Business Groups, Strategic Acquisitions and Innovation*

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Abstract

We analyze the acquisitions of innovative standalone firms by large corporations organized into Business Groups (BGs), at the world level during the period 2007 to 2018. Consistent with the literature, we find a higher probability of acquisition for firms that exhibit an ex-ante upward trend in innovation performance (measured in terms of patents or citations), relative to non-acquired firms. We find systematic evidence of a post-acquisition decline in the innovation activity of acquired firms, primarily among firms with a patent portfolio similar to that of the acquiring BG. In contrast, acquired firms innovating in a technological space different from that of the acquiring BG maintain their positive innovation trend after acquisition. The results are confirmed by considering acquisitions within the same industry or in highly concentrated industries. The evidence supports the hypothesis that large incumbent firms engage in defensive acquisitions to mitigate competitive threats. In this way they reduce the diffusion of knowledge, thereby preserving their market dominance. A number of robustness checks are performed and in addition the findings are consistent with indirect evidence from a policy shock that exogenously affected the cost of acquisition for incumbent firms.

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1 Introduction

Recent research has drawn attention to a concerning slowdown in business dynamism in the US, coinciding with an increase in market concentration of economic activities, possibly induced by a decline in the diffusion of knowledge. The latter in turn has coincided, especially since the early 2000s, with a trend of increasing concentration of patents among market leaders, as well as their strategic use, as shown by Akcigit and Ates [2023]. In particular, there is evidence of preemptive acquisitions by incumbent firms aimed at eliminating potential future competitors. This may lead to increased consolidation, thus hampering the spread of knowledge to smaller firms. Cunningham et al. [2021], for example, discuss what they call "killer acquisitions" in the US pharmaceutical industry, where big companies may acquire innovative targets primarily to discontinue the development of competing drugs, thus reducing competition.

Given the potentially ambiguous role of market leaders in driving innovation and knowledge diffusion, we attempt to shed light on the effect of acquisitions of ex-ante innovative firms by incumbents on innovation, as measured by patents and citations. To that end, we analyze the acquisitions of innovative standalone firms undertaken by large corporations organized into Business Groups (BGs) at the world level during the period 2007 to 2018.[1]

We identify market leaders as the world's largest corporations by consolidated revenue, as classified in the Fortune 500 list, all of which are organized as BGs. Moreover, it is well known in the literature that BGs play a crucial role in generating and diffusing knowledge [Belenzon and Berkovitz, 2010, Choi et al., 2011], with international BGs responsible for roughly half of global R&D spending and at least two-thirds of corporate R&D investment [UNCTAD, 2005, 2016].

Specifically, we first examine the post-acquisition innovation trajectory of acquired standalone firms. Consistent with the literature, we find that BGs tend to acquire standalone firms that exhibit an upward trend in innovation performance (as measured in terms of patents or citations) prior to acquisition, compared to non-acquired firms.[2] However, we also find that these firms experience a significant post-acquisition decline in their innovative activity.

We then analyze potential defensive behaviours exhibited by BGs, by examining whether specific characteristics of the acquired firms' patent portfolio, or the market structure in which they operate, might drive the post-acquisition drop in patents and citations. In particular, we explore the similarity in patent portfolios between an acquired firm and the acquiring BG, by examining

[1] A BG is an organizational form of economic activity in which at least two legally autonomous firms function as a single economic entity through hierarchical control, in which a parent company owns, directly or indirectly, the majority of the equity shares of at least one legally independent affiliated firm.

[2] The number of patent citations is extensively used in the literature as an indicator of the impact and quality of a firm's patent portfolio [Agarwal et al., 2009, Stuart, 2000, Rosenkopf and Nerkar, 2001, Moser et al., 2018].

the technological class of each patent.[3] The results show that the downward trend in innovation activity is driven specifically by a significant post-acquisition drop in the patents and/or citations of acquired standalone firms with a patent portfolio similar to that of the acquiring BG, particularly in the case of cited patents. In contrast, acquired firms that are innovating in a technological space different from that of the acquiring BG maintain a positive trend in innovation both before and after acquisition.[4] This observation is consistent with the hypothesis that BGs may be engaging in defensive acquisitions to mitigate competitive threats. The result is a reduction in the diffusion of knowledge, which preserves their market dominance.

These results are confirmed by acquisitions that take place within the same industry, or in industries characterized by high concentration or an increasing average age of leading firms, as proxies for innovation appropriability. These cases are associated with a stark reduction in the post-acquisition innovation activity of target firms. In contrast, the post-acquisition innovation activity of target firms is less affected in more competitive markets, or when the target firms and acquiring BGs operate in different industries. This pattern aligns with the defensive acquisition narrative, suggesting that BGs leverage these transactions as strategic manoeuvres to solidify their market position in the face of potential competition.

We provide a number of robustness checks of the estimation strategy, including the use of a staggered difference-in-differences estimator à la Borusyak et al. [2024], and a one-to-one firm-matching technique (as opposed to the TWFE estimator we employ in our analysis). We also provide more general support for our hypothesis by exploiting a policy shock that exogenously affected the cost of acquisition for a BG, and hence the propensity to acquire an innovative firm, without necessarily affecting the probability of engaging in activities that suppress post-acquisition innovation among target firms. More specifically, we take advantage of a change in the EU Mergers and Acquisition framework in 2014, which makes it possible to compare the behavior of ex-ante similar acquired firms in terms of innovation activity before and after the policy shock. We find no significant differences in the pre-trend or post-acquisition outcomes between firms acquired before and after the policy change, with treated firms always characterized by a decline in their innovation activity in the post-acquisition period.

To perform the analysis, we rely on two primary data sources: the Orbis Intellectual Property (Orbis IP) database, which provides detailed information on firms' patenting activity, and the

[3] Several studies have looked at the similarity of technical knowledge between the acquiring firm and the target firm as an important predictor of the former's post-acquisition performance. See, among others, Cassiman et al. [2005], Cloodt et al. [2006], Makri et al. [2010], Ahuja and Katila [2001].

[4] To correctly identify these effects, we employ Two-Way Fixed Effects Difference-in-Differences (TWFE DID) techniques with staggered treatment, which is the current practice in the literature. See Section 3.2 for details.

Orbis Ownership Database, which makes it possible to identify the boundaries of BGs, and their changes over time due to, among other things, acquisitions. These two datasets are matched, patent and citation data are cleaned to avoid multiple counting, and firm-level data are complemented by additional balance-sheet information retrieved from Orbis, as well as market concentration data from CompNet. A BG is defined as a parent company owning (directly or indirectly) more than 50.01% equity in at least one affiliate, thus avoiding the complexities of BGs' internal organization, as explored in for example Altomonte et al. [2021]. Acquisitions are then identified as changes in a firm's status from standalone to BG affiliate, based on equity stake changes.

This results in a panel of 169,205 legally operational Orbis firms worldwide that received at least one cross-citation with a priority date within the period 2007-2018, irrespective of their BG affiliation. These firms applied for 2.4 million patents with at least one equivalent at the EPO/USPTO/JPO and received 9 million citations, including 3 million during the first three years of priority. The final sample includes 36% of all patenting firms in the raw sample (see Section 2.2 for details); however, they account for more than two-thirds of raw patents and almost three-quarters of raw citations, highlighting the weight of our sample in the overall data. Around 70% of the sample consists of standalone firms that never join a BG at any point in time, 11% are part of a BG (2% as parents and 9% as affiliates), and the remaining 19% consist of firms whose status changes from standalone to affiliate of a BG during the period 2007-2018. The combined 30% of firms that are or become part of a BG account for some three-quarter of all innovation activity in our sample, as measured by the number of patents and citations. This suggests the existence of an innovation premium associated with BG affiliation, which is consistent with the findings of Belenzon and Berkovitz [2010], who highlight the importance of BGs in leveraging and enhancing innovation (see Section 2.3 for statistical evidence from our sample).

There is an extensive literature on innovation creation and diffusion within BGs. It is widely agreed that affiliates of BGs tend to engage in innovative activity more than standalone firms [Belenzon and Berkovitz, 2010, Choi et al., 2011]. Additionally, cross-border innovation among affiliates of the same BG is more extensive when there is overlap in business hours [Bircan et al., 2021]. Moreover, a firm's propensity to pursue innovative endeavors increases when the technology is perceived as more likely to be used internally rather than by competitors [Arora et al., 2021], thus emphasizing the importance of protecting innovation.

However, many critical aspects of innovation creation and diffusion, which are particularly pertinent in the context of declining knowledge diffusion and rising concentration, remain underexplored. Specifically, there is limited understanding of the acquisition of firms by BGs and its implications for innovation. Evidence suggests that innovative firms are more likely to be acquired [Wu and Chung, 2019]. Nevertheless, there remains a lack of consensus regarding the subsequent effects on innovation. Cunningham et al. [2021] present evidence for the existence of "killer acquisitions" in the US pharmaceutical industry, where big companies may acquire innovative targets primarily to discontinue the development of competing drugs, thus reducing competition. Similar behaviours have been observed in the context of mergers [Morzenti, 2022]. Alternative findings suggest a positive effect of acquisitions on the innovation capabilities of acquired companies [Guadalupe et al., 2012].

There is a broader literature on the impact of technological acquisitions on innovation. Ahuja and Katila [2001] have examined the potential positive effects of technological acquisitions, relative to non-technological acquisitions. Several studies corroborate the notion that technology-based acquisitions enhance the competitiveness of acquiring firms in dynamic markets [Nicholls-Nixon and Woo, 2003, Higgins and Rodriguez, 2006]. This is especially true for acquiring firms that were previously less innovative [Zhao, 2009]. The possibility of balancing post-acquisition integration with the preservation of the acquired firm's organizational autonomy is essential in sustaining post-acquisition innovative performance [Graebner, 2004, Puranam et al., 2006]. Acquiring firms often realize greater benefits in technological performance when their acquisition targets are R&D intensive [Hagedoorn and Duysters, 2002].

The rest of the paper is organized as follows. Section 2 presents the data sources, data coverage, the variables used in the analysis, and descriptive statistics . Section 3 describes the empirical methodology, results, and robustness checks. Section 5 concludes.

2 Data

2.1 Data sources and construction

An extensive dataset is constructed to track the worldwide innovation activity of firms over time, as well as their affiliation with a BG, if any. We rely on the Orbis Ownership database, which provides yearly information on firm-level ownership structures, and makes it possible to link parent firms worldwide to their corresponding affiliates, thus creating a panel of firms with their BG affiliation. We use patenting activity as a measure of innovation, since patent data are widely available across countries and there is detailed information on patent documentation.[5] In particular,

[5] We are aware of the possible shortcomings in the use of patent data as a proxy for innovative activity, due to heterogeneity across patent offices, multiple counting of patents, the existence of redundant patent applications meant to hinder competition [Jaffe and Lerner, 2011], the presence of self-citation, and truncation in citation counts. These concerns are taken into account in the analysis.

we retrieve patent data from the Orbis Intellectual Property database (Orbis IP), which provides information at the patent level from the three leading patent offices in the US, the EU and Japan. This includes an applicant firm's identifier which can be traced back to the Orbis Ownership database and makes it possible to match innovation activity at the firm level to potential BG affiliation over time.

Innovation data. The core of our analysis is based on two measures of innovation: the number of patent applications and the number of patent citations received. The yearly firm-level number of patents is our measure of innovation intensity and frequency. We focus on patent applications at the three leading patent offices: the European Patent Office (EPO), the United States Patent and Trademark Office (USPTO), and the Japan Patent Office (JPO), including patents at other offices worldwide with at least one equivalent at the EPO, USPTO or JPO.[6] We avoid multiple counting of inventions protected by more than a single patent application by taking into consideration affiliation to a patent family. More explicitly, we count as one patent all patents belonging to a single simple patent family which includes different patent applications protecting the same invention (also referred to as patent equivalents). Hence, each patent included in our sample uniquely identifies one invention.[7] Furthermore, patent count is decomposed into patents that get cited in the first three years of priority and those that don't, so as to disentangle patents supporting real inventions from strategic patenting intended to hinder competition [Jaffe and Lerner, 2011].

The construction of the citation data starts from patent-level data obtained from Orbis IP for the period 2007-2018. We construct a novel firm-linked patent citation network dataset that connects citing and cited patents to their corresponding applicant firms.[8] This enables the identification of the subset of patents that were cited, and most importantly, provides a full understanding and control over the timing and citation source. Relying on citation counts that are pre-compiled or other sources of data does not allow for such flexibility in defining citations.[9]

[6] Each patent application is associated with several dates that correspond to the various stages of the application process. We focus on the priority date since it is the first date observed in the application process and best reflects the date of the innovation.

[7] We use the earliest priority date possible for patent equivalents.

[8] We utilize backward citations as a key variable to establish patent citation links. Backward-cited patents include all cited patent applications for each filed patent application, making it possible to retrospectively trace the citations of each patent. Each patent application includes an exhaustive list of cited patent applications identified by the applicant, as well as those introduced by patent examiners during the application process, similar to academic papers. We can easily attribute a citation link to patents appearing in backward citations. Forward citations on the other hand require tracking efforts in the following years as new patents emerge.

