with the largest control group; nonetheless, the results remain robust when employing the more restrictive control groups.

Table 1: The Effect of Technological M&A on Firm Markup, 2008-2020

	(1)	(2)	(3)
Tech M&A	0.0190**	0.0186**	0.0151*
	[0.0059]	[0.0059]	[0.0063]
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Control Group	Not Yet + Pre M&A + Post M&A	Not Yet + Post M&A	Not Yet
F-test	10.552	9.768	5.823
R^2	0.810	0.843	0.821
N (firm × year)	86 673	53 524	9 251

Based on annual firm-level data over 2008–2020. Each column reports a separate OLS regression; the dependent variable is the logarithm of markup of firm i in year t. $TechM\&A$ is the absorbed treatment, taking value 1 from the year of first technological M&A for firm i onward. Column (1) keeps the full sample as control group, which comprises firms conducting technological M&A before and after treatment (not yet treated firms) and firms conducting general M&A before and after treatment (Pre M&A and Post M&A). Column (2) drops from the control group observations for firms conducting general M&A before treatment. Column (3) retains only firms conducting technological M&A before and after treatment (not yet treated firms). All models include firm and year fixed effects, with standard errors clustered by firm. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$.
Source: Orbis, Zephyr, Orbis IP (Moody's analytics), analysis by authors

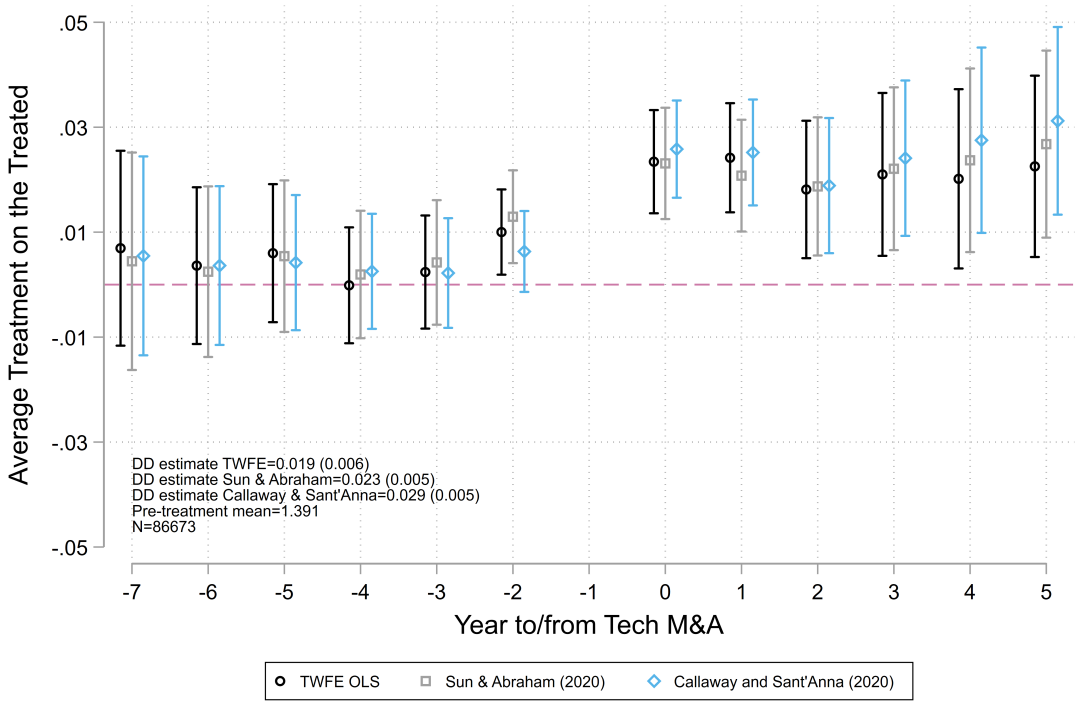
Estimates of equation 4 for the event study are reported in Figure 5. There is no evidence of systematic pre-treatment trends. Although the coefficient at $t-2$ is significant and positive, pointing to a potential anticipation effect, the p-values associated to the joint significance of the pre-treatment coefficients (0.2157) provide support to the implementation of our approach.

Results from Figure 5 provide evidence that conducting a technological M&A leads to a permanent increase in the firm markup. The magnitude of the increase is stable through time, although confidence interval increase due to the decreasing number of observations in the years far away from treatment. In fact, all six of the post-treatment estimates of Tech M&A are positive and significant at conventional levels.

To address the issue of potential bias of the two-way fixed effect under treatment heterogeneity in staggered timing diff-in-diff (Goodman-Bacon, 2021), Figure 5 also shows results for Sun and Abraham (2021) and Callaway and Sant'Anna

(2021). Both models provide evidence that conducting technological M&A increases firm's markup. Coefficients from all three models are very much in line in terms of magnitude (ranging from 0.02 to 0.03), providing further support to the robustness of our results.

Figure 5: Effect of Technological M&A on Markup



Note: The figure shows the estimated effects of a technological M&A on firm markup. The figure reports the coefficients and standard errors from: i) Two-way fixed effect (TWFE) OLS estimator, ii) Sun and Abraham (2021) and iii) Callaway and Sant'Anna (2021). Coefficients shown are: up to 7 years before adoption, up to 5 years after adoption and the year of adoption. All effects are relative to the year before adoption. Controls include firm and year fixed effects. Confidence intervals are at the 95% level and based on standard errors clustered at the firm level. Reported difference-in-differences (DD) estimates are: i) the analogue of equation 4, which is $\text{Markup}_{it} = \omega_0 + M\&A_{it} + \alpha_i + \lambda_t + \epsilon_{it}$ where $M\&A_{it}$ is the absorbed treatment; ii) similar DD estimates for Sun and Abraham (2021) and Callaway and Sant'Anna (2021) models.
Source: Orbis, Zephyr, Orbis IP (Moody's analytics), analysis by authors

3.2 Effect of Technological M&A by Firm Type, Industry and Region

The overall effect illustrated above conceals significant nuances at the firm-, industry- and geographical-levels. As discussed in Section 1, superstar firms have been shown to contribute disproportionately to the rise in market power (De Loecker et al., 2020). We investigate whether the impact of technological M&A on markups is driven by firms with superstar status by distinguishing between top and non-top R&D investors. We define top R&D investors as those companies in our sample that appear at least once among the top 2 500 R&D investors in the EU Industrial R&D Investment Scoreboard over the period 2003–2024 (Nindl et al., 2024).[12]

Estimates of the effect of technological M&A on firm markup differentiating between top non-top R&D investors are reported in Figure 6. The post-treatment estimate of technological M&A is positive and significant for the group of top R&D investors. The magnitude of the effect is much higher than the overall effect in section 3 (0.046 vs 0.02), pointing to a stronger effect of technological M&A on firm markup for top R&D investors. The effect for the group of non-top R&D investors is much lower (0.01) and statistically insignificant.

