Centre for Economic Performance

Discussion Paper

ISSN 2042-2695

No. 1996
April 2024

Business groups, strategic acquisitions and innovation

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Abstract
We build a novel worldwide database merging information on patent-citations of firms paired with information on firms' affiliation to Business Groups (BGs). We exploit these data to document how BGs appropriate knowledge through standalone firm acquisition. First, we confirm that innovative standalone firms have a higher probability of becoming part of a BG. Second, we document how BGs tend to acquire firms that are on an upward trend in patents and citations. We also show that innovating activity significantly deteriorates post-acquisition, particularly for firms with high-quality, cited patents. Third, we show that such a deterioration in innovation activity is driven by acquired firms patenting within the same technological classes of the acquiring BG, while the latter does not hold for acquired firms patenting in different technologies than the BG's. We also find that acquisitions occurring in environments characterized by higher market concentration and more mature leading firms are associated with a relatively more pronounced reduction in innovation. These results generalize the defensive acquisition narrative, suggesting that BGs leverage these transactions as a strategic manoeuvre to solidify their market position in the face of potential competition.

Keywords: business groups, innovation

This paper was produced as part of the Centre's Growth Programme. The Centre for Economic Performance is financed by the Economic and Social Research Council.

We thank for their valuable comments and suggestions Ufuk Akcigit, Jan Bakker, Italo Colantone, Beata Javorcik, Myriam Mariani, Gianmarco Ottaviano, Armando Rungi. We are grateful for their comments to participants in seminars at Bocconi University, the CompNet EIB Conference, European Trade Study Groups conferences, and the PRIN Meeting at Rimini.

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Published by
Centre for Economic Performance
London School of Economic and Political Science
Houghton Street
London WC2A 2AE

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1 Introduction

Recent research has drawn attention to a concerning slowdown in business dynamism in the United States, coinciding with an increase in market concentration, primarily attributed to a decline in the diffusion of knowledge [Akcigit and Ates, 2022]. Business groups (BGs) play a crucial role in generating and diffusing knowledge, with multinational enterprises contributing roughly half of global R&D spending and at least two-thirds of corporate R&D investments [UNCTAD, 2005, 2016]. Still, preemptive acquisitions aimed at eliminating potential future competitors by the same BGs could lead to increased consolidation, hampering the spread of knowledge to smaller firms.

Given the potentially ambiguous role of BGs in knowledge diffusion, in this paper, we present a comprehensive empirical examination of the relationship between the strategic acquisition behaviour of BGs and the innovation outcomes of acquired firms at the world level.

To that extent, we rely on two primary data sources: the Orbis Intellectual Property database, which provides detailed information on firms' patenting activities, and the Orbis Ownership Database, which outlines the boundaries of Business Groups, and their changes over time due to, e.g., acquisitions. These two datasets are matched, and complemented by additional balance-sheet data from Orbis and market concentration data from CompNet. In defining BGs, the paper adopts the criteria that a BG consists of a parent company owning (directly or indirectly) more than 50.01% equity in at least one affiliate, simplifying the analysis to focus on the effects of BG affiliation and acquisitions on innovation, rather than the internal organizational complexities of BGs explored e.g. in 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.

The Ownership dataset encompasses over 6.3 million BGs and 12.8 million affiliates across more than 200 countries from 2007 to 2018. We match to that a novel firm-linked patent citation network dataset, including all patenting Orbis firms over the same period accounting for more than 19 million patent applications. The analysis further refines the data to focus on high-quality patents filed at major patent offices (EPO, USPTO, JPO), so as to capture significant and influential innovations.

Descriptive statistics reveal that although only a small percentage of firms in the sample are part of BGs, these firms account for a disproportionate share of innovation activities, as measured by patents and citations. This suggests an innovation premium associated with BG affiliation, consistently with findings of Belenzon and Berkovitz [2010], highlighting the importance of BGs in leveraging and enhancing innovation. Additionally, we observe how BGs tend to target young, high-performing standalone firms for acquisition. This not only reflects BGs' aspirations to integrate innovative capabilities, but also suggests a deliberate strategy to reinforce their competitive position in the marketplace.