[9] Knowledge of the citing patent application and corresponding applicant firm allows us to control for within-

Importantly, we exclude citation links in three specific cases. First, we exclude mechanical within-patent citations from patent equivalents, which are defined as a patent application that cites another in the same simple patent family. Second, we drop firm self-citations and consider only cross-firm citations, thus making it possible to assess the quality of a patent, as validated by other firms.[10] Third, given the truncated nature of citations, we only take into consideration the three-year forward citation links starting from priority, and fix the citation span to that window. This excludes citations received over three years since declaration of the invention at the patent office.[11] This ensures consistency across all patents, in line with the construction of the OECD Citations database.

To measure the impact and quality of a firm's overall innovation in a given year, we calculate its total number of citations by other firms of its patenting activity during that year. This is done in two steps. First, we compute the total number of citations received directly for each patent while taking into account citations of patent equivalents, as previously defined. Second, we aggregate this restricted patent citation count at the firm-year-level by summing the three-year forward citation count for all patents applied for by a firm in a specific year. The higher the number of a firm's citations the more influential its innovation is considered to be.

Finally, we use the International Patent Classification (IPC) classes provided by the World Intellectual Property Organization (WIPO) to establish a patent-based technological domain for each firm, and use this to compute a measure of portfolio similarity between firms, based on the proportion of common technological classes in which they innovate. This makes it possible to compare the technological distance between the acquiring and acquired firms based on their patent portfolios.[12] Overall, the raw dataset includes approximately 470,000 patenting firms, accounting for 19 million patent applications and 24 million citation links.[13]

Business groups data. We rely on BG panel data obtained from the Orbis Ownership database, which link parent firms worldwide to their corresponding affiliates and their layer in the hierarchy

firm self-citations, which can't be disentangled by using pre-compiled citation counts from Orbis or other sources, such as the OECD.

[10] Given the relevance of cumulative innovation within a firm in building its market value [Belenzon, 2012], it is important to stress that our results hold when including self-citations as a measure of cumulative knowledge creation within firms.

[11] For example, in the case of a patent first announced at the patent office in year t, we sum citations received directly or indirectly (by way of equivalents), in year t, t+1, and t+2. In other words, we consider the three-year forward citation count.

[12] Additional details regarding the construction of our measure for patent portfolio similarity are provided in Appendix D.

[13] Non-patenting firms are not considered in any of the analysis.

of control. This methodology was developed by Sonno [2020] and used in subsequent work [such as Altomonte et al., 2021]. In line with this literature, we define BGs as an entity composed of at least two firms, i.e. a parent company that directly or indirectly owns more than a 50.01% share of equity in at least one affiliate.[14] We abstract from the internal organization and hierarchy of the BG and focus instead on BG affiliation and acquisitions. An acquisition is defined simply by a change in the status of a firm, from standalone to BG affiliate.[15] The acquisition of shares can be made directly by the parent of the acquiring BG and/or indirectly by one or more of its affiliates. This final dataset represents a network of more than 6.3 million parents, with 12.8 million affiliates across more than 200 countries, during the period 2007 to 2018.[16]

2.2 Data coverage

The raw Orbis IP data includes 469,389 firms worldwide which submitted 18,851,288 patent applications during the sample period and received 24,787,116 citations in the three patent offices. Table 1 shows the raw coverage of firms and their patenting activity before and after data cleaning. As previously discussed, the number of patents and number of citations in column (1) do not reflect the actual number of innovations involved given the multiple counting of patent equivalents. Once multilple counting is taken into account, the number of patents is reduced by more than 70% and citations by more than 40% (column 2). The three patent offices, i.e. EPO, USPTO, or JPO, account for 64% of all patents and 95% of citations (column 3). The large share of citations from these three patent offices underscores their dominance. If we consider only firms and patents that were cross-cited in the first three years of priority (column (4)), there is a substantial decline of 46% in the number of firms, a 60% decline in the number of patents and a 66% decline in the number of citations.

A positive trend in patenting activity is observed during the period, with some fluctuation from year to year, which is consistent with the WIPO's World Intellectual Property Indicators report published in 2021. We also observe a decline in firm participation in patenting activity, which indicates increasing concentration of patenting among leading firms, as confirmed by the findings of Akcigit and Ates [2023] for the US economy.

In the empirical analysis, we focus on patenting activity over a firm's life span, i.e. during its period of operations and starting from the date of incorporation. Therefore, the sample con-

[14] Complex BG structures can include numerous affiliates in many hierarchical layers, as long as the parent directly or indirectly owns strictly more than 50% of the equity in each affiliate.

[15] We exclude the very few standalone firms that become the parent of a BG.

[16] See the appendix in Sonno [2020] for an extensive description of the data and their validation using available country-year-specific census data, including OECD FATS Statistics.

Table 1: Orbis IP data coverage

Number of:	(1) Raw data	(2) Clean data	(3) EPO/USPTO/JPO	(4) Cited
Firms	469.389	469.389	372.597	203.064
Patents	18,851,288	5,220,530	3,316,936	1,307,202
Citations	24,787,116	13,055,209	12,468,805	4,222,765

Notes: This table summarizes Orbis IP data coverage for firms' patenting activity over the period 2007-2018. Orbis IP data version: July 2022. Columns are organized as follows: (1) presents raw data, (2) presents coverage after addressing multiple counts due to patent equivalents, (3) presents clean data for the sub-sample of patents with at least one equivalent at the EPO/USPTO/JPO, and (4) presents the sub-sample of patents in column (3) that received at least one citation within the first three years of priority, excluding self-citations.

sists of legally operational Orbis firms worldwide that received at least one cross-citation with a priority date within the period 2007-2018, irrespective of their BG affiliation. This results in a panel of 169,205 firms that applied for 2.4 million patents with at least one equivalent at the EPO/USPTO/JPO and received nine million citations, including three million during the first three years of priority as presented in Table 2 (column 3). Although the sample includes only 36% of all patenting firms, they account for more than two-thirds of raw patents and almost three-quarters of raw citations, highlighting the weight of our sample with respect to the overall data.[17]

Table 2: Sample data coverage

Number of:	(1) Raw data	(2) Clean data	(3) EPO/USPTO/JPO	(4) Cited
Patents	12,784,653	3,618,124	2,405,275	980.579
Citations	17,862,338	9,513,853	9,078,913	3,015,119

Notes: This table summarizes the coverage of patenting data for our sample of 169,205 firms obtained from Orbis IP after data cleaning. Column (1) relates to the raw data, column (2) presents coverage after addressing multiple counts due to patent equivalents, column (3) relates to the cleaned data for the sub-sample of patents with at least one equivalent at the EPO/USPTO/JPO, and column (4) relates to the subset of patents in column (3) that received at least one citation within the first three years of priority, excluding self-citations.

2.3 Descriptive statistics

Patenting activity by BG affiliation during the sample period is presented in Table 3. On the one hand, only around 11% of firms in the sample are part of a BG (2% as parents and 9% as affiliates). Nonetheless, these firms account for more than 60% of all innovation activity as measured by the number of patents and citations, with parents alone accounting for approximately 40%. This is consistent with the concentration of knowledge within BGs as observed by Belenzon and Berkovitz [2010]. In contrast, around 70% of the sample consists of standalone firms that were

[17] These figures are obtained by comparing column (1) in Table 2 to column (1) in Table 1.

never part of a BG, which account for only one quarter of the innovation activity. The remaining 19% consists of firms that changed their status. Of these, 17,722 went from standalone to being part of a BG, with the remainder going from BG affiliate to standalone.

Table 3: BG affiliation and patenting activity during the period 2007-2018

	(1) Firms	(2) Patents	(3) Citations	(4) Patents	(5) Citations
Sample		Full		EPO/USPTO/JPO & Cited	
size	169,205	3,618,124	9,513,853	980,579	3,015,119
Breakdown by status:					
Parents	2%	35%	39%	40%	37%
Affiliates	9%	26%	22%	23%	21%
Standalone firms	70%	24%	27%	25%	29%
Changing status	19%	15%	12%	12%	13%

Notes: The distribution of firms according to their BG affiliation and participation in patenting activity for the period 2007-2018. Columns (2) and (3) present all patenting activity after data cleaning, while columns (4) and (5) present patenting activity at one of the 3 leading patent offices (EPO/USPTO/JPO) at which the patent received at least one cross-citation within the first three years of priority.

Of the 17,722 firms acquired by BGs, 7.6% were acquired more than once. Therefore, we focus on 15,493 firms that were acquired only once during the sample period in order to simplify the analysis to a single treatment.[18] Acquisitions in our sample are observed in 87 2-digit NACE industries and are predominantly to be found in high-tech industries such as Research and Development, Manufacture of Computer, Electronic and Optical Products, Manufacture of Machinery and Wholesale Trade (except motor vehicles, see Appendix A).

The distribution of firms by BG affiliation and their patenting activity is suggestive of the existence of an innovation premium that BGs leverage. We document this premium in Table 4, which shows that, on average, a firm that is part of a BG (as parent or affiliate) has a patent application premium of around 3.9 patents over a standalone firm. Furthermore, on average, these firms receive 4.6 more citations. Differences in means between the two samples are statistically significant at the 99% confidence level.

In addition to the innovation premium accruing to firms already affiliated with BGs, the data also confirm another finding in the literature, namely that standalone firms which are characterized by higher levels of innovation face a greater probability of being acquired by a BG [Wu and Chung, 2019]. Appendix B describes these results, which show that the probability of acquisition for a standalone firm is positively correlated with ex-ante innovation performance. The data also show that, on average, acquired standalone firms tend to be younger, larger in terms of

[18] The total number of firms acquired once during the period is 16,354. However, we exclude 861 acquired standalone firms for which industry information is missing.

Table 4: BG patenting and citation premium

Sample		(1) Parents/affiliates	(2) Standalone firms	(3) Difference
Patents:	Mean	4.411	0.547	3.863***
	Std. Err.	(0.099)	(0.004)	
Citations:	Mean	5.381	0.791	4.590***
	Std. Err.	(0.192)	(0.009)	
Observations		383,229	1,370,745	

Notes: Patenting activity of BG affiliation during the period 2007-2018. Data is in panel format, and therefore, each observation is at firm-year level. In column (1), the sample includes all firms that are part of a BG, whether as an affiliate or a parent, while in column (2), the sample strictly includes only standalone firms that never become part of a BG. The differences in means between the two samples are significant at the 99% confidence level.

revenue and employment; and they tend to possess more assets and liabilities than standalones that were never acquired. This evidence is consistent with the claim that BGs tend to cherry-pick young, high-performing firms for acquisition.

3 Empirical Analysis

In this section, we analyze the innovation performance of target firms after acquisition by a BG. We first examine the innovation trajectory of acquired standalone firms by comparing their patenting and citation activity before and after the acquisition. We then explore whether post-acquisition trends in the innovative activity of target firms are correlated with the similarity between their patent portfolios and those of acquiring BGs. This is in view of the fact that BGs may have differing motives underlying their acquisition strategy. The results show an overall decline in innovative activity among acquired standalone firms, particularly in the case of similar patent portfolios between the acquired standalone and the acquiring BG. In contrast, an acquired firm that is innovating in a technological space different from that of the acquiring BG tends to maintain their innovation trend after acquisition. These results in turn suggest a pattern of defensive acquisition behaviour by BGs, which target high-performing standalones that are potential competitors, as well as expansionary acquisition behaviour that involves the acquisition of high-performing complementary firms. In section 4, we provide a number of additional checks to validate these results, while taking into consideration, among other things, the staggered nature of the treatment and the comparability between acquired firms and the control group of non-acquired firms. We also make use of an exogenous policy shock that affected the propensity to acquire firms for some BGs in our dataset, which confirms that the strategic behaviour of BGs is one of the main channels determining the innovation outcomes of acquired firms.

3.1 The effect of acquisition on patents and citations

We conduct a Two-Way Fixed Effects Difference-in-Differences (TWFE DID) analysis to assess the effect of acquisition on acquired targets, in comparison to the average performance of never-acquired standalone firms. The treatment group is comprised of innovative standalone firms that were acquired only once during the sample period, as explained in section 2.2. In contrast, the control group consists of innovative standalone firms that were never acquired.[19] The estimation equation is:

$$Y_{i,t} = \theta + \sum_{t=-11;t\neq-1}^{+10} \delta_t \, T_{i,t} + \lambda_i + \alpha_t + \eta_{i,t} \tag{1}$$

where $Y_{i,t}$ represents different measures of innovation: (i) number of citations, (ii) number of patents, (iii) number of cited patents, and (iv) number of uncited patents, all in logs. Given the staggered treatment of firms, we rescale the time periods with respect to the firm-specific acquisition year. Hence, $T_{i,t}$ are time-specific and firm-specific period dummies. The omitted period is the one before treatment. The estimation includes firm and year fixed effects, denoted by λ_i and α_t respectively, in order to account for firm heterogeneity and technological trends at the macro-level. Thus, the coefficients δ_t, for t ranging from -11 to 10, indicate the average within-firm effect of acquisition on the outcome variable Y, relative to the year before acquisition.