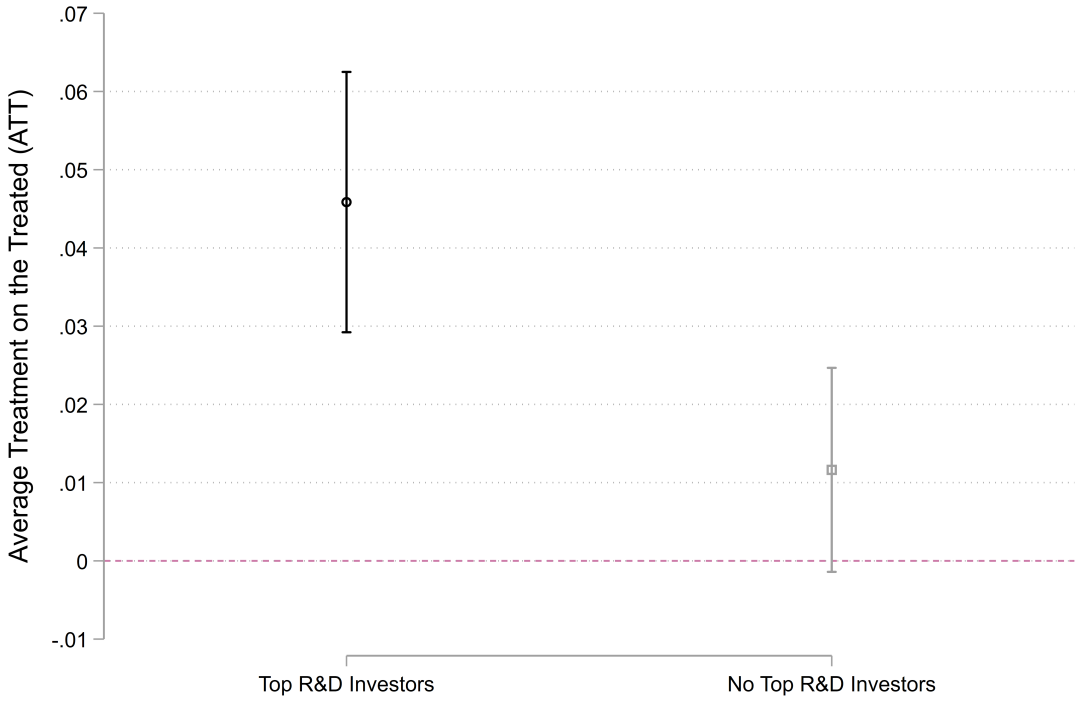
Figure 7 shows the estimated ATT of a technological M&A on firm markups for companies headquartered in five different geographic regions. The EU estimate is larger than the overall effect in section 3 (0.03 vs 0.02) although weakly significant. Japanese firms see an estimated markup rise of about +0.02 and statistically significant. US firms exhibit a sizable and statistically significant markup increase of around 0.06. For China and the rest of the world, the point estimates are very small and statistically insignificant.

Results for the effect of technological M&A on markup across industries are reported in Figure 8. The sectors where the 95% confidence interval lies entirely above zero are high-tech manufacturing — with an estimated ATT of roughly +0.05 — and low-tech manufacturing, which shows an ATT of about +0.03. In all other industry groups (medium-high-tech manufacturing, medium-low-tech manufacturing, knowledge-intensive services and less knowledge-intensive services), the coefficients are not statistically significant. The positive and non-negligible effect observed in low-technology manufacturing appears at odds with the expectation that technological M&A primarily strengthens market power in high-tech industries. Notably, this effect is entirely driven by firms operating in two NACE 2-digit sectors: manufacture of leather and related products (NACE code 15) and manufacture of beverages (NACE code 11). These sectors include

[12]The EU Industrial R&D Investment Scoreboard is an annual publication by the European Commission's Joint Research Centre that, since 2004, systematically monitors and benchmarks the R&D expenditures of the world's leading industrial investors—over 2,000 companies collectively investing more than 1,257 billion euros in 2023—comparing EU-based firms with their global peers across key sectors to inform policymakers, researchers and industry stakeholders.

major multinationals—such as Coca-Cola, PepsiCo, adidas and Nike—that have historically held strong market-leading positions, engaged in extensive M&A activity and maintained sizeable patent portfolios.

Figure 6: Effect of Technological M&A on Markup, Top R&D Investors

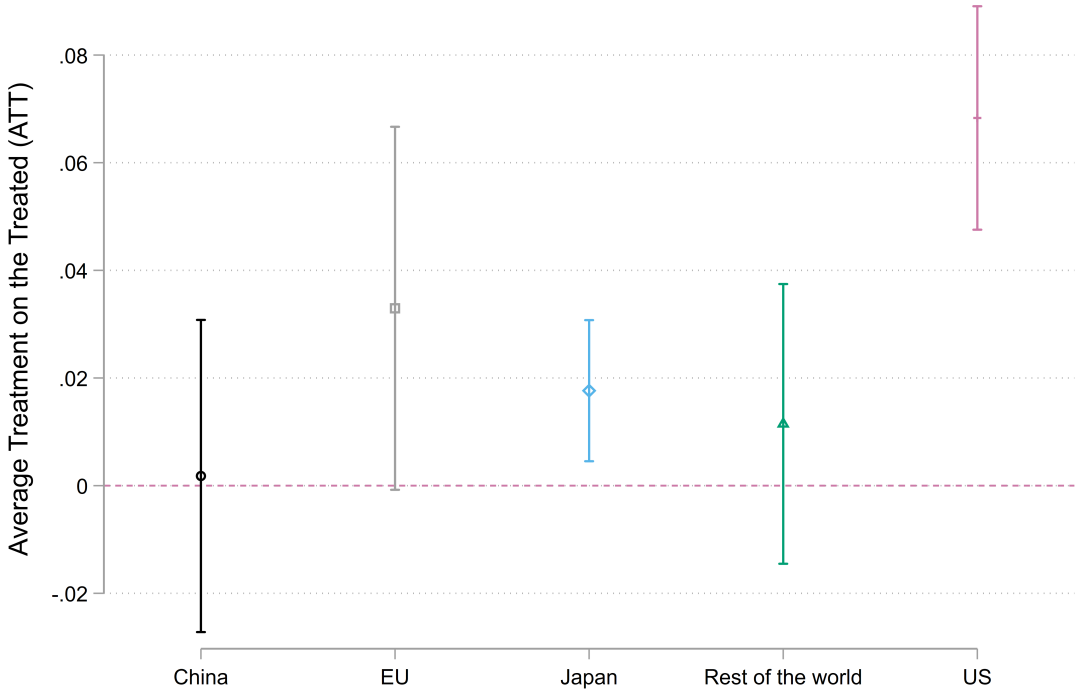


Note: The figure shows the estimated effects of a technological M&A on firm markup distinguishing between top R&D investors and non top R&D investors: top R&D investors are companies which appeared at least once in the list of the top 2,500 R&D investors during the period 2003-2024 (Nindl et al., 2024). The figure reports the coefficients and standard errors from the estimator of Callaway and Sant'Anna (2021) for the average post-treatment effect. Controls include firm and year fixed effects. Confidence intervals are at the 95% level and based on standard errors clustered at the firm level. *Source:* Orbis, Zephyr, Orbis IP (Moody's analytics), analysis by authors