More specifically, the paper outlines four main findings. First, we confirm a well-documented phenomenon: standalone firms exhibiting higher levels of innovation, quantified through citations and patent counts, significantly increase their likelihood of being acquired by BGs [Wu and Chung, 2019]. This initial finding establishes a foundational understanding of the selection criteria employed by BGs in their acquisition strategies.

Second, delving deeper into the post-acquisition phase, our study reveals a notable deterioration, on average, in the innovation output of acquired firms. This phenomenon is particularly evident when comparing these entities to their pre-acquisition trend and non-acquired counterparts, suggesting that the assimilation into a BG might (inadvertently or purposely) hamper the innovative momentum previously enjoyed by these standalone firms.[1]

Third, through an examination of the patent portfolios belonging to both the acquired firms and their respective BGs prior to the acquisition, we uncover a nuanced dynamic in the motives underpinning BG acquisitions. The evidence points towards a pronounced decline in innovation activities among acquired firms whose patent portfolios closely mirror those of their acquirers, while no similar effect is found for acquired firms patenting in technological classes different than the one of the acquiring group. This observation lends credence to the hypothesis that BGs may engage in defensive acquisitions to mitigate competitive threats, thereby preserving their market dominance.

Fourth, we find that acquisitions occurring in environments characterized by higher market concentration and an increasing average age of leading firms are associated with a stark reduction in innovation. This pattern aligns with the defensive acquisition narrative, suggesting that BGs leverage these transactions as a strategic manoeuvre to solidify their market position in the face of potential competition.

An extensive literature has explored knowledge creation and diffusion within BGs. It is widely agreed that BG affiliates tend to engage in innovative activities more than standalone firms [Belenzon and Berkovitz, 2010, Choi et al., 2011]. Additionally, cross-border innovation among affiliates of the same BG is notably pronounced when there is overlap in business hours [Bircan et al., 2021]. Moreover, firms' 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.,

[1] To correctly identify these effects, we employ Two-Way Fixed Effects Difference-in-Differences (TWFE DID) techniques with staggered treatment, as the current benchmark in the literature.

2021], thus emphasizing the importance of protecting innovation.

However, many critical aspects, which are particularly pertinent in the context of decreasing knowledge diffusion and rising concentration, remain under-explored. Specifically, there is limited understanding regarding 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] show evidence on the existence of "killer acquisitions", specifically in the pharmaceutical industry in the US, 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]. Conversely, alternative findings suggest a positive effect of acquisitions on the innovation capabilities of the acquired companies [Guadalupe et al., 2012].

Our contribution to the existing literature is threefold. First, we provide compelling evidence on the impact of acquisitions on innovation activities of acquired firms. Our results provide support to the defensive acquisition behaviour of BGs. BGs that acquire standalone firms on an upward innovation trend in the same technological classes as the acquiring BG, tend to cause a sharp decrease in innovation of acquired targets. In contrast, BGs tend to foster innovation of their acquired targets with a different patent portfolio, consistently with an expansionary acquisition intention. Second, these insights help to better assess the role of BG acquisitions in the context of the increasing gap between leading and laggard firms Akcigit and Ates [2022]. Finally, we are able to provide general evidence of this BG behaviour that is not limited to single industries or countries, as e.g. in [Cunningham et al., 2021] or [Guadalupe et al., 2012]. Our newly built firm-linked patent citation network dataset, together with ownership linkages data, includes all patenting Orbis firms in 200 countries over the period 2007-2018.

The rest of this paper is organized as follows. Section 2 presents data sources, data coverage, variables used in the analysis, and descriptive statistics . Section 3 describes the empirical methodology, results, and robustness checks. Finally, section 4 concludes.

2 Data

We undertake an extensive data work to track over time the innovation activity and the BG affiliation of firms worldwide, together with their relationship, if any. The latter allows us to observe acquisitions and identify the possible effect of acquisitions on the innovation of target firms. We use patenting activity as a measure of innovation activity. Patents are a particularly convenient proxy, due to the availability of patent data in all countries and the level of detail in patent documentation, offering a wide range of variables we could exploit to assess the quality and scope of inventions and thus, the innovation portfolios of firms.