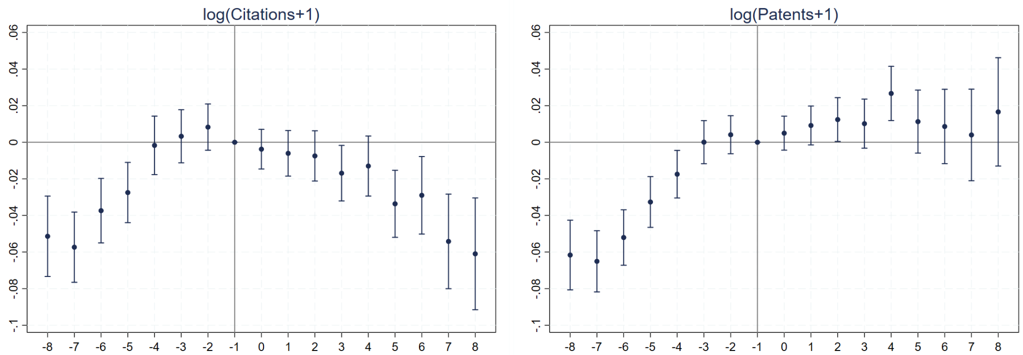
Figure 1 illustrates the estimation results, which point to a decline in the innovation activity of acquired firms subsequent to their acquisition, in terms of both citations and patents.[20] The innovative performance of an acquired firm improves over time, reaching its highest level in the omitted pre-acquisition period (Pre 1). More specifically, the negative (positive) coefficients should be interpreted as low (high) levels of innovation among acquired firms relative to the baseline period -1, after deducting the average level of innovation of a standalone firm in the same year. The event of acquisition disrupts this trend, in the case of both citations and patents, with a stronger effect observed for citations. Thus, treated firms are cited less frequently than before their acquisition. In addition, the positive trend in patent activity displayed by acquired firms slows down after acquisition, with the yearly number of patents stabilizing near its level in the pre-acquisition year.[21] In Section 4, we take into account that a firm's treatment is staggered over time, and thus not necessarily uniform across treated units. Results however are entirely similar in terms of disruption to the innovative activity of acquired firms.

[19] Standalone firms acquired more than once are excluded from the analysis. They account for only 7.5% of the observations, and including them would increase the estimation noise.

[20] In the graphical representation, we plot only the 7 years before and 9 years after acquisition. Columns 1 and 2 of Table A6 in Appendix C presents all of the regression coefficients depicted in Figure 1.

[21] Running the same regression without the control group generates the same results.

Figure 1: The effect of acquisition on patenting activity of acquired firms



Notes: The graphs plot TWFE-DID estimates of the effect of acquisition on acquired firms as in equation (1) for seven years before and nine years after treatment. Displayed coefficients pertain to firm-specific period dummies with respect to the pre-acquisition period (Pre 1) that is excluded. Estimations also include firm and year FEs. Standard errors are clustered at firm level and 95% confidence intervals are presented. Columns 1 and 2 of Table A6 in Appendix C present the regression coefficients plotted in this graph.

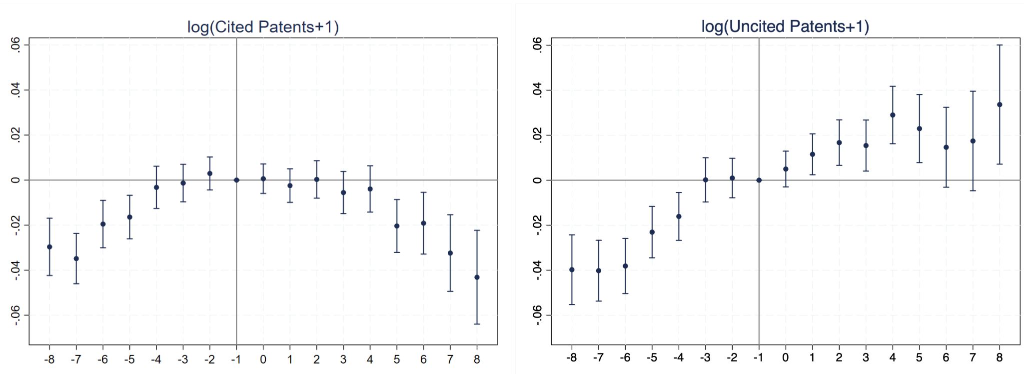
To further explore the mechanism, in Figure 2 we disentangle the preliminary results according to cited and uncited patents.[22] The analysis reveals that the effect observed post-acquisition in terms of the number of patents produced (right panel of Figure 1) is, in fact, the outcome of two opposing forces. Specifically, the right panel of Figure 2 confirms that there is no difference in the trend of uncited patents before and after acquisition. In other words, the production of uncited patents maintains its positive trend throughout the entire period, and the acquisition event does not seem to alter this dynamic. Conversely, the positive trend in the production of cited patents before acquisition is abruptly interrupted by acquisition, resulting in a complete reversal in the trend, which becomes negative and significant.

3.2 Strategic acquisitions of innovative firms

The evidence presented so far indicates that, on average, acquisition has a detrimental effect on innovation particularly in the case of high-quality, cited patents, while the production of patents that do not end up being cited seems to be unaffected by the acquisition event. This result is inconsistent with the idea that BGs acquire innovative firms in order to diversify and expand their activities into new industries and technologies, as one would expect innovation outcomes of target firms to continue to grow after acquisition. To further clarify this point, we classify the patent portfolio of firms according to technological class, and then examine the technologi-

[22] In the graphical representation, we plot only the seven years before and nine years after acquisition. Columns 3 and 4 of Table A6 in Appendix C present all of the regression coefficients depicted in Figure 2.

Figure 2: The effect of acquisition on patenting activity of acquired firms: cited and uncited



Notes: The graphs plot TWFE-DID estimates of the effect of acquisition on acquired firms with respect to the year of acquisition. The regression includes acquisition period dummies for the sample of acquired firms excluding acquisition period -1 (Pre 1). Estimations also include firm and year FEs. Standard errors are clustered at firm level and 95% confidence intervals are presented. Columns 3 and 4 of Table A6 in Appendix C present the regression coefficients plotted in this graph.

cal overlap between the acquired firm and the BG, and whether the post-acquisition pattern of innovation activity is influenced by the technological similarity between the patent portfolios.

Specifically, conditional on observing a patent portfolio for the acquired firm and the acquiring BG,we calculate the median truncation-adjusted proportion of technological class overlap between patent portfolios of the acquired firm and the acquiring BG during the pre-acquisition period, and then define two types of acquisition. The first relates to acquired firms with an equal or above median-level of technological similarity to the BG, thus implying the acquisition of a potential competitor in the innovation space. The second relates to acquired firms with a below-median level of similarity to the acquiring BG, thus indicating an acquisition possibly aimed at expanding the BG's technological space. Given that we observe patent portfolios from 2006 onwards, firms acquired earlier (later) in the period may systematically exhibit less (more) similarity with the acquiring BG due to the shorter (longer) pre-acquisition window. We alleviate this truncation bias by absorbing the fixed effects of the acquisition year.[23] A detailed description of the index of technological similarity, together with the identification of the two types of acquisition appears in Appendix D.

We therefore estimate the following equation:

$$Y_{i,t} = \omega + \sum_{t=-11;t\neq-1}^{+10} \gamma_t \left(T_{i,t} \times \mathit{SameTech}_i\right) + \sum_{t=-11;t\neq-1}^{+10} \eta_t \left(T_{i,t} \times \mathit{DifferentTech}_i\right) + \rho_i + \sigma_t + \mu_{i,t} \tag{2}$$

where $Y_{i,t}$ represents the different measures of innovation: (i) number of citations, (ii) number

[23] See Appendix D for details.

of patents, (iii) number of cited patents, and (iv) number of uncited patents, all in logs. $T_{i,t}$ are period- and firm-specific dummies, as defined in the previous section. The dummy variable $\mathit{SameTech}_i$ ($\mathit{DifferentTech}_i$) equals one if the technological class of the acquired firm in the pre-acquisition period is similar to (different from) that of the acquiring BG as previously explained. The control group includes never-acquired standalone firms. All the estimations include firm and year fixed effects (ρ_i and σ_t respectively), in order to account for firm-specific or aggregate technological change. Thus, the coefficients γ_t, for t ranging from -11 to 10, measure the effect for acquired firms with a technology portfolio similar to that of the acquiring BG relative to their pre-acquisition performance (in Pre 1) and to non-acquired firms, on the outcome variable Y. The η_t coefficients provide analogous effects for acquired standalone firms with a different technology portfolio than that of the acquiring BG.

Figure 3 displays 16 regression coefficients of the period dummies – seven before and nine after acquisition – by level of portfolio similarity between the acquiring BG and the acquired firm.[24] In the left panel, the dependent variable is the number of citations, while in the right panel it is the number of patents (both logged and incremented by one unit). The year before the acquisition is the omitted period.

The results in Figure 3 reveal that, on average, there is a decline in innovation activity among target firms innovating within the same technological class as the acquiring BG. Among firms with divergent portfolios, innovation continues to grow post-acquisition.[25] More specifically, five years after acquisition, acquired firms with similar portfolios experience a 30% decline in the number of citations, relative to the year before acquisition, while those with different portfolios experience a more than 10% increase in citations relative to the year before acquisition. In the case of patents, firms with similar portfolios show a decline of almost 15% five years after acquisition, while firms with different technology portfolios experience a 20% increase.[26] Results are robust to using the 2-digit NACE industry as a measure of similarity (Same/Different industry), as well as other measures (see Section 4).

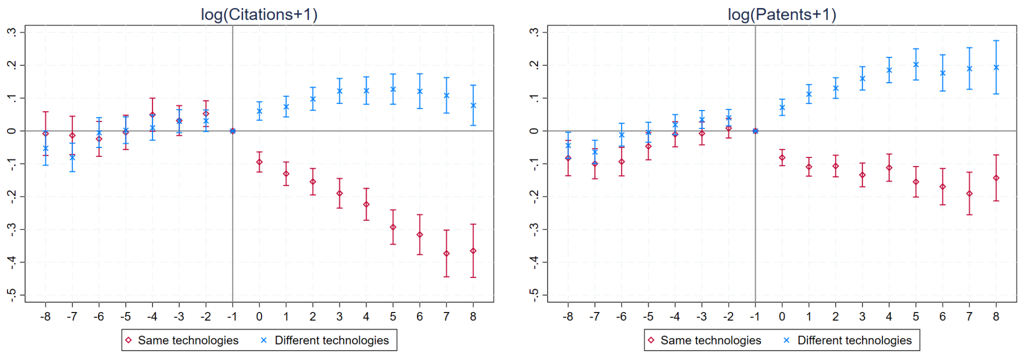
As in Section 3.1, we repeat the analysis while distinguishing between cited and uncited patents. Comparing the left and right panel of Figure 4, it is clear that the post acquisition disruption to innovative activity is predominantly concentrated in high-quality, cited patents that are in the

[24] The sample includes a maximum of 11 years pre-acquisition and 10 years post-acquisition, and we exclude the period -1, i.e. the year before the acquisition. For symmetry, the graphs display only the coefficients from -8 to +8, but all period dummies are incorporated into the regression, as presented in Table A6 in Appendix C.

[25] Note that the pre-trends in Figure 1 are very similar to those in Figure 3. However, they are not identical, since the sample of firms included in Figure 3 is limited to firms and groups for which we observe a pre-period technological portfolio, as previously mentioned.

[26] See Table A7 in Appendix C for a more detailed presentation of the coefficients.

Figure 3: Acquisition and technological similarity



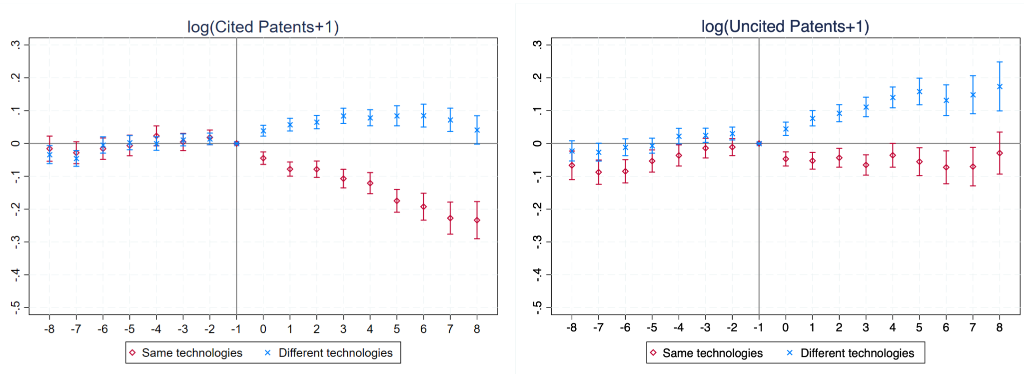
Notes: The graphs display TWFE-DID estimates illustrating the effect of the acquisition on acquired firms relative to the year of acquisition and non-acquired firms, given the technological class alignment between the acquired firm and the acquiring BG. The omitted period is the period before the acquisition (Pre 1). Same Technologies (Different Technologies) refer to acquisitions in which the patent portfolio of the acquired firm is similar to (differs from) that of the acquiring BG. Estimations include firm and year FEs. Standard errors are clustered at firm level and 95% confidence intervals are presented. Table A7 in Appendix C presents the regression coefficients plotted in this graph.

same technological class as that of the acquiring BG (left panel, same technology), while there is only a mild disruption in the case of uncited patents of target firms active in the same technological class (right panel, same technology). Conversely, positive trends for both cited and uncited patents are preserved after acquisitions in the case of standalone firms acquired by a BG operating in a different technological class.