3.3 Technological M&A and Patenting Activity

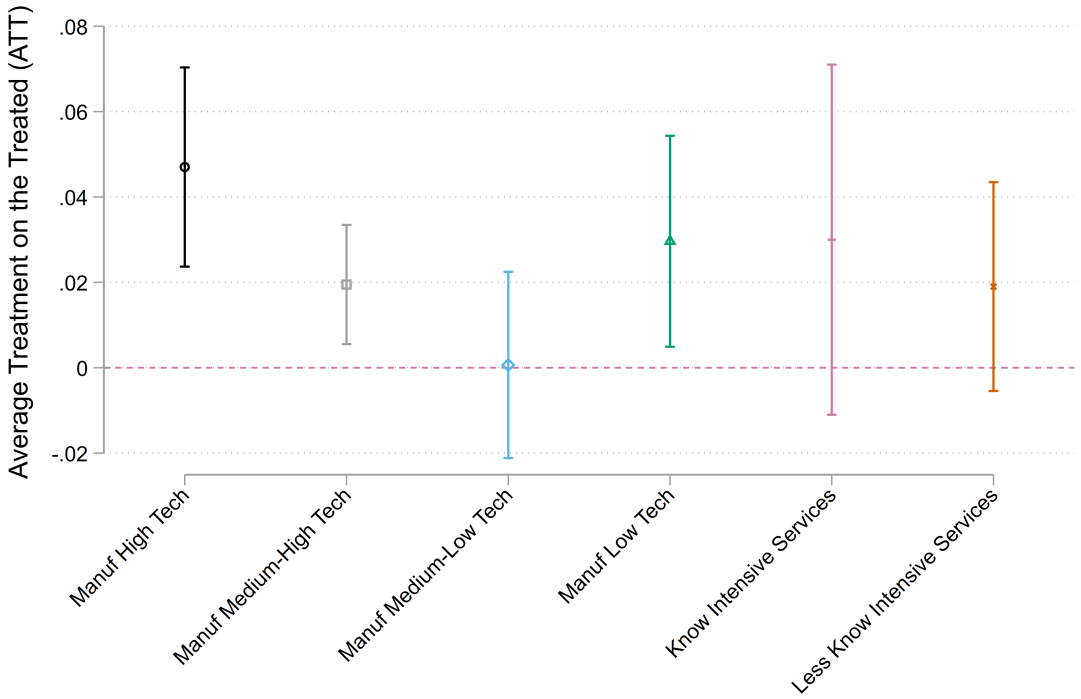
This section examines whether the observed effect is driven primarily by: (i) increased inventive activity following the M&A and/or (ii) incorporation of the acquired firm's knowledge stock. In the first channel, technological M&As serve primarily to augment the acquirer's inventive capacity by generating synergies between acquirer and acquiree through enhanced productivity of the merged R&D laboratories. This yields increasing returns to scale in intangible assets that affect the firm's markup. We proxy this channel by measuring the acquirer's patent flow post-acquisition and its impact on markup. In the second channel, we consider whether the M&A effectively insulates proprietary technology from rival firms, thereby curtailing knowledge spillovers and enhancing market power. We proxy this mechanism using the stock of patents acquired through the trans-

Figure 7: Effect of Technological M&A on Markups across Regions



Note: The figure shows the estimated effects of a technological M&A on firm markup distinguishing between world regions. The figure reports the coefficients and standard errors from the estimator of Callaway and Sant'Anna (2021) for the average post-treatment effect. Controls include firm and year fixed effects. Confidence intervals are at the 95% level and based on standard errors clustered at the firm level.
Source: Orbis, Zephyr, Orbis IP (Moody's analytics), analysis by authors

Figure 8: Effect of Technological M&A on Markups across Industries



Note: The figure shows the estimated effects of a technological M&A on firm markup distinguishing between major industry aggregates. Industrial aggregation is based on Eurostat sectoral approach (Eurostat, 2014). The figure reports the coefficients and standard errors from the estimator of Callaway and Sant'Anna (2021) for the average post-treatment effect. Controls include firm and year fixed effects. Confidence intervals are at the 95% level and based on standard errors clustered at the firm level.
Source: Orbis, Zephyr, Orbis IP (Moody's analytics), analysis by authors

action and its effect on the acquirer's markup.

Investigating these channels requires a non-absorbing treatment —i.e. one activated only in the years when the technological M&A occurs— so as to isolate changes in patenting behaviour and markup immediately following the event. A non-absorbing treatment can imply reversals in treatment status, reflecting the fact that firms may undertake multiple M&As over the sample period.[13]

Figure 9 implements the estimator of De Chaisemartin and d'Haultfoeuille (2024), which is robust to such reversals, and confirms that our results hold under this alternative treatment definition. In fact, no pre-treatment trends are apparent and post-treatment coefficients are all positive and significant. The magnitude of the effect is also in line with the one obtained in our baseline specification (Figure 5 in Section 3).

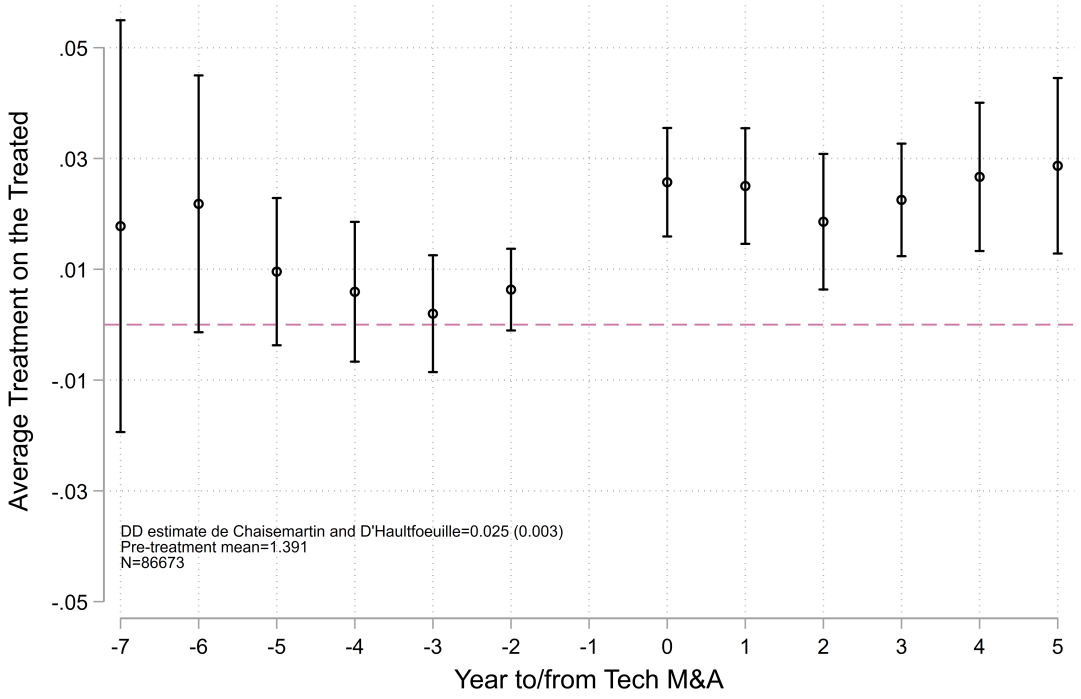
In Tables 2 and 3, we present standard difference-in-differences estimates to examine the two mechanisms outlined above. Table 2 assesses whether, following an M&A event, an increase in patents filed by the merged firms contributes to an increase in the firm's markup. We allow for four lag structures between the M&A event and its potential impact on markup via patenting activity (contemporaneous, one-year, two-year and three-year forward windows). In all specifications, the coefficient on the interaction term is close to zero and statistically non-significant. We interpret this as evidence of no productivity enhancement in the merged R&D laboratories.[14]