2.1 Data sources

We rely on two main sources of information. On the one hand, we need to identify the network of BGs worldwide, in order to map the ownership boundaries of BGs and their changes over time (e.g., acquisitions). On the other hand, we need comprehensive information on innovating firms, and whether they are part of a BG or not at any moment in time. These two sets of information require data collection from several sources. We develop our datasets based on (i) Orbis Intellectual Property (Orbis IP) providing information on Orbis firms' patenting activity including, among others, firms' BvD identifier, patent applications' identifier, patent office, priority date, forward and backward citations, technological scope, and patent family identifiers, (ii) Orbis Ownership Database providing information on BG affiliation, (iii) additional Orbis balance-sheet data, and (iv) market concentration data from CompNet.[2]

Business groups data. We rely on panel data on the BG structure from the Orbis Ownership database, linking parent firms worldwide to their corresponding affiliates and the hierarchical layer of the latter in the chain of control. The methodology has been developed by Sonno [2020] and used in subsequent works [e.g., Altomonte et al., 2021]. In line with this literature, we define BGs as an entity composed of at least 2 firms, i.e. a parent company owning directly or indirectly at least one affiliate with more than 50.01% share of equity.[3] In this paper, we abstract from the internal organization and hierarchy of the BG and focus instead on the BG affiliation and acquisitions. We identify an acquisition simply by a change of status of a firm from one period to the next, from standalone to BG affiliate.[4] This change in status reflects a share purchase of the target standalone firm by the acquiring BG, resulting in a final stake share of at least 50.01% of the target firm. The acquisition of shares could be made directly by the parent of the acquiring BG and/or indirectly by one or more affiliates of the latter. This dataset results in a network of business groups for more than 6.3 million parents, comprising 12.8 million affiliates across more than 200 countries, from 2007 to 2018.[5]

[2] We compute the HHI index of firms' market shares at the industry level based on CompNet data (https://www.comp-net.org).

[3] More complex structures of BGs could be composed of many affiliates over many hierarchical layers, as long as the parent owns directly or indirectly strictly more than 50% share of equity in each affiliate.

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

[5] See the Appendix of Sonno [2020] for an extensive description of the data and their validation with the avail-

Knowledge data. We build a new firm-linked patent citation network dataset connecting citing and cited patents to their corresponding applicant firms based on data from Orbis IP. This allows us to identify cited patents but, most importantly, to have full understanding and control over the citation source and timing, as opposed to taking the full citation count from other sources of data.[6] More details on the citation count methodology will follow. Overall our dataset includes around 470 thousand firms, accounting for 19 million patent applications and 24 million citation links. The core of our analysis is based on two measures of innovations: 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 European Patent Office (EPO), the United States Patent and Trademark Office (USPTO), the Japan Patent Office (JPO), and patents at country offices worldwide with at least one equivalent at the EPO, USPTO or JPO.[7] Furthermore, we decompose this number into patents that get cited in the first 3 years of priority and patents that don't, so as to disentangle patents supporting real inventions from strategic patenting intended to hinder competition [Jaffe and Lerner, 2011]. We also avoid multiple counting of inventions protected by multiple patent applications, by taking into consideration affiliation to a patent family. More explicitly, we consider one patent count for all patents belonging to a single simple patent family that identifies different patent applications (equivalents) protecting the same invention. Hence, in our sample, each patent included uniquely identifies one invention.[8]

To measure firms' overall innovation impact and quality in a given year, we rely on our own measure of the total number of citations a firm receives from other firms for all its patenting activity invented during that year. We compute this measure in two steps. First, we compute the total number of citations received directly for each patent and indirectly taking into account citations received by patent equivalents, as previously defined. We build on backward citations as a key variable to establish patent citation links. Backward citations depict all cited patents for each patent application, allowing us to trace retrospectively citations received per patent.[9]

able country-year-specific census data, among which the OECD FATS Statistics.

[6] Understanding the citing patent and corresponding firm allows us to control for self-citations, which we can't disentangle if we rely on pre-compiled citation counts from other sources, such as the OECD.

[7] Each patent application is associated with several dates corresponding to different stages in the application process. We chose the priority date as it is the first date observed for the initiation of the application process and best reflects the date of the innovation.

[8] For patent equivalents, we use the earliest priority data possible.

[9] Each patent application includes the exhaustive list of other related patents identified by the applicant, as well as introduced by patent examiners during the application process, very much like academic papers. We can easily attribute a citation link to patents appearing in backward citations. Forward citations on the other hand requires tracking efforts by patent offices as new patents appear over the years.