The findings presented in this section, together with the evidence described in section 3.1, suggest a pattern of defensive acquisition behaviour by BGs that targets high-performing standalone competitors, and a pattern of expansionary acquisition behaviour when acquiring high-performing complementary firms. Specifically, the evidence indicates a suppression of innovation activity among acquired firms that are active in areas of technology that are potentially competitive to the BGs, and a promotion of innovation in acquired firms involved in new areas of technology.

Before proceeding to the robustness checks in Section 4, it may be worthwhile considering the effect of acquisition on the BG, i.e. whether its innovation activity increases and/or its overall performance is improved. Appendix E shows that there are no significant post-acquisition spillover effects on the overall number of citations or patents (cited and uncited) at the affiliate level among acquiring BGs. Finding an effect at the group level is unlikely, since it may be mediated by the average performance of all the group affiliates. An effect is more likely to be found at the level of the specific legal entity within the BG carrying out the acquisition (i.e. the direct acquirer

Figure 4: The effect of acquisition on the patenting activity of acquired firms by technological similarity: cited and uncited patents



Notes: The graphs display TWFE-DID estimates of the effect of the acquisition on acquired firms relative to the year of acquisition and non-acquired firms, given the technological similarity between the acquired firm and the acquiring BG. The omitted period is the period before the acquisition (Pre 1). Same Technologies (Different Technologies) refer to acquisitions in which the patent portfolio of the acquired firm is similar to (differs from) that of the acquiring BG. Estimations include firm and year FEs. Standard errors are clustered at firm level and 95% confidence intervals are presented. Table A8 in Appendix C presents the regression coefficients plotted in this graph.

which is either the parent or one of its affiliates). This calls for future research that is beyond the scope of this paper. However, we do document a post-acquisition increase in a BG's turnover and employment. The latter appears to be driven mainly by BGs that acquire standalone firms operating in different technological classes, which is consistent with our hypothesis of defensive versus expansionary acquisition strategies. We also observe some evidence of a reorganization of innovation activity within BGs after the acquisition of firms operating in similar technological spaces. In particular, patents tend to be concentrated over time in the parent company and away from affiliates. There also tends to be a change in the number of affiliates and their positions in the overall control hierarchy after the acquisition event. Such an analysis, however, goes beyond the scope of this paper, and hence we report these findings as only anecdotal evidence, emphasizing the need for a more detailed investigation of the effects on BG structure in future research.

4 Robustness and alternative channels

In this section, we test the robustness of the results, as well as rule out any potential alternative explanations. We first show that the results hold when we define an acquired firm and the acquiring BG as similar according to whether they are in the same industry, rather than technological class. We then show greater disruption to the innovative activity of target firms in highly concentrated industries, and in industries where the age of the leading firm is increasing. These findings are consistent with the idea that when BGs operate in market structures with higher innovation appropriability, they are ceteris paribus more likely to adopt defensive strategies.

We then check the robustness of our empirical strategy with respect to two concerns: (i) the staggered nature of the treatment, and (ii) the comparability between acquired firms and the control group of non-acquired firms. We tackle the first concern by employing a staggered differences-in-differences estimation à la Borusyak et al. [2024], and the second by using a propensity score matching technique. The results of both approaches confirm a negative post-acquisition effect on acquired firms competing in the same technological space as the acquiring BGs.

Finally, we discuss potential alternative channels that might result in a correlation between the probability of a target firm of being acquired and the subsequent change in its innovation trend, and show that they do not necessarily weaken our results. In particular, we carry out the analysis around an exogenous policy shock (a change in the EU Merger Law in 2014) that affected the cost of acquiring European standalone firms without necessarily affecting the probability of BGs to engage in defensive strategies, and again we obtain similar results.

Clearly, we do not claim that the strategic behaviour of BGs with respect to the innovation activities of their acquired firms is the *only* factor contributing to our results. Nonetheless, we contend that the analysis presented above, along with the robustness exercises that follow, provides strong support for the hypothesis that BGs engage in defensive acquisitions in order to mitigate competitive threats. This results in reduced diffusion of knowledge, thereby preserving their market dominance.

4.1 Additional results

Industry competition. The previous analysis may be sensitive to our definition of competition in the innovation space, which was based on the technological similarity between the patent portfolios of a target firm and the acquiring BG. We now show that the results are confirmed when using a different grouping method. Specifically, panel A of Table 5 demonstrates that all the evidence described so far is confirmed when the proxy used for competition in the innovation space is a grouping that distinguishes between acquired firms active in the same 2-digit NACE industry as that of the acquiring BG and those active in a different one. In particular, acquired firms competing in the same industry as the acquiring BG are subject to a similar drop in the post-acquisition number of cited patents and citations, while acquired firms in a different industry experience an increase.

Market power - Concentration. We also check whether competitive market conditions influence a BG's choice of a defensive strategy versus an expansionary one. We start by constructing the Herfindahl-Hirschman Index (HHI) for every industry in the sample for 2001 (a pre-period baseline year) as a proxy for market concentration.[27] Results in panel B of Table 5 reveal that when a standalone firm is acquired in a concentrated market (*High HHI*), there is a significant post-acquisition decrease in the number of citations, while the upward trend in the number of cited patents levels off.[28] In contrast, acquisitions occurring in more competitive markets (*Low HHI*) lead to an increase in the number of patents (both cited and uncited). These results align well with the analysis presented in the previous sections, since we expect defensive behaviour toward potentially risky competitors to be more common in concentrated industries.

Market power - Firm age. Panel C of Table 5 presents the relationship between the average age of leading firms in an industry and the acquisition pattern of BGs.[29] We hypothesize that an increasing average age of the leading firms in an industry is an indicator that they are consolidating their market share, including by means of defensive strategies to protect their market position. Conversely, a decreasing average age suggests that younger, often smaller, firms are making significant inroads in the industry. Our findings are consistent with this hypothesis. Thus, in industries with an increasing average age of leading firms, there is a reduction in citations and a halt in the post-acquisition trend of cited patents. On the other hand, innovation is stimulated in industries with a decreasing average age of leading firms, as evidenced by an increase in both citations and total patents after the acquisition event.

4.2 Alternative empirical strategies

Staggered treatment. Our event study design involves staggered treatment, i.e. a treatment whose timing is not uniform across treated units, making standard econometric approaches less efficient. To mitigate the problem, we employ the difference-in-differences estimation technique proposed by Borusyak et al. [2024] which can take into account the staggered nature of acquisitions, and enhance causal inference of their effect on innovation. Appendix F presents the results

[27] We retrieve the HHI based on market shares of firms at the country-industry-year level from the CompNet database. The market share of each firm is squared and the results are summed by country-industry-year. We then construct the industry-level index for 2001 by taking the average across countries.

[28] We consider an industry to be highly concentrated (*High HHI*) if its average HHI, at the NACE 2-digit level, is greater than or equal to the median level, and vice versa (*Low HHI*).

[29] We analyze the effect of the average age of leading firms using balance sheet turnover data for 2001-2007 as retrieved from the BvD Orbis database. We focus on the top 8 firms by market share, which is standard practice in the literature.

Table 5: Market concentration and innovation appropriability

Dep. Variable	(1) Citations(i,t)	(2)	(3) Patents(i,t)	(4)
Sample	All	All	Cited Patents(i,t)	Uncited Patents(i,t)
Panel A: By industry				
Post × Same Industry	-0.0632***	-0.0030	-0.0256***	0.0165**
	(0.011)	(0.010)	(0.007)	(0.008)
Post × Different Industry	0.0203***	0.0319***	0.0124***	0.0240***
	(0.005)	(0.004)	(0.003)	(0.004)
Obs.	1,302,739	1,302,739	1,302,739	1,302,739
R2	0.320	0.430	0.386	0.433
Panel B: By HHI				
Post × High HHI	-0.0185**	0.0275***	-0.0022	0.0322***
	(0.007)	(0.007)	(0.004)	(0.006)
Post × Low HHI	0.0147***	0.0178***	0.0077**	0.0110***
	(0.006)	(0.005)	(0.003)	(0.004)
Obs.	1,295,185	1,295,185	1,295,185	1,295,185
R2	0.318	0.428	0.384	0.431
Panel C: By age growth				
Post × Increasing age top 8	-0.0199***	0.0106*	-0.0050	0.0159***
	(0.007)	(0.006)	(0.004)	(0.005)
Post × Decreasing age top 8	0.0125**	0.0323***	0.0083**	0.0270***
	(0.006)	(0.006)	(0.004)	(0.005)
Obs.	1,302,739	1,302,739	1,302,739	1,302,739
R2	0.319	0.430	0.386	0.433
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Notes: Difference-in-Differences estimation results for the effect of acquisition on the innovation level of acquired firms by industry (Panel A), the level of industrial concentration (Panel B) and the increase in age of the top 8 leading firms (by market share) (Panel C). The sample is divided between acquired standalone firms (treated group) and non-acquired standalone firms (control group), during the period 2007-2018. Citations(i,t): 3-years forward count of citations received for patents by firm i in year t-1. Log(Patents+1) (i,t-1): number of patents submitted by firm i in year t-1. In each panel, the treated group is divided into two sub-groups according to the position of the firm with respect to: industry similarity (Panel A), median of the average HHI at the NACE 2-digit level (Panel B) and the increase in age of the top 8 firms in the industry (Panel C). Post × Same (Different) Industry is a dummy variable equal to one for acquired firms in the same (different) 2-digit NACE industry as the BG, and zero otherwise. Post × High (Low) HHI is a dummy variable equal to one for acquired firms in a highly (slightly) concentrated industry, and zero otherwise. Post × Increasing age top 8 (Decreasing age top 8) HHI is a dummy variable equal to one for acquired firms with an increasing (decreasing) age of the 8 leading firms, and zero otherwise. Standard errors are clustered at the firm-level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

for this estimator, which confirm the disruption of the innovation trend for acquired firms (in the case of both citations and patents), particularly firms operating in the same technological class as the acquiring BG (Figure A2 in Appendix F). The additional evidence provided by this estimator is related to the pre-acquisition performance of target firms, since we can now directly interpret a negative (positive) coefficient as a lower (higher) number of citations or patents of acquired firms relative to non-acquired firms. The evidence shows positive and significant pre-treatment coefficients, which is consistent with a cherry-picking strategy among BGs. In other words, they will tend to acquire the most innovative firms, as discussed in Appendix B.

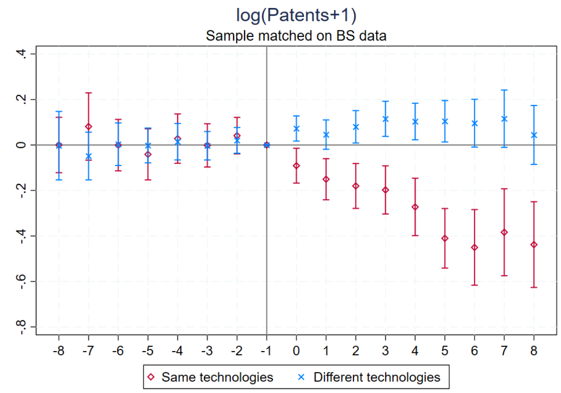
Sample matching. Another concern in interpreting the results is that acquired firms might be significantly different from non-acquired firms in dimensions other than (though correlated with) innovation activity. Therefore, we perform a one-to-one propensity score matching in Appendix G, in which each acquired firm is matched with the most similar non-acquired firm (based on observables such as age, turnover, and employment) within the same industry (NACE at the 2-digit level) and for the same (pre-acquisition) year. We then pool the sample of matched non-treated firms and in Figure 5 (analogous to Figure 3) compare each firm to this control group. Details of the sample used in this exercise, together with alternative matching criteria (including a within-matched-pair estimation), are presented in Appendix G. Our results are reassuringly robust to the various specifications.