Table 3 investigates whether the observed effect is instead driven by the sudden increase in patent stock following the acquisition of a subsidiary. The coefficient on subsidiary patent stock is consistently positive and statistically significant. This finding supports the view that M&A serves to insulate a firm's knowledge stock from rivals, thereby reducing involuntary knowledge spillovers and increasing market power (Akcigit and Ates, 2021, 2023).

[13]The event remains relatively rare: 14 per cent of firms conducting a technological M&A engage in more than one such transaction between 2008 and 2020.

[14]This finding is corroborated by the absence of any effect of post-M&A patenting on firm productivity; detailed results are available from the authors upon request.

Figure 9: Effect of Technological M&A on Markup, Robust to Reversals (De Chaisemartin and d'Haultfoeuille, 2024)



Note: The figure shows the estimated effects of a technological M&A on firm markup. The figure reports the coefficients and standard errors from the estimator of De Chaisemartin and d'Haultfoeuille (2024) for the dynamic treatment effects: up to 7 years before adoption, up to 5 years after adoption and the year of adoption. All effects are relative to the year before adoption. Controls include firm and year fixed effects. Confidence intervals are at the 95% level and based on standard errors clustered at the firm level.
Source: Orbis, Zephyr, Orbis IP (Moody's analytics), analysis by authors

Table 2: The Role of Increased Inventive Activity in the Effect of Technological M&A on Firm Markup, 2008-2020

	(1)	(2)	(3)	(4)
Tech M&A	0.018*	0.013*	0.007	0.007
	[0.008]	[0.007]	[0.006]	[0.006]
Tech M&A X Pat Flow	0.000			
	[0.003]			
Tech M&A X Pat Flow$^{[+1]}$		0.001		
		[0.002]		
Tech M&A X Pat Flow$^{[+2]}$			0.003	
			[0.002]	
Tech M&A X Pat Flow$^{[+3]}$				0.003
				[0.002]
Pat Flow	-0.000			
	[0.001]			
Pat Flow$^{[+1]}$		-0.001		
		[0.002]		
Pat Flow$^{[+2]}$			-0.001	
			[0.002]	
Pat Flow$^{[+3]}$				-0.001
				[0.002]
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
F-test	4.117	4.470	4.015	4.541
R sq	0.810	0.845	0.868	0.888
N (firm X year)	86,673	87,373	87,701	87,923

Based on annual firm-level data over 2008–2020. Each column reports a separate OLS regression; the dependent variable in columns 1-4 is the logarithm of markup of firm i in year t, the 1-year, 2-year and 3-year forward averages of the logarithm of markup of firm i with t included. *Tech M&A* is the non absorbed treatment, taking value 1 in the year t of technological M&A for firm i. *Pat Flow* is the number of patents filed by firm i in year t. *Pat Flow*$^{[+1]}$, *Pat Flow*$^{[+2]}$ and *Pat Flow*$^{[+3]}$ are respectively the 1-year, 2-year and 3-year forward averages of *Pat Flow* with t included. All patent variables are transformed using the inverse hyperbolic sine transformation. All models include firm and year fixed effects, with standard errors clustered by firm. + p<0.1, * p<0.05, ** p<0.01.

Source: Orbis, Zephyr, Orbis IP (Moody's analytics), analysis by authors

Table 3: The Role of Incorporation of Target Knowledge Stock in the Effect of Technological M&A on Firm Markup, 2008-2020

	(1)	(2)
Tech M&A	0.007	0.007
	[0.005]	[0.005]
Pat Flow		-0.000
		[0.001]
Subsidiary Pat Stock	0.009**	0.009**
	[0.003]	[0.003]
Firm FE	Yes	Yes
Year FE	Yes	Yes
F-test	8.406	5.626
R sq	0.821	0.821
N (firm X year)	80,246	80,246

Based on annual firm-level data over 2008–2020. Each column reports a separate OLS regression; the dependent variable is the logarithm of markup of firm i in year t. *Tech M&A* is the non absorbed treatment, taking value 1 in the year t of technological M&A for firm i. *Pat Flow* is the number of patents filed by firm i in year t. *Subsidiary Pat Stock* is the patent portfolio stock from the subsidiary following acquisition. All patent variables are transformed using the inverse hyperbolic sine transformation. All models include firm and year fixed effects, with standard errors clustered by firm. + p<0.1, * p<0.05, ** p<0.01.
Source: Orbis, Zephyr, Orbis IP (Moody's analytics), analysis by authors

4 Conclusions and Policy Recommendations

The results from our work show that acquisitions of innovative subsidiaries carrying substantive patent portfolios induce a sustained increase in acquirer market power, raising firm markups by approximately 2% over the long term. This effect is amplified among large R&D investors, US-headquartered firms, and high-tech manufacturing acquirors, underscoring that incumbents may strategically deploy M&As to internalise spillovers, raise barriers to entry, and insulate themselves from competitive pressures. In doing so, these transactions distort the balance between dynamic efficiencies and market contestability, risking of advantaging even more "superstar" firms whose dominant positions are detrimental to both consumer welfare and the broader innovation ecosystem.

This paper contributes to three interrelated streams of economic literature. First, it enriches the burgeoning field of innovation and competition economics by providing causal evidence on how technological M&A affects firm markups,

complementing studies that document the link between general M&A, innovation, productivity and market power (Stiebale and Szücs, 2022; Blonigen and Pierce, 2015; Bena and Li, 2014). Second, it advances the literature on M&A strategy by showing that technological acquisitions can serve as a tool for incumbents to internalise spillovers, rather than merely pursue operational efficiency (Akcigit and Ates, 2021). Third, it adds to industrial organisation literature on barriers to entry by identifying patent-based insulation as a mechanism through which consolidation alters competitive dynamics and challenges traditional static efficiency evaluation of market power (Czarnitzki et al., 2020).

The causal link we document between technological M&A activity and firm markups also offers valuable insights for the refinement of policy instruments. By translating our quantitative findings into targeted merger-review criteria, conditional consolidation terms, and industrial policy measures, policymakers can distinguish between M&A that foster welfare-enhancing innovation and those that primarily strengthen market power, thereby crafting actionable, evidence-based policy recommendations.