4.3 Alternative channels

To further validate our results, we need to rule out alternative channels that might results in a correlation between a BG's decision to acquire a firm and changes in the innovation activity of the acquired firm. For example, acquired standalone firms might have less incentive to maintain productivity in terms of innovation once they achieve their goal of being acquired. Alternatively, BGs might decide to acquire standalone firms only once they are thought to have reached their peak of innovative capability, since the plateau in patent production might lead to a relative cheap valuation in terms of future discounted cash flow. Therefore, the subsequent post-acquisition decrease in innovation activity might occur independently of the acquisition itself.[30] While these alternative channels might play a role in explaining the average post-acquisition disruption of innovation activity, they cannot account for the systematic post-acquisition heterogeneity in patent/citation

[30] When analyzing the characteristics of bidding firms, it has been observed that less innovative companies with declining internal productivity are more inclined to pursue acquisitions [Higgins and Rodriguez, 2006]. These firms also tend to gain more from acquisitions by leveraging the influx of new resources and capabilities [Zhao, 2009].

Figure 5: The effect of acquisition on the patenting activity of acquired firms by same/different technology: Matched sample



Notes: Estimated effect of acquisition on acquired firms relative to the year before acquisition and relative to similar non-acquired firms, given the technological class of the acquired firm relative to the acquiring BG. The omitted period is the period before the acquisition (Pre 1). Same Technologies (Different Technologies) refer to the similarity (difference) in technology of the patent portfolio between an acquired firm and the acquiring BG. The control group of non-acquired firms is a subset of all non-acquired firms that match the acquired firms based on age, turnover, and employment (within the same industry and in the same pre-acquisition year). For further details, see Appendix G. Estimation includes firm and year FEs. Standard errors are clustered at the firm level and 95% confidence intervals are presented.

trends observed between firms operating in the same industry/technological segment as the acquiring BG and those operating in different ones.

Another way to provide support for our hypothesis is to exploit an exogenous shock to the cost of acquisition for a BG, and hence the propensity to acquire an innovative firm, without necessarily affecting the probability that the post-acquisition innovation of target firms will decline. The shock that we take advantage of is the adoption in November 2014 of the Antitrust Damages Directive (Directive 2014/104/EU) by the European Union. This was meant to facilitate the process by which victims of anti-competitive practices can claim damages. The directive introduced several key provisions that increased the complexity and potential costs associated with mergers and acquisitions.[31] This led to increased legal and financial risks associated with mergers and acquisitions, since acquiring companies now faced increased scrutiny and potential liabilities for anti-competitive practices. In Appendix H, we report evidence that the policy change did indeed have a large negative impact on the number of acquisitions in the EU market.

[31] First, the Directive mandated measures to improve access to evidence possessed by parties involved in antitrust violations, making it easier for claimants to gather necessary information. Second, it harmonized the rules on limitation periods for bringing damage claims, thus ensuring a consistent time frame across member states. Finally, the Directive established that national court decisions on competition law infringements would be binding in subsequent damage claims, thus creating a more predictable and enforceable legal environment.

To carry out the analysis, we have retrieved a sub-sample of 5,225 acquisitions that took place in the EU (out of the 15,493 in total), and then split it into 3,412 acquisitions that occurred before the policy implementation, and 1,813 that took place afterward. We then ran our analysis in order to compare the post-acquisition patterns between the two sub-samples. Reassuringly, the analysis indicates no significant differences in the pre-trend or post-acquisition outcomes between firms acquired before the policy change and those acquired afterward. Irrespective of the change in the cost of acquisition, the treated firms always exhibit a disruption of their innovation activity (as measured by citation counts) in the post-acquisition period.

5 Conclusion

We have studied the effect of acquisitions of ex-ante innovative firms by incumbent BGs on the generation of patents and citations. The findings confirm that BGs tend to acquire standalone firms that exhibit an upward trend in innovation performance before acquisition. However, it was also found that target firms experience a significant decline in their post-acquisition innovating activity.

We attribute this decline in innovative activities to a specific strategy adopted by BGs, namely defensive acquisitions to mitigate competition. To support this hypothesis, we presented significant and robust evidence that acquired standalone firms with a patent portfolio similar to that of the acquiring BG experience a significant post-acquisition drop in the number of their cited patents. On the other hand, acquired firms innovating in a technological space different from that of the acquiring BG maintain their positive innovation trend after acquisition. These results are confirmed by acquisitions that take place within the same industry, or acquisitions in an industry characterized by high concentration or an increasing average age of the leading firms, as proxies for innovation appropriability.

These findings are consistent with the hypothesis that BGs actively engage in defensive acquisitions to mitigate competitive threats. This reduces the diffusion of knowledge, thereby preserving their market dominance. At the same time, they endeavor to acquire firms in innovation spaces complementary to their own.

The findings thus contribute to the existing literature by shedding light on several mechanisms that can explain the slower pace of knowledge diffusion in developed countries.

Finally, the research underscores the multifaceted nature of the relationship between innovation and strategic acquisitions. With respect to future directions for research, preliminary evidence reported in our analysis calls for further exploration of these dynamics, in particular the organization of knowledge within BGs once an innovative firm has been acquired.

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Appendix

A Acquisitions by industry

In the clean data, there are 17,722 firms that were acquired during the sample period, of which 7.6% were acquired more than once. We focus on the 15,493 firms acquired only once, and exclude 861 for which the industry information is missing. Acquisitions in our sample are observed in the 87 2-digit NACE industries listed below, which are dominated by high-tech industries such as Wholesale Trade (except motor vehicles), Scientific Research and Development, Manufacture of Computer, Electronic and Optical products, and Manufacture of Machinery.

Table A1: Breakdown of acquisitions by industry

NACE code	Description	Nbr. Acquisitions	NACE code	Description	Nbr. Acquisitions
46	Wholesale except motor vehicles	1337	9	Mining support service activities	50
72	Scientific R&D	1325	14	Manufacture of wearing apparel	42
26	Manufacture of computer, electronic, optical prod	1291	49	Land transport and via pipelines	39
28	Manufacture of machinery and equipment n.e.c.	1269	1	Crop and animal production	37
62	Computer programming, consultancy	851	59	Multimedia services	37
71	Architectural and engineering	743	38	Waste collection, treatment and disposal activities	34
25	Manufacture of fabricated metal prod	621	81	Services to buildings and landscape	30
32	Other manufacturing	618	85	Education	29
27	Manufacture of electric equipment	542	11	Manufacture of beverages	28
20	Manufacture of chemicals products	476	56	Food and beverage services	26
82	Office admin, office support and other business support	432	80	Security services	22
22	Manufacture of rubber and plastic	418	93	Sports activities and amusement	20
74	Other professional, scientific and technical activities	401	55	Accommodation	14
21	Manufacture of basic pharmaceutical products	385	36	Water collection, treatment and supply	13
29	Manufacture of motor vehicles, trailers	338	6	Extraction of crude petroleum and natural gas	13
70	Activities of head offices; consultancy	334	19	Manufacture of coke and refined petroleum products	12
47	Retail except motor vehicles	320	65	Insurance	11
64	Financial intermediation	319	7	Mining of metal ores	11
58	Publishing	255	15	Manufacture of leather and related	11
43	Specialised construction	200	78	Employment activities	11
10	Manufacture of food	163	60	Programming and broadcasting activities	11
86	Human health activities	147	3	Fishing and aquaculture	10
23	Manufacture of non-metallic mineral products	143	75	Veterinary activities	10
30	Manufacture of other transport equipment	139	79	Travel services	9
24	Manufacture of basic metals	129	8	Other mining and quarrying	9
61	Telecommunications	121	12	Manufacture of tobacco	9
63	Information services	117	90	Creative, arts and entertainment activities	8
77	Rental and leasing activities	114	94	Activities of membership organisations	8
68	Real Estate activities	110	37	Sewerage	8
13	Manufacture of textiles	110	88	Social work activities without accommodation	7
96	Other personal service activities	102	95	Repair of computers and personal and household goods	7
45	Wholesale, retail and repair of motor vehicles	100	92	Gambling and betting activities	6
35	Electricity, gas, steam and air conditioning supply	100	98	Undifferentiated goods and services of households	6
33	Repair and installation of machinery	96	50	Water transport	5
66	Other financial activities	83	51	Air transport	5
17	Manufacture of paper products	80	84	Public administration and defence	5
69	Legal and accounting	76	53	Postal and courier activities	4
73	Advertising and market research	73	39	Remediation activities and other waste management services	4
31	Manufacture of furniture	73	2	Forestry and logging	4
41	Construction of buildings	69	91	Libraries, archives, museums and other cultural activities	3
52	Warehousing and support for transportation	65	87	Residential care activities	3
16	Manufacture of wood, cork, straw and plaiting	63	99	Activities of extraterritorial organisations	1
42	Civil engineering	61	5	Mining of coal and lignite	1
18	Printing and reproduction of recorded media	51			

Notes: Number of standalone firm acquisitions in the sample by industry classified at the NACE 2-digit level. We exclude firms that get acquired more than once during the period. This results in a total of 15,493 acquisitions.

B The acquisition premium

Table A2 presents the relationship between the innovation activity of a standalone firm, as measured by number of patents and citations, and its probability of being acquired by a BG. Specifically, and as outlined in Section 2, we assess a firm's innovation level using two proxies: (i) the number of citations received, and (ii) the number of patents. In the case of both, we examine their value at a specific point in time (Panel A of Table A2), as well as their accumulation over a specific time span (Panel B). Ignoring fixed effects, column 1 of Panel A in Table A2 presents the estimation results for the following specification:

$$Acquired_{i,t} = \alpha + \beta \; ln(Citations{+}1)_{i,t-1} + u_{i,t} \tag{3}$$

where i denotes a generic firm and t a generic year; $Acquired_{i,t}$ is a dummy variable that equals one if firm i becomes part of a BG in year t; and $ln(Citations{+}1)_{i,t-1}$ is firm's i number of citations (logged) in year *t-1* (plus one). Including firm and year fixed effects makes it possible to exploit within-firm variation in the data. The sample for this estimation includes all standalone firms acquired once or not at all during the sample period (2007-2018).

Column 1 indicates that a higher number of citations is associated with a greater likelihood of the firm being acquired by a BG. Column 2 repeates the analysis of the first column except that the number of patents replaces the number of citations. The results confirm that when a firm's patenting activity increases, it is more likely to be acquired by a BG.

In columns 3 and 4 of Panel A, we restrict the analysis to firms with at least one citation or one patent in the period *t-1* and the results remain unchanged. Taken together, these results confirm that when firms increase their level of citations and/or patents, they are more likely to be acquired by a BG in the following period.

Panel B of Table A2 focuses on a firm's lagged inventory of citations/patents. The inventory of citations or patents accumulated in the previous three years *(t-3,t-1)* is used as an explanatory variable in columns 1 and 2, respectively. In columns 3 and 4, the analysis is repeated for firms with at least one citation or one patent during the sample period *(t-3,t-1)*.

The results confirm that an increase in a firm's citation level and/or patent count at a specific point in time, or an increase in their patent inventory over a given period, is associated with a higher likelihood of acquisition by a BG.

We demonstrate below that (i) this result is predominantly driven by firms in the highest category of citation/patenting intensity, as shown in Table A3, and (ii) distinguishing between the effects of cited and uncited patents does not change our findings, as detailed in Table A4.

Table A2: Patents and the probability of acquisition

	(1)	(2)	(3)	(4)
Dep. Variable	Acquired(i,t)			
Sample	Full		Citations(i,t-1)>0	Patents(i,t-1)>0
Panel A: Lagged patents				
log(Citations+1) (i,t-1)	0.0010***		0.0012**	
	(0.000)		(0.001)	
log(Patents+1) (i,t-1)		0.0026***		0.0028***
		(0.000)		(0.001)
Obs.	1,133,357	1,133,357	77,264	158,696
R2	0.107	0.107	0.0661	0.0666
Panel B: Lagged patent stock				
log(Citations+1) (i,t-3,t-1)	0.0014***		0.0046***	
	(0.000)		(0.001)	
log(Patents+1) (i,t-3,t-1)		0.0030***		0.0071***
		(0.000)		(0.001)
Obs.	882,459	882,459	52,092	109,976
R2	0.121	0.121	0.0766	0.0710
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Notes: All standalone firms i acquired once or not at all during the period 2007-2018. Acquired (i,t): a dummy that equals 1 if firm i is acquired by a BG in year t, zero otherwise. Log(Citations+1) (i,t-1): 3-year forward count of citations received for firm i's patents in year t-1. Log(Patents+1) (i,t-1): number of firm i's patents in year t-1. Log(Citations+1) (i,t-3,t-1): total of citations received for patents during the period t-3 to t-1. Log(Patents+1) (i,t-3,t-1): number of patents submitted by firm i during the period t-3 to t-1. Column (3) relates to the sub-sample of firms that receive at least one citation in year t-1, and column (4) relates to the sub-sample of firms that have at least one patent in year t-1. Standard errors are clustered at the firm level and reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

In Table A3, we disentangle the intensive margin of the correlation highlighted in Table A2 by replacing the explanatory variable in equation (3) with two dummy variables, which indicate whether the firm's number of citations is below or equal to the median (*Citations Low*), or above the median (*Citations High*), where the omitted group is number of patents (citations) equal to zero. Therefore, in columns 1 and 2 of Table A3, Panel A, we estimate the following specification while ignoring fixed effects, where the control group is uncited firms in year t-1:

$$Acquired_{i,t} = \sigma + \eta \; Citations\ Low_{i,t-1} + \rho \; Citations\ High_{i,t-1} + e_{i,t} \tag{4}$$

The estimation shows that the result is mainly driven by firms in the highest quantile of citations. This remains the case when we examine different categories of innovation intensity in terms of number of patents. Repeating the same dummy analysis with patents, we see that firms with an above-median level of patents (*Patents High*) are more likely to be acquired than firms below the median (*Patents Low*) and firms without any patents. These results continue to hold if we restrict the analysis to firms with at least one citation or patent (see columns 3 and 4 of Table A3) and when we consider the inventory of citations/patents, rather than the flow (see Panel B). Table A4 expands on the findings in Table A2 by examining the potential differential impact of cited and uncited patents. Specifically, we repeat the analysis conducted in Table A2, while distinguishing between the heterogeneous effects of cited and uncited patents (columns 1 and 3 and columns 2 and 4, respectively). Panels A and B delve further into the heterogeneous effects by considering the inventory of patents in the previous period (A) and the cumulative number of patents over the three preceding periods (B). Interestingly, the results are consistent across these analyses, suggesting that they are robust to this differentiation. We observe a positive and significant effect in all specifications examined.

Table A3: Innovation intensity and acquisitions

	(1)	(2)	(3)	(4)
Dep. Variable	Acquired(i,t)			
Sample	Full		Citations(i,t-1)>0	Patents(i,t-1)>0
Panel A: Lagged Patents				
Citations Low (i,t-1)	0.0012***			
	(0.000)			
Citations High (i,t-1)	0.0023***		0.0011	
	(0.001)		(0.001)	
Patents Low (i,t-1)		0.0016***		
		(0.000)		
Patents High (i,t-1)		0.0035***		0.0016**
		(0.000)		(0.001)
Obs.	1,133,357	1,133,357	77,264	158,696
R2	0.107	0.107	0.0660	0.0665
Panel B: Lagged patent stock				
Citations Low (i,t-1)	0.0018***			
	(0.000)			
Citations High (i,t-1)	0.0029***		0.0053***	
	(0.000)		(0.001)	
Patents Low (i,t-1)		0.0022***		
		(0.000)		
Patents High (i,t-1)		0.0042***		0.0057***
		(0.000)		(0.001)
Obs.	882,459	882,459	52,092	109,976
R2	0.121	0.121	0.0761	0.0706
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Notes: All standalone firms i acquired once or not at all during the period 2007-2018. Acquired (i,t): a dummy that equals 1 if firm i is acquired by a BG in year t, zero otherwise. Citations Low (High) (i,t-1): a dummy variable that equals 1 if the 3-year forward count of citations received for firm i's patents in year t-1 is below or equal (above) to the median. Patents Low (High) (i,t-1): a dummy that equals 1 if the number of firm i's patents in year t-1 is below or equal (above) to the median. Column (3) relates to the sub-sample of firms that receive at least one citation in year t-1, and column (4) relates to the sub-sample of firms that have at least one patent in year t-1. Standard errors are clustered at the firm level and reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A4: Innovation, citations, and acquisitions

	(1)	(2)	(3)	(4)
Dep. Variable	Acquired(i,t)			
Sample	Full		Patents(i,t-1)>0	
Panel A: Lagged patents				
log(Cited Patents+1) (i,t-1)	0.0021***		0.0014**	
	(0.000)		(0.001)	
log(Uncited Patents+1) (i,t-1)		0.0030***		0.0015**
		(0.000)		(0.001)
Obs.	1,133,357	1,133,357	158,696	158,696
R2	0.107	0.107	0.0665	0.0665
Panel B: Lagged patent stock				
log(Cited Patents+1) (i,t-3,t-1)	0.0026***		0.0040***	
	(0.000)		(0.001)	
log(Uncited Patents+1) (i,t-3,t-1)		0.0035***		0.0057***
		(0.000)		(0.001)
Obs.	882,459	882,459	109,976	109,976
R2	0.121	0.121	0.0705	0.0708
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Notes: All standalone firms i acquired once or not at all during the period 2007-2018. Acquired (i,t): a dummy that equals 1 if firm i is acquired by a BG in year t, zero otherwise. Log(Cited Patents+1) (i,t-1): number of firm i's cited patents in year t-1. Log(Uncited Patents+1) (i,t-1): number of firm i's uncited patents in year t-1. Log(Cited Patents+1) (i,t-3,t-1): number of firm i's cited patents during the period t-3 to t-1. Log(Uncited Patents+1) (i,t-3,t-1): number of firm i's uncited patents during the period t-3 to t-1. Columns (3) and (4) relate to the sub-sample of firms that have at least one patent in year t-1. Standard errors are clustered at the firm level and reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

To understand the difference between standalone firms that were acquired and those that were not, we regress a set of five firm-level characteristics on a dummy that equals one if a standalone firm is acquired, and zero otherwise. We focus only on the pre-acquisition period. The chosen dependent variables are age, employment, turnover, assets and liabilities. The regression also includes year fixed effects and all other firm-level characteristics not used as the dependent variable in the regression. We exclude post-acquisition periods so as not to capture the effect of acquisition. Data coverage is significantly reduced when balance sheet data is included. Table A5 reports the results for 4,243 firms that were acquired and 24,651 that were not and for which we observe firm-level data. The results indicate that firms that were acquired are on average younger, bigger, and have more assets and liabilities than their never-acquired peers. This evidence suggests that BGs cherry-pick by choosing young high-performing firms.

Table A5: The acquisition premium

	(1)	(2)	(3)	(4)	(5)
Dep. Variable	Age (i,t)	Employment (i,t)	Turnover (i,t)	Assets (i,t)	Liabilities (i,t)
Eventually acquired (i)	-0.2009***	0.2117***	0.0541**	0.0565*	0.1148***
	(0.016)	(0.018)	(0.024)	(0.032)	(0.028)
Obs.	153,170	153,170	153,170	153,170	153,170
R2	0.258	0.628	0.673	0.588	0.522
Year FE	Yes	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	Yes	Yes

Notes: Differences between acquired firms (in the pre-acquisition period) and never-acquired firms. All the dependent variables are at the firm-year level with an added unit and logged. Eventually acquired (i) is a firm-level dummy for all pre-acquisition periods that equals one if a standalone firm is eventually acquired, and zero if the firm is never acquired by a BG. Post-acquisition periods for acquired firms are excluded from the regression. The set of firm-level controls includes age, employment, turnover, assets, liabilities and number of patents. We exclude from each specification the dependent variable from the firm-level controls. Standard errors are clustered at the firm level and reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

C Additional Tables

In this section, we present additional tables that are discussed but not included in the main text, and some additional estimation equations.

C.1 Acquisitions and the innovation level of acquired firms

The following equation (equation (1) in Section 3.1), excluding fixed effects, is used in the estimation presented in Figure 1, while Table A6 presents the estimated coefficients:

$$Y_{i,t} = \theta + \sum_{t=-11;t\neq-1}^{+10} \delta_t \, T_{i,t} + \lambda_i + \alpha_t + \eta_{i,t}$$

where, $Y_{i,t}$ is the measure of innovation: either (i) number of citations, (ii) number of patents, (iii) number of cited patents, or (iv) number of uncited patents; logged and incremented by one unit. $T_{i,t}$ are period-specific dummies (which are also firm-specific, since we re-scale all the years with respect to the firm-specific acquisition year). The estimation includes firm and year fixed effects. Thus, the coefficients δ_t, for t ranging from -11 to 10, indicate the average within-firm effect of acquisition on the outcome variable , relative to the year before acquisition and the control group.

C.2 Acquisitions and the level of innovation of acquired firms by technological similarity

The following equation (equation (2) in Section 3.2), excluding fixed effects, is used in the estimation presented in Figure 3, while Table A7 presents the estimated coefficients:

$$Y_{i,t} = \omega + \sum_{t=-11;t\neq-1}^{+10} \gamma_t \, (T_{i,t} \times \mathit{SameTech}_i) + \sum_{t=-11;t\neq-1}^{+10} \eta_t \, (T_{i,t} \times \mathit{DifferentTech}_i) + e_{i,t}$$

where, $Y_{i,t}$ is either the number of citations or patents (both logged and incremented by one unit). $T_{i,t}$ are period-specific dummies (which are also firm-specific, since we re-scale all the years with respect to the firm-specific acquisition year). The dummy variable $\mathit{SameTech}_i$ equals one if the pre-acquisition technological class of the acquired firm closely matches that of the acquiring BG. Conversely, the dummy variable $\mathit{DifferentTech}_i$ indicates dissimilarity in technological class. All of the estimations include firm and year fixed effects. Thus, the coefficients γ_t, for t ranging from -11 to 10, indicate the average effect on the outcome variable Y, relative to the year before acquisition, for firms with a technology portfolio similar to that of the acquiring BG. The coefficients η_t capture the analogous effects for acquired standalone firms with different technology portfolios.

Table A6: Effect of acquisition on patenting activity of acquired firms

	(1)	(2)	(3)	(4)
Dep. Variable	Citations(i,t)		Patents(i,t)	
Sample	All	All	Cited Patents(i,t)	Uncited Patents(i,t)
Pre 11	-0.0382*	-0.1007***	-0.0229*	-0.0847***
	(0.022)	(0.017)	(0.012)	(0.013)
Pre 10	-0.0704***	-0.0956***	-0.0472***	-0.0614***
	(0.015)	(0.013)	(0.009)	(0.010)
Pre 9	-0.0674***	-0.0818***	-0.0355***	-0.0543***
	(0.012)	(0.011)	(0.007)	(0.009)
Pre 8	-0.0514***	-0.0616***	-0.0296***	-0.0398***
	(0.011)	(0.010)	(0.006)	(0.008)
Pre 7	-0.0574***	-0.0651***	-0.0349***	-0.0402***
	(0.010)	(0.009)	(0.006)	(0.007)
Pre 6	-0.0374***	-0.0521***	-0.0195***	-0.0381***
	(0.009)	(0.008)	(0.005)	(0.006)
Pre 5	-0.0275***	-0.0326***	-0.0164***	-0.0231***
	(0.008)	(0.007)	(0.005)	(0.006)
Pre 4	-0.0017	-0.0175***	-0.0032	-0.0161***
	(0.008)	(0.007)	(0.005)	(0.005)
Pre 3	0.0033	0.0001	-0.0013	0.0002
	(0.007)	(0.006)	(0.004)	(0.005)
Pre 2	0.0083	0.0041	0.0029	0.0010
	(0.006)	(0.005)	(0.004)	(0.004)
Post 0	-0.0038	0.0050	0.0006	0.0050
	(0.006)	(0.005)	(0.003)	(0.004)
Post 1	-0.0061	0.0092*	-0.0025	0.0115**
	(0.006)	(0.005)	(0.004)	(0.005)
Post 2	-0.0075	0.0124**	0.0003	0.0167***
	(0.007)	(0.006)	(0.004)	(0.005)
Post 3	-0.0169**	0.0102	-0.0055	0.0154***
	(0.008)	(0.007)	(0.005)	(0.006)
Post 4	-0.0130	0.0267***	-0.0039	0.0290***
	(0.008)	(0.008)	(0.005)	(0.007)
Post 5	-0.0336***	0.0113	-0.0204***	0.0229***
	(0.009)	(0.009)	(0.006)	(0.008)
Post 6	-0.0290***	0.0086	-0.0191***	0.0146
	(0.011)	(0.010)	(0.007)	(0.009)
Post 7	-0.0542***	0.0040	-0.0324***	0.0174
	(0.013)	(0.013)	(0.009)	(0.011)
Post 8	-0.0610***	0.0166	-0.0431***	0.0336**
	(0.016)	(0.015)	(0.011)	(0.014)
Post 9	-0.0530***	0.0105	-0.0411***	0.0247
	(0.019)	(0.020)	(0.013)	(0.018)
Post 10	-0.0899***	0.0468*	-0.0664***	0.0734***
	(0.028)	(0.027)	(0.020)	(0.025)
Obs.	1,302,739	1,302,739	1,302,739	1,302,739
R2	0.320	0.431	0.386	0.433
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Notes: All standalone firms i acquired once or not at all during the period 2007-2018. The independent variables are period dummies relative to the year of acquisition with the omitted category being the year of acquisition (Pre 1). Standard errors are clustered at the firm level and reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A7: The effect of acquisition on the patenting activity of acquired firms by patent portfolio similarity