To address this tension, merger review processes could be recalibrated to integrate forward-looking innovation metrics—such as patent quality, citation indices, and R&D intensity—alongside traditional static assessments of market concentration. An "innovation defence" could allow firms to justify consolidation only when clear, verifiable R&D synergies are demonstrable *ex ante*, while *ex post* monitoring of cleared M&A deals would ensure that anticipated dynamic efficiencies materialise rather than simply strengthen market power. Such suggestions are in line with the Draghi Report's advocacy (Draghi, 2024) for a merger control framework that systematically incorporates innovation potential and permits rigorous post-merger evaluation, thus deterring opportunistic "killer acquisitions" of nascent innovators (Cunningham et al., 2021).

At the same time, broader industrial policies must be aligned to foster organic growth paths that reduce reliance on scaling via acquisitions. For example, under the EU Industrial Strategy and Clean Industrial Deal[15], conditional consolidation in strategic sectors—such as clean energy and advanced manufacturing—should be permitted only when enforceable commitments on open licensing of pooled patents and collaborative R& D consortia are secured. Co-ordination between state-aid decisions and merger assessments can further ensure that public support for transformative investments is accompanied by safeguards against undue market foreclosure (Fumagalli et al., 2020).

Finally, the pursuit of European economic security strategy demands intensi-

[15]Communication From The Commission To The European Parliament, The Council, The European Economic And Social Committee and The Committee of The Regions. The Clean Industrial Deal: A joint roadmap for competitiveness and decarbonisation, COM(2025) 85 final, https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex:52025DC0085

fied oversight of cross-border technology deals.[16] Early-warning mechanisms for transactions involving critical patent technologies, coupled with a unified monitoring platform for R&D disclosures and M&A intentions, would provide policymakers with timely indicators of consolidation risks.

Despite the robustness of our identification strategy and the granularity of our firm-level patent and markup data, our work has limitations. First, our analysis is confined to publicly listed firms, which may bias our findings towards larger incumbents and overlook consolidation dynamics in private or start-up segments. Second, while patent-based insulation emerges as the predominant mechanism, our measure does not capture other strategic activities—such as corporate venture capital or R&D alliances—that may also reinforce post-M&A market power. Third, our time frame (2008–2020) spans major global shocks, including the financial crisis and early COVID-19 period, which could interact with M&A incentives in ways not fully disentangled in our specification.

These caveats suggest directions for future research and policy interest. Further work should extend the empirical framework to private and venture-funded firms, exploring whether tech start-up buyouts generate analogous markup effects. Scholars could also integrate information about corporate venture capital investments and strategic alliances to investigate potential complementarities or substitutabilities with M&A activity and the joint effect on post-merger outcomes.

[16] Joint Communication To The European Parliament, The European Council And The Council On "European Economic Security Strategy", Join/2023/20 Final, https://eur-lex.europa.eu/legal-content/EN/ALL/?uri=JOIN:2023:20:FIN

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Appendix A: Data Cleaning

The balance sheet and income statement data recorded in Orbis is obtained from company accounts, therefore its coverage may differ across countries or across years. Before computing the markup estimates, it is necessary to carry out some data cleaning, and impose some homogenising criteria. The cleaning steps we perform are closely in line with previous OECD analyses estimating production functions (and TFP) using Orbis data (Gal, 2013; Andrews et al., 2016), and with Kalemli-Özcan et al. (2019).

A well-known limitation of using Orbis accounts data is that it usually underrepresents smaller and younger firms, depending on the country of reporting. In addition, differences in reporting requirements (for example, in the US compared to Europe) exist and might also compromise the representativeness and comparability of the data. For this reason, we select listed firms for our analysis. Furthermore, we drop accounts that report limited financials (which contain rounded or class level figures for a very limited number of variables, particularly affecting countries where detailed financials are not available for most companies such as the US).

We then apply some further cleaning steps aimed at removing potential distortions to our estimates arising from erratic or implausible firm performance or behaviour. First, we drop the entire company if the number of persons employed is negative in any year. Second, we assess whether there are unusual data jumps based on growth rates of firms' values of operating revenues. We drop full firm observations if the growth rate is above (below) the top (or bottom) 1% decile.

We interpolate the main output and input variables used in the estimation of the production function if there is one missing value in the middle of the time series for a given firm.

We identify and drop outliers using the ratios of the production function output and inputs[17]. Outliers are defined as any value that is more than 3 IQRs (Inter-Quartile Range) away from the median. Instead of using the traditional IQR method cantered at Q1 and Q3, we use a median-cantered (Q2) rule, making it more robust to skewed distributions. Finally, we apply this outlier detection procedure to the level we use for the posterior markup estimation (i.e. the two-digit NACE sector level).

Note that we also apply the same outlier detection method to the estimates of markups estimates we computed.

We perform further cleaning steps of the sample to prepare it for the estimates. In order to avoid attrition and be able to estimate medium-term effects, we exclude firms that appear in the panel for less than 6 years. We also drop firms

[17]Namely: capital/labour, output/material costs, output/capital, and output/labour.

that performed a tech M&A in the first 4 years of observations to address the assumption of no anticipation and stable unit treatment value (SUTVA). The idea is that—since we do not observe whether firms have done a tech M&A in the years before the beginning of our sample period (2008)—we may, for these firms, risk to compare them with counterparts that may have performed a tech M&A just a few years before, hence not constituting a valid control group. Dropping these firms we make sure that we compare tech M&A performing firms with companies that have not done a tech M&A at least in the last 4 years. Additionally, we drop firms for the 2020 treated group due to the low number of observations for this cohort and the Covid-19 pandemic that may significantly alter the results. Finally, we drop firms for which we have missing financial information for the first year of tech M&A. These cleaning steps leave us with our final estimating sample comprehending 8,314 firms from 79 different countries.

Appendix B: Variables Description

Table B.1: Description of variables used in the markup estimation

Variable	Definition and source
Operating revenue (Turnover)	Total operating revenues (i.e. net sales + other operating revenues + stock variations). The figures do not include VAT. Source: Orbis.
Fixed assets	Total amount (after depreciation) of non current assets (i.e. intangible assets + tangible assets + other fixed assets). Source: Orbis.
Cost of employees	Detail of all the employees costs of the company (including pension costs). Source: Orbis.
Cost of goods sold	Cost of sold goods, production, and services. Includes costs directly related to the production of the goods sold plus the depreciation of those costs. Source: Orbis.
Material costs	Detail of the purchases of goods (raw materials + finished goods). No services. Source: Orbis.
GDP deflator	Retrieved from the World Bank database. The precise reference is the following: NY.GDP.DEFL.ZS - GDP deflator (base year varies by country).

Source: Orbis, Zephyr, Orbis IP (Moody's analytics), analysis by authors

Appendix C: Theory of Markups

The empirical approach used to recover firm level markups relies on standard cost minimization conditions for variable inputs free of adjustment costs and on the estimation of output elasticity. In particular, we assume a production technology of firm i at time t as: $Q_{it} = Q_{it}(X_{it}^1, ..., X_{it}^V, K_{it}, \omega_{it})$ where V are variable inputs such as labor or intermediate inputs and ω is the productivity level. We assume the production function to be continuous and twice differentiable in its arguments and that firms employ labor, intermediate inputs and capital to produce. Hence, they face the following cost minimization problem:

$$\min_{\{K_{it}, L_{it}, M_{it}\}} w_{it}L_{it} + r_{it}K_{it} + p_{it}^M M_{it},$$
$$s.t. : Q_{it}(L_{it}, M_{it}, K_{it}) \leq Q_{it},$$

where w_{it} , r_{it} , and p_{it}^M denote the wage rate, the interest rate on capital, and the intermediate input price respectively. We can derive the associated Lagrangian as:

$$\mathrm{L}(L_{it}, K_{it}, M_{it}, \lambda_{it}) = w_{it}L_{it} + r_{it}K_{it} + p_{it}^M M_{it} + \lambda(Q_{it} - Q_{it}(\cdot))$$

We then derive the FOCs for any variable inputs associated with the Lagrangian function such that:

$$\frac{\partial L_{it}}{\partial X_{it}^v} = P_{it}^{X^v} - \lambda_{it}\frac{\partial Q_{it}(\cdot)}{\partial X_{it}^v} = 0$$

where the shadow price λ_{it} is the marginal cost of production at a given level of output. Rearranging terms, multiplying both sides by $\frac{X_{it}}{Q_{it}}$ and defining $\mu_{it} \equiv \frac{P_{it}}{\lambda_{it}}$ the following expression for markups can be derived:

$$\mu_{it} = \theta_{it}^X(\alpha_{it}^X)^{-1}$$

where θ_{it}^X is the output elasticity on an in input X and α_{it}^X is the share of expenditures on input X_{it} in total sales $(P_{it}Q_{it})$.

Appendix D: Sample description

Table D.1: Number of Firms by Treatment Cohort

Treatment Cohort	Number of firms treated
2012	79
2013	95
2014	114
2015	110
2016	105
2017	98
2018	106
2019	92
Never treated	7,515

Source: Orbis, Zephyr, Orbis IP (Moody's analytics), analysis by authors

Table D.2: Sample Distribution by Region

Region	Number of firms	Number of observations
Africa	66	579
Asia	4,181	44,228
Europe	1,853	19,451
Latin America and the Caribbean	215	2126
Northern America	1,753	17,981
Oceania	246	2,308

Source: Orbis, Zephyr, Orbis IP (Moody's analytics), analysis by authors

Appendix E: Robustness Checks

E.1 Including Covariates

Our main specifications do not include control variables. Following recent contributions in the econometrics literature, we deliberately omit controls owing to the bias they can introduce into ATT estimates. Baker et al. (2025) highlight that this concern compounds the issue of "bad controls" emphasised by Angrist and Pischke (2009).[18] Both Baker et al. (2025) and Caetano and Callaway (2024) further demonstrate that—even when covariates are correctly chosen, measured without error, and modelled in the proper functional form—treatment-effect estimates may still be biased if effects vary across covariate strata.

However, excluding covariates may jeopardise the plausibility of the parallel-trends assumption, since firms that engage in technological M&A differ markedly from the control group along several dimensions. We showed that acquiring firms tend to be larger, older, more profitable, and to possess higher levels of capital and patent stock. Controlling for the most relevant of these characteristics can thus increase confidence in the plausibility of post-treatment parallel trend assumption.

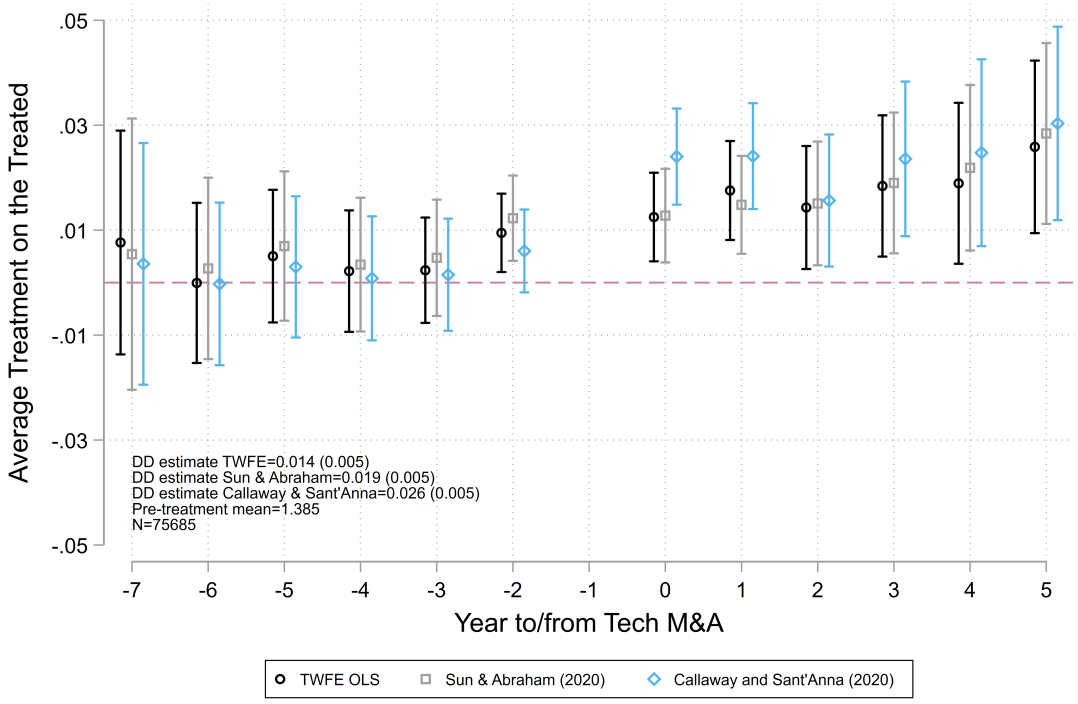
Accordingly, we introduce three covariates into our model: firm age; firm size (measured by operating revenues); and firm capital stock (constructed as the annual change in fixed assets and calculated via the perpetual-inventory method).[19] These covariates serve as standard controls in the two-way fixed-effects specification. For the Callaway and Sant'Anna estimator, we adopt the double-robust approach of Sant'Anna and Zhao (2020), which combines inverse-probability weighting with outcome regression.

Results from this robustness check are reported below and confirm our main findings.

[18] In our case "bad controls" refer to variables that capture only the benefits (or only the disadvantages) associated with technological M&A, thereby inducing bias in our estimates of its effect.