Dep. Variable	(1) Citations(i,t)	(2) Patents(i,t)
Pre 11 × Same Tech	0.0897	-0.0295
	(0.057)	(0.046)
Pre 10 × Same Tech	0.0307	-0.0683*
	(0.043)	(0.035)
Pre 9 × Same Tech	0.0152	-0.0840***
	(0.035)	(0.030)
Pre 8 × Same Tech	0.0186	-0.0609**
	(0.030)	(0.026)
Pre 7 × Same Tech	0.0053	-0.0697***
	(0.026)	(0.022)
Pre 6 × Same Tech	-0.0026	-0.0802***
	(0.025)	(0.020)
Pre 5 × Same Tech	0.0150	-0.0403**
	(0.024)	(0.020)
Pre 4 × Same Tech	0.0514**	-0.0167
	(0.023)	(0.018)
Pre 3 × Same Tech	0.0386*	-0.0048
	(0.021)	(0.016)
Pre 2 × Same Tech	0.0695***	0.0232
	(0.019)	(0.014)
Post 0 × Same Tech	-0.0881***	-0.0780***
	(0.015)	(0.012)
Post 1 × Same Tech	-0.1272***	-0.1080***
	(0.017)	(0.014)
Post 2 × Same Tech	-0.1536***	-0.1156***
	(0.019)	(0.015)
Post 3 × Same Tech	-0.1770***	-0.1328***
	(0.021)	(0.017)
Post 4 × Same Tech	-0.2120***	-0.1367***
	(0.022)	(0.018)
Post 5 × Same Tech	-0.2603***	-0.1640***
	(0.023)	(0.019)
Post 6 × Same Tech	-0.2871***	-0.1968***
	(0.025)	(0.022)
Post 7 × Same Tech	-0.3310***	-0.2161***
	(0.027)	(0.025)
Post 8 × Same Tech	-0.3279***	-0.1887***
	(0.031)	(0.027)
Post 9 × Same Tech	-0.3142***	-0.2037***
	(0.033)	(0.030)
Post 10 × Same Tech	-0.3490***	-0.1779***
	(0.039)	(0.036)
(…)	(…)	(…)
(…)	(…)	(…)
Pre 11 × Different Tech	-0.0888**	-0.1060***
	(0.040)	(0.029)
Pre 10 × Different Tech	-0.0566*	-0.0689***
	(0.031)	(0.023)
Pre 9 × Different Tech	-0.0318	-0.0350
	(0.028)	(0.023)
Pre 8 × Different Tech	-0.0621***	-0.0344*
	(0.022)	(0.018)
Pre 7 × Different Tech	-0.0787***	-0.0517***
	(0.019)	(0.016)
Pre 6 × Different Tech	-0.0164	-0.0063
	(0.019)	(0.015)
Pre 5 × Different Tech	-0.0079	-0.0015
	(0.018)	(0.014)
Pre 4 × Different Tech	0.0036	0.0224
	(0.017)	(0.014)
Pre 3 × Different Tech	0.0181	0.0328***
	(0.016)	(0.013)
Pre 2 × Different Tech	0.0242	0.0367***
	(0.015)	(0.012)
Post 0 × Different Tech	0.0575***	0.0671***
	(0.014)	(0.012)
Post 1 × Different Tech	0.0735***	0.1055***
	(0.015)	(0.014)
Post 2 × Different Tech	0.0876***	0.1278***
	(0.016)	(0.014)
Post 3 × Different Tech	0.0901***	0.1364***
	(0.016)	(0.015)
Post 4 × Different Tech	0.0910***	0.1422***
	(0.017)	(0.016)
Post 5 × Different Tech	0.0951***	0.1514***
	(0.018)	(0.018)
Post 6 × Different Tech	0.0905***	0.1545***
	(0.019)	(0.020)
Post 7 × Different Tech	0.1014***	0.1476***
	(0.020)	(0.023)
Post 8 × Different Tech	0.0942***	0.1423***
	(0.022)	(0.027)
Post 9 × Different Tech	0.0898***	0.1169***
	(0.027)	(0.037)
Year FE	Yes	Yes
Firm FE	Yes	Yes

Notes: Standalone firms i acquired once during the period 2007-2018. The independent variables are period dummies relative to the year of acquisition with the omitted category being the year of acquisition (Pre 1). Standard errors are clustered at the firm level and reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A8: The effect of acquisition on the patenting activity of acquired firms by patent portfolio similarity and cited / uncited patents

	(1)	(2)
	Cited	Uncited
Dep. Variable	Patents(i,t)	Patents(i,t)
Pre 11 × Same Tech	0.0408	-0.0423
	(0.031)	(0.038)
Pre 10 × Same Tech	0.0113	-0.0662**
	(0.026)	(0.028)
Pre 9 × Same Tech	0.0120	-0.0763***
	(0.020)	(0.025)
Pre 8 × Same Tech	0.0091	-0.0596***
	(0.018)	(0.021)
Pre 7 × Same Tech	-0.0069	-0.0682***
	(0.015)	(0.018)
Pre 6 × Same Tech	-0.0036	-0.0768***
	(0.015)	(0.017)
Pre 5 × Same Tech	0.0062	-0.0504***
	(0.015)	(0.016)
Pre 4 × Same Tech	0.0267*	-0.0440***
	(0.014)	(0.015)
Pre 3 × Same Tech	0.0123	-0.0149
	(0.012)	(0.014)
Pre 2 × Same Tech	0.0318***	-0.0013
	(0.011)	(0.012)
Post 0 × Same Tech	-0.0417***	-0.0448***
	(0.010)	(0.011)
Post 1 × Same Tech	-0.0742***	-0.0565***
	(0.010)	(0.012)
Post 2 × Same Tech	-0.0804***	-0.0565***
	(0.012)	(0.013)
Post 3 × Same Tech	-0.0997***	-0.0690***
	(0.013)	(0.014)
Post 4 × Same Tech	-0.1169***	-0.0627***
	(0.014)	(0.015)
Post 5 × Same Tech	-0.1557***	-0.0723***
	(0.015)	(0.017)
Post 6 × Same Tech	-0.1759***	-0.0987***
	(0.017)	(0.019)
Post 7 × Same Tech	-0.2001***	-0.1091***
	(0.019)	(0.022)
Post 8 × Same Tech	-0.2043***	-0.0817***
	(0.022)	(0.025)
Post 9 × Same Tech	-0.1960***	-0.1093***
	(0.023)	(0.027)
Post 10 × Same Tech	-0.2345***	-0.0614*
	(0.027)	(0.034)
(…)		
(…)		
Pre 11 × Different Tech	-0.0488**	-0.0735***
	(0.022)	(0.023)
Pre 10 × Different Tech	-0.0335**	-0.0474**
	(0.015)	(0.019)
Pre 9 × Different Tech	-0.0083	-0.0278
	(0.016)	(0.017)
Pre 8 × Different Tech	-0.0338***	-0.0107
	(0.012)	(0.015)
Pre 7 × Different Tech	-0.0417***	-0.0159
	(0.011)	(0.013)
Pre 6 × Different Tech	-0.0085	0.0001
	(0.011)	(0.012)
Pre 5 × Different Tech	0.0000	0.0008
	(0.010)	(0.011)
Pre 4 × Different Tech	-0.0042	0.0287***
	(0.009)	(0.011)
Pre 3 × Different Tech	0.0086	0.0272***
	(0.008)	(0.010)
Pre 2 × Different Tech	0.0140*	0.0274***
	(0.008)	(0.009)
Post 0 × Different Tech	0.0370***	0.0403***
	(0.008)	(0.010)
Post 1 × Different Tech	0.0553***	0.0723***
	(0.009)	(0.011)
Post 2 × Different Tech	0.0607***	0.0945***
	(0.009)	(0.012)
Post 3 × Different Tech	0.0654***	0.1002***
	(0.010)	(0.013)
Post 4 × Different Tech	0.0616***	0.1061***
	(0.010)	(0.013)
Post 5 × Different Tech	0.0662***	0.1163***
	(0.012)	(0.015)
Post 6 × Different Tech	0.0649***	0.1220***
	(0.012)	(0.017)
Post 7 × Different Tech	0.0667***	0.1108***
	(0.013)	(0.020)
Post 8 × Different Tech	0.0529***	0.1132***
	(0.014)	(0.024)
Post 9 × Different Tech	0.0491***	0.0920***
	(0.018)	(0.034)
Year FE	Yes	Yes
Firm FE	Yes	Yes

Notes: Standalone firms i acquired once during the period 2007-2018. The independent variables are period dummies relative to the year of acquisition with the omitted category being the year of acquisition (Pre 1). Standard errors are clustered at the firm level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

D Technological similarity between patent portfolios

In this appendix, we explain in detail the procedure used to create an indicator of similarity between the patent portfolios of an acquired firm and the acquiring BG.[32]

We determine the technology class of each patent application according to the International Patent Classification (IPC) and classify them into 35 goups based on the World Intellectual Property Organization (WIPO)'s aggregation of IPC classes. To do so, we first collect information on the WIPO classes of all patent applications for each acquired firm from the first year of the data, i.e. 2007, until the year before acquisition. Similarly, we collect that same information for all patent applications submitted by the acquiring BG, whether applied for by the parent or an affiliate, from 2007 to the year before acquisition. We can then compute the number of common technological classes between the acquiring BG and the acquired firm, conditional on observing at least one patent application by each. This reduces the sample significantly to 5,690 acquisitions (38.5%).[33]

We then define the proportion of common technological classes between acquired firm i and acquiring BG j in year *pre 1* (the year before acquisition) and define $\textit{Share common classes}_{i,j,pre1}$ as the ratio of the number of common technological classes, denoted by $\textit{Nbr. common classes}_{ij,pre1}$, to the total number of technological classes in the BG patent portfolio, denoted by $\textit{Nbr. classes}_{j,pre1}$. Thus:

$$\textit{Share common classes}_{i,j,pre1} = \frac{\textit{Nbr. common classes}_{ij,pre1}}{\textit{Nbr. classes}_{j,pre1}} \tag{5}$$

This ratio takes a value between zero and one. The value zero corresponds to no overlap between the acquired firm's space of innovation and that of the acquiring BG. In other words, the acquired firm is patenting in a different technology space than the BG. The value one corresponds to an acquired firm that is innovating in the same technological classes as the BG. Hence, this measure captures the level of competition/complementarity between their patent portfolios.

This measure suffers from data truncation since we only observe data starting in 2007, which systematically generates a smaller patent overlap of patent portfolios for acquisitions earlier in the sample period. This is so because we observe more years in the pre-acquisition period for acquisi-

[32] Various methods have been proposed to measure patent similarity. Part of the literature utilizes the technological classes in the International Patent Classification [Zhang et al., 2016, Boyack and Klavans, 2008]. Citations are also used as a measure of technological similarity, based on the approaches of co-citations, i.e. forward citations shared by two patents, and bibliographic coupling, i.e. number of joint backward citations [Yan and Luo, 2017]. Another alternative is direct and indirect citation paths [Wu et al., 2010]. More recent studies have promoted the use of text-based approaches, which analyze the content of patents, including titles, keywords, and abstracts, to determine technological similarity [Arts et al., 2018, Hain et al., 2022, Arts et al., 2021].

[33] This is in part driven by data truncation, as discussed later in this appendix.

tions later in the period, allowing for more opportunities to observe a patent portfolio overlap in technological classes. In order to mitigate this bias, we consider the residual from a regression of the proportion of common technological classes, as previously defined, on the acquisition year fixed effect, which is meant to capture this systematic bias:

$$\textit{Share common classes}_{ij,pre1} = \beta + \lambda_{t0} + \epsilon_{ij,pre1} \tag{6}$$

where β is a constant, λ_{t0} is the acquisition year fixed effect and $\epsilon_{ij,pre1}$ is the adjusted proportion of common technological classes after subtracting the acquisition year fixed effect.

Finally, we define acquisitions with similar technologies as those with a level higher than or equal to the median level of the adjusted proportion of common technological classes, while acquisitions with different technologies are those with a level below the median.

E The effect of acquisitions on a BG

This appendix presents preliminary findings for the effect of acquisitions on the innovation and performance of BG affiliates. However, it is important to stress that this requires a comparison of BGs before and after the acquisition of a standalone firm, while taking into account any other factors that might affect these outcomes. Therefore, we need to restrict the analysis to BGs that did not acquire/sell any other affiliate in the year before and the year after the relevant acquisition. Moreover, when we include balance sheet information, the number of observations decreases to an even greater extent. Therefore, the anecdotal evidence presented in this section must be treated with caution and is only intended to provide directions for future research.

Table A9 focuses on affiliates of acquiring BGs that undergo no change in composition (with the exception of the acquisition of a standalone firm) during the first post-acquisition year. The results A9 show no effect on the within-affiliate number of citations or level of patenting activity (columns 1 to 4). In contrast, two measures of affiliate performance, namely turnover and number of employees, show a post-acquisition increase in profitability and size.