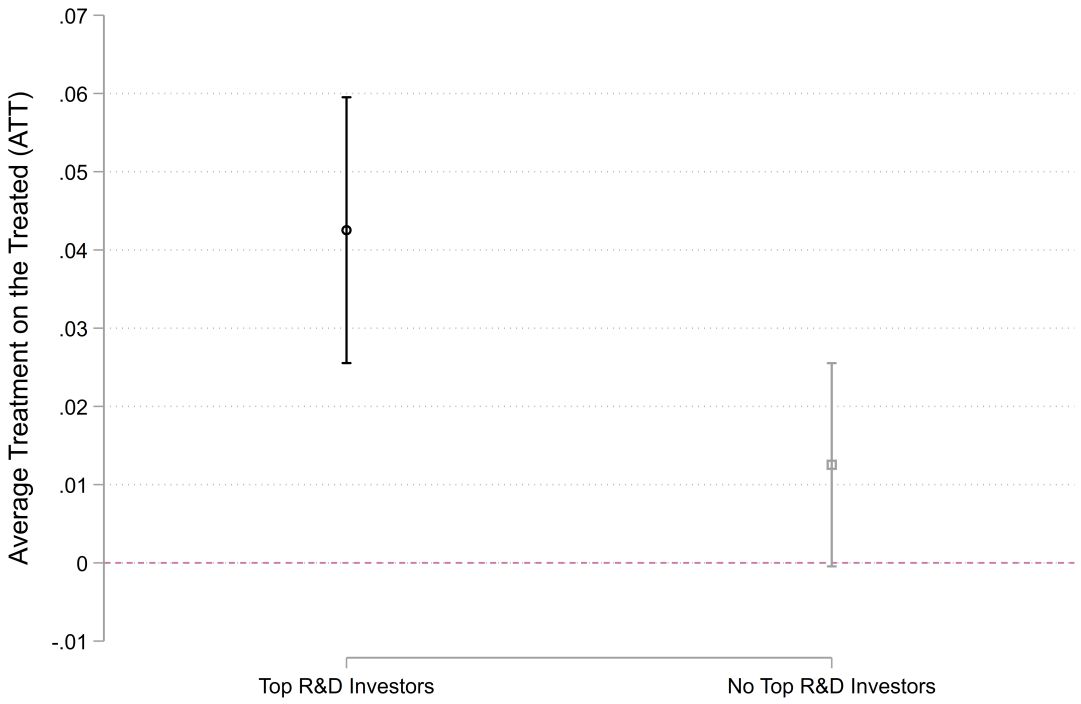
[19] Patent stock and profits were excluded because their correlations with other controls exceed 0.7.

Figure E.1: Effect of Technological M&A on Markup, with Controls



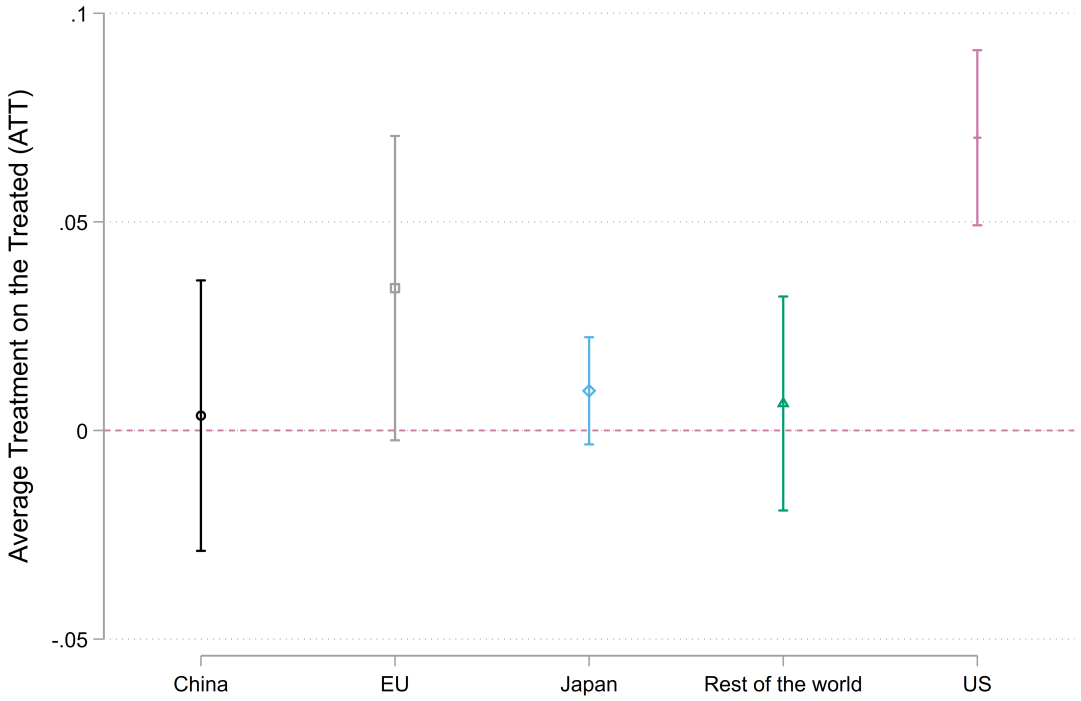
Note: The figure shows the estimated effects of a technological M&A on firm markup. The figure reports the coefficients and standard errors from: i) Two-way fixed effect (TWFE) OLS estimator, ii) Sun and Abraham (2021) and iii) Callaway and Sant'Anna (2021). Coefficients shown are: up to 7 years before adoption, up to 5 years after adoption and the year of adoption. All effects are relative to the year before adoption. Controls include firm age, size, capital stock, as well as firm and year fixed effects. Callaway and Sant'Anna (2021) estimates adjust for the inclusion of pre-treatment covariate values using the double robust methodology discussed in Sant'Anna and Zhao (2020). Confidence intervals are at the 95% level and based on standard errors clustered at the firm level. Reported difference-in-differences (DD) estimates are: i) the analogue of equation 4, which is $\text{Markup}_{it} = \omega_0 + M\&A_{it} + \alpha_i + \lambda_t + \epsilon_{it}$ where $M\&A_{it}$ is the absorbed treatment; ii) similar DD estimates for Sun and Abraham (2021) and Callaway and Sant'Anna (2021) models.
Source: Orbis, Zephyr, Orbis IP (Moody's analytics), analysis by authors

Figure E.2: Effect of Technological M&A on Markup, Top R&D Investors with Controls



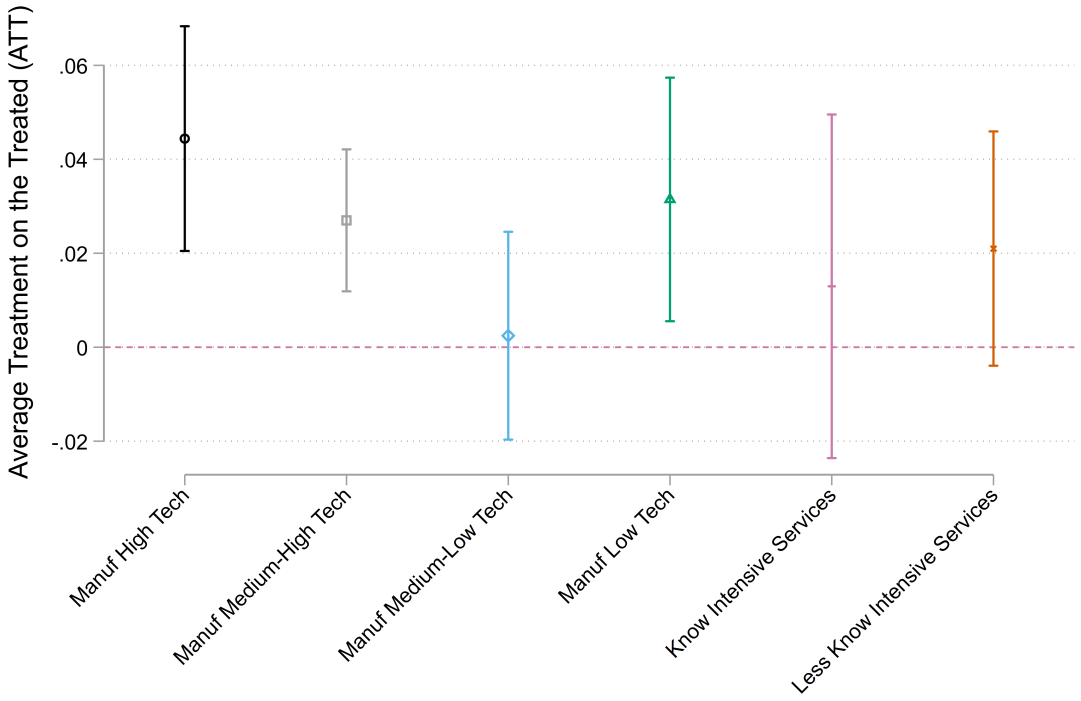
Note: The figure shows the estimated effects of a technological M&A on firm markup distinguishing between top R&D investors and non top R&D investors: top R&D investors are companies which appeared at least once in the list of the top 2,500 R&D investors during the period 2003-2024 (Nindl et al., 2024). The figure reports the coefficients and standard errors from the estimator of Callaway and Sant'Anna (2021) for the average post-treatment effect. Controls include pre-treatment values of firm age, size, capital stock, as well as firm and year fixed effects. Estimates adjust for the inclusion of pre-treatment covariate values using the double robust methodology discussed in Sant'Anna and Zhao (2020). Confidence intervals are at the 95% level and based on standard errors clustered at the firm level. *Source:* Orbis, Zephyr, Orbis IP (Moody's analytics), analysis by authors

Figure E.3: Effect of Technological M&A on Markups across Regions with Controls



Note: The figure shows the estimated effects of a technological M&A on firm markup distinguishing between world regions. The figure reports the coefficients and standard errors from the estimator of Callaway and Sant'Anna (2021) for the average post-treatment effect. Controls include pre-treatment values of firm age, size, capital stock, as well as firm and year fixed effects. Estimates adjust for the inclusion of pre-treatment covariate values using the double robust methodology discussed in Sant'Anna and Zhao (2020). Confidence intervals are at the 95% level and based on standard errors clustered at the firm level. *Source:* Orbis, Zephyr, Orbis IP (Moody's analytics), analysis by authors

Figure E.4: Effect of Technological M&A on Markups across Industries with Controls



Note: The figure shows the estimated effects of a technological M&A on firm markup distinguishing between major industry aggregates. Industrial aggregation is based on Eurostat sectoral approach (Eurostat, 2014). The figure reports the coefficients and standard errors from the estimator of Callaway and Sant'Anna (2021) for the average post-treatment effect. Controls include pre-treatment values of firm age, size, capital stock, as well as firm and year fixed effects. Estimates adjust for the inclusion of pre-treatment covariate values using the double robust methodology discussed in Sant'Anna and Zhao (2020). Confidence intervals are at the 95% level and based on standard errors clustered at the firm level. *Source:* Orbis, Zephyr, Orbis IP (Moody's analytics), analysis by authors

Table E.1: The Role of Increased Inventive Activity in the Effect of Technological M&A on Firm Markup, 2008-2020 including Covariates

	(1)	(2)	(3)	(4)
Tech M&A	0.009	0.006	0.001	0.001
	[0.007]	[0.006]	[0.005]	[0.005]
Tech M&A X Pat Flow	-0.001			
	[0.002]			
Tech M&A X Pat Flow$^{[+1]}$		-0.000		
		[0.002]		
Tech M&A X Pat Flow$^{[+2]}$			0.002	
			[0.002]	
Tech M&A X Pat Flow$^{[+3]}$				0.002
				[0.002]
Pat Flow	0.005**			
	[0.001]			
Pat Flow$^{[+1]}$		0.006**		
		[0.002]		
Pat Flow$^{[+2]}$			0.006**	
			[0.002]	
Pat Flow$^{[+3]}$				0.005*
				[0.002]
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
F-test	101.779	87.102	77.032	76.608
R sq	0.841	0.871	0.892	0.908
N (firm X year)	75685	76253	76510	76682

Based on annual firm-level data over 2008–2020. Each column reports a separate OLS regression; the dependent variable in columns 1-4 is the logarithm of markup of firm i in year t, the 1-year, 2-year and 3-year forward averages of the logarithm of markup of firm i with t included. *Tech M&A* is the non absorbed treatment, taking value 1 in the year t of technological M&A for firm i. *Pat Flow* is the number of patents filed by firm i in year t. *Pat Flow*$^{[+1]}$, *Pat Flow*$^{[+2]}$ and *Pat Flow*$^{[+3]}$ are respectively the 1-year, 2-year and 3-year forward averages of *Pat Flow* with t included. All patent variables are transformed using the inverse hyperbolic sine transformation. Controls include firm age, size, capital stock, as well as firm and year fixed effects, with standard errors clustered at the firm level. + p<0.1, * p<0.05, ** p<0.01.
Source: Orbis, Zephyr, Orbis IP (Moody's analytics), analysis by authors

Table E.2: The Role of Incorporation of Target Knowledge Stock in the Effect of Technological M&A on Firm Markup, 2008-2020 including Covariates

	(1)	(2)
Tech M&A	-0.003	-0.004
	[0.005]	[0.005]
Pat flow		0.004**
		[0.001]
Subsidiary Pat Stock	0.006**	0.006*
	[0.002]	[0.002]
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
F-test	159.498	133.810
R sq	0.850	0.850
N (firm X year)	71011	71011

Based on annual firm-level data over 2008–2020. Each column reports a separate OLS regression; the dependent variable is the logarithm of markup of firm i in year t. *Tech M&A* is the non absorbed treatment, taking value 1 in the year t of technological M&A for firm i. *Pat Flow* is the number of patents filed by firm i in year t. *Subsidiary Pat Stock* is the patent portfolio stock from the subsidiary following acquisition. All patent variables are transformed using the inverse hyperbolic sine transformation. Controls include firm age, size, capital stock, as well as firm and year fixed effects, with standard errors clustered at the firm level. + $p<0.1$, * $p<0.05$, ** $p<0.01$.

Source: Orbis, Zephyr, Orbis IP (Moody's analytics), analysis by authors

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