Table A9: Effect on a BG

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	Citations(i,t)	Patents(i,t)			Turnover	Employment
Sample	All	All	Cited Patents(i,t)	Uncited Patents(i,t)	All	All
Post	-0.0132	-0.0003	-0.0073	-0.0100	0.3226***	0.1064**
	(0.036)	(0.029)	(0.024)	(0.019)	(0.097)	(0.043)
Obs.	1,557,975	1,557,975	1,557,975	1,557,975	1,557,975	1,557,975
R2	0.634	0.677	0.671	0.618	0.876	0.933
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

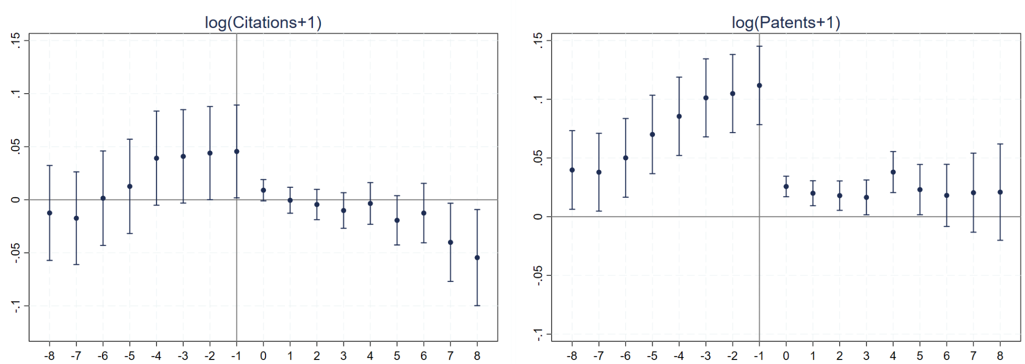
Notes: Estimated effect of the acquisition of a standalone firm on the acquiring BG affiliates' patenting activity and firm performance. The sample includes affiliates of acquiring BGs that undergo no change in structure, with the exception of the acquisition of a standalone firm, for at least 1 year pre- and 1 year post-acquisition. Post is a dummy equal to one for post-acquisition years for BG i, zero otherwise. Standard errors are clustered at the BG level and reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

F Difference-in-Differences with staggered treatment effects

In this section, we repeat the analysis presented in Figure 1 (as discussed in Section 3.1) except that we adopt the approach of difference-in-differences with staggered treatment, as proposed by Borusyak et al. [2024].

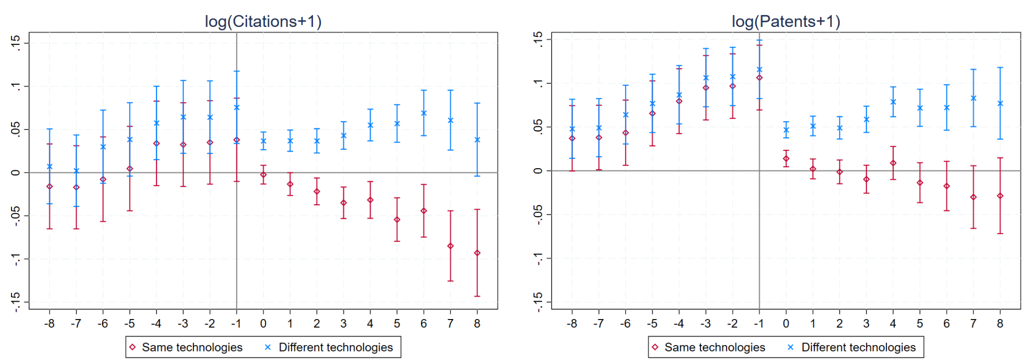
Figures A1 and A2 reaffirm the findings illustrated in Figure 1 and 3, respectively. Prior to acquisition, acquired firms outperform non-acquired firms, as measured by both the number of citations and the number of patents. However, following acquisition, they receive fewer citations and generate fewer patents than prior to their acquisition and fewer than the average for non-acquired firms. This effect is even more pronounced when the acquired firm has a patent portfolio in the same technological space as the acquiring BG, which reinforces the use of a defensive strategy. Figure 3 illustrates the effect of acquisition on acquired firms by technological class alignment between the acquired firm and the acquiring BG using a difference-in-differences estimation à la Borusyak et al. [2024]. Estimating the effect of acquisition for each sub-sample (one with similar patent portfolios and the other with different patent portfolios) is not possible in this setting. Thus, we estimate the effect of acquisition on each sub-sample separately and combine the results for citations in the left panel and the results for patents in the right panel, for ease of comparison.

Figure A1: The effect of acquisition on patenting activity of acquired firms, Borusyak et al. [2024]



Notes: The graphs present the results for the effect of acquisition on acquired firms patenting activity based on difference-in-differences estimation à la Borusyak et al. [2024], thus accounting for the staggered nature of the treatment (acquisitions). 95% confidence intervals are presented.

Figure A2: The effect of acquisition on patenting activity of acquired firms by similarity of innovation, Borusyak et al. [2024]



Notes: The graphs present the effect of acquisition on acquired firms by technological class alignment between the acquired firm and the acquiring BG based on difference-in-differences estimation à la Borusyak et al. [2024]. Since interactions are not possible in this setting, we estimate the effect of acquisition on the sub-sample of acquired firms with similar patent portfolios separated from the sub-sample with different patent portfolios. We combine the results for citations in the left panel and those for patents in the right panel. 95% confidence intervals are presented.

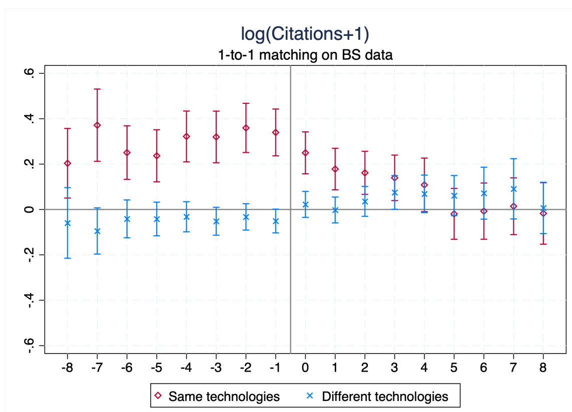
G Sample Matching

In this section, we provide details of the one-to-one matching between acquired and non-acquired firms used in the within-matched-pair estimation, as well as the matching presented in Section 4.

We start by performing a one-to-one propensity score matching in which each acquired firm is matched with the most similar non-acquired firm (based on age, turnover, and employment) within the same industry (NACE at the 2-digit level) and in the same (pre-acquisition) year. The within-matched-pair estimation includes firm-matched-pair and year fixed effects in order to compare the pre-trends and outcomes of each treated firm to those of the most similar non-acquired firm operating in the same industry.

Figure A3 presents the results for the effect of acquisition on the innovation of target firms. Reassuringly, the findings confirm that within the most comparable acquired/non acquired pairs, acquired firms in the same technological space are performing significantly better than non acquired firms and that their level of post-acquisition innovation is significantly lower. Meanwhile, in the case of dissimilar technologies, the acquired firms exhibit similar levels of pre-acquisition innovation relative to non-acquired firms and higher levels of innovation post-acquisition.

Figure A3: An alternative matching approach: one-to-one



Notes: Estimated within-matched-pair effect of the acquisition on acquired firms relative to the year of acquisition, and the most similar non-acquired firm, given the technological class of the acquired firm relative to the acquiring BG. The omitted period is the period before the acquisition (Pre 1). Same Technologies (Different Technologies) refer to acquisitions in which the acquired firm and the acquiring BG have similar (different) patent portfolios. Details appear in Appendix D. Estimation includes a matched-pair and year FE. Standard errors are clustered at the matched-pair level and 95% confidence intervals are presented.

The analysis presented in Figure 5 is a repetition of that in Figure 3, except that only matched non-acquired firms serve as the control group. In that sense, the sample of matched non-treated firms is pooled and results can be interpreted as the impact of acquisition on acquired firms relative to non-acquired firms with similar characteristics.

H An exogenous Policy Change

In order to explore potential alternative explanations, we examine an exogenous policy change that increased the cost of acquisitions while holding constant the probability of post-acquisition innovation suppression.

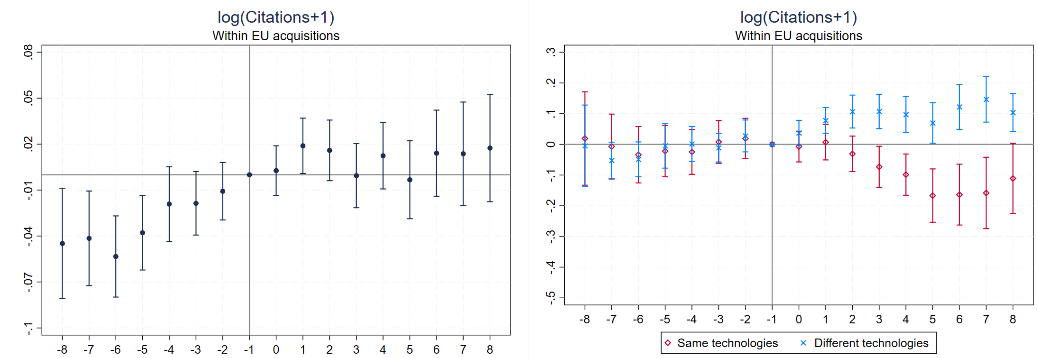
Specifically, we focus on the adoption of the Antitrust Damages Directive (Directive 2014/104/EU) by the European Union in November 2014. Its aim was to facilitate the process by which victims of anti-competitive practices can seek damages and it introduced several key provisions to achieve that goal. First, it mandated measures to improve access to evidence possessed by parties involved in antitrust violations, thereby enhancing the transparency of legal proceedings. Second, it harmonized rules on limitation periods for submitting damage claims across EU member states, thus achieving a uniform time frame for claims. The directive also established that national court decisions on competition law infringements would have a binding effect in subsequent damage claims, thus promoting legal certainty and predictability. These provisions collectively increased the legal and financial risks associated with mergers and acquisitions within the EU, as firms faced heightened scrutiny and potential liability when engaging in anti-competitive behaviours. Indeed, our data show that acquisitions increased steadily in the EU until 2014, declined by some 15% in 2015, and continued to decline in subsequent years.

The implementation of antitrust policy in an acquisition depends on the jurisdiction/location of both the acquiring and acquired firms. Therefore, we focus on the acquisitions of firms located in the EU by BGs also located in the EU. This subset comprises 33.7% of all acquisitions in the dataset. Since this is significantly different from the total number of acquisitions used in the rest of the paper, we first show that our main result is robust to using the aforementioned sub-sample of firms.

Figure A4 is analogous to Figure 1 (left panel) and Figure 3 (right panel) except that it is based on the 5,225 EU acquisitions (out of 15,493), and uses the standalone firms as the control group. Reassuringly, the results are fully consistent with those obtained in sections 3.1 and 3.2 using the entire sample.

In order to delve deeper into the effect of acquisition on acquired firms, before and after the policy change, Figure A5 presents a comparison of the two periods. The control group consists of standalone firms, while the treated group consists of 3,412 firms acquired before the policy change, and 1,813 firms acquired afterward. The graph shows the estimated effect on citations, with the blue markers representing acquisitions before the policy change and the red markers representing acquisitions after the policy change.

Figure A4: Repetition of the analysis using only within-EU acquisitions

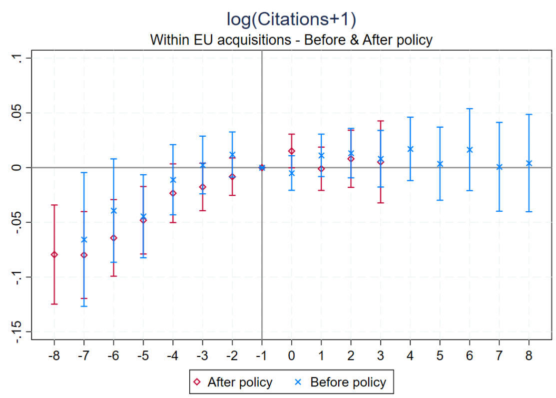


Notes: Estimated effect of acquisition on acquired firms relative to the year of acquisition and relative to non-acquired firms, given the technological class alignment between the acquired firm and the acquiring BG. The sample of acquired firms is limited to within-EU acquisitions and accounts for 33.7% of all acquisitions. The omitted period is the period before the acquisition (Pre 1). *SameTech* (*DifferentTech*) refers to acquisitions in which the acquired firm and the acquiring BG have very similar (different) patent portfolios. Estimations include firm and year FEs. Standard errors are clustered at the firm level and 95% confidence intervals are presented.

The analysis indicates no significant differences in pre-trend and post-acquisition outcomes between firms acquired before and after the policy change. This suggests that the policy change did not substantially affect the innovation performance of the acquired firms, as measured by citation counts. Both groups exhibit similar trends, with no notable deviations in the post-acquisition trajectory of citation effects.

Reassuringly, these results align with our broader findings, thus reinforcing the robustness of our main conclusions. Despite the exogenous increase in acquisition costs due to the policy change, the innovation activity of acquired firms remained unchanged, indicating that other factors play a more critical role in determining post-acquisition innovation performance.

Figure A5: A comparison of within-EU acquisitions (before/after a policy change)



Notes: Estimated effect of acquisition on acquired firms relative to the year of acquisition and relative to non-acquired firms. The sample of acquired firms is limited to within-EU acquisitions and accounts for 33.7% of all acquisitions. The omitted period is the period before the acquisition (Pre 1). *Before policy* (*After policy*) relates to 3,412 (1,813) within-EU acquisitions before end of 2014 (starting from 2015). Estimations include firm and year FEs. Standard errors are clustered at the firm level and 95% confidence intervals are presented.