Importantly, we exclude citation links in three specific cases. First, we exclude mechanical patent self-citations between patent equivalents identified as a patent application citing another patent application from the same simple patent family. Second, we drop firm self-citations for different patents and consider only cross-firm patent citations. We exploit the firm citation network dataset to identify these links. That allows us to assess the quality of a patent, validated by other firms.[10] Third, we only count citations received in the first 3 years of priority and fix the citation span to that period, i.e. the count of citations received during 3 years starting the day the applicant declares the invention at the patent office. For example, for a patent first announced at the patent office in year t, we sum citations received directly or indirectly, through equivalents, in year t, t+1, and t+2. In other words, we consider the 3-year forward citation count. This ensures consistency of the measure for each patent and avoids data truncation, in line with the construction of the OECD Citations database.

Subsequently, we aggregate this restricted patent citations' count at the firm-year level by taking the sum of the 3-year forward citations count for all patents applied for by a firm in a specific year. We interpret a high number of citations received as a highly-influential innovation for the firm.

Finally, we use the correspondence of the International Patent Classification (IPC) classes provided by the World Intellectual Property Organization (WIPO) to establish a patent-based technological scope for firms, and use this to compute a measure of portfolio similarity between firms. This allows to compare the technological distance between the acquiring BG and acquired firms based on their patent portfolio.[11]

2.2 Data coverage

In the raw Orbis IP data over the period 2007-2018, we observe 469,389 firms worldwide applying for 18,851,288patent applications receiving 24,787,116 citations in all patent offices. In Table 1, we show the raw coverage of firms and their patenting activity and the coverage after several data cleaning steps. The number of patents and citations in column (1) does not reflect the actual number of innovations protected, due to multiple counting of patents equivalents. After accounting for this, the number of patents is reduced by more than 70% and citations by more than 40% (column 2). Patents that are protected in at least one of the 3 top offices, EPO, USPTO,

[10] Considering the relevance of cumulative innovation within firms 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] Additional details regarding the construction of our measure for patent portfolio similarity are provided in Appendix F.

or JPO, account for 64% of all patents and 95% of citations (column 3). The predominance of citations from these top 3 patent offices underscores the significance and influence of the patents granted by them. Considering only firms and patents that get cross-cited in the first 3 years of priority in column (4), we observe a substantial drop of 46% in the number of firms, 60% in the number of patents and 66% in the number of citations.

Table 1: Orbis IP data coverage

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

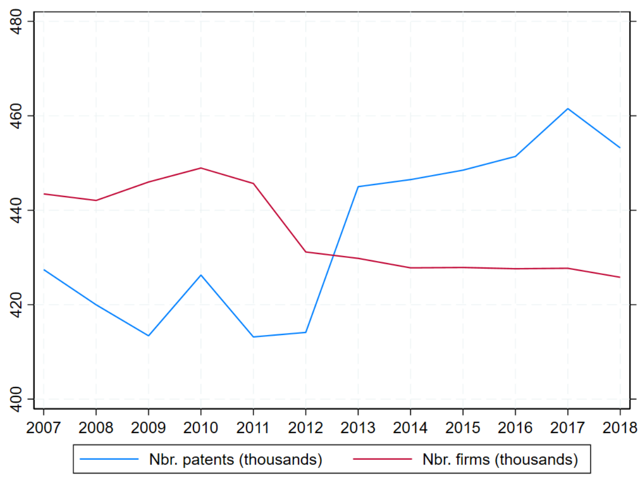
Notes: This table summarizes Orbis IP data coverage for firms' patenting activity over the period 2007-2018. Orbis IP data version: July 2022. Columns are organized as follows: (1) presents raw data, (2) presents coverage after addressing multiple counts due to patent equivalents, (3) clean data for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

Figure 1 presents the number of patents and firms engaging in patenting activity, over the period 2007-2018, as observed in our data after cleaning for multiple counts of patents. A positive trend in patenting activity is observed over the period, with some fluctuations from year to year which is consistent with WIPO's World Intellectual Property Indicators report published in 2021. We also observe a decrease in firm participation in patenting activity, indicating an increasing concentration of patenting among leading firms, consistent with findings of Akcigit and Ates [2022] for the US economy.

For the empirical analysis, we focus on firms' patenting activity during their life span, i.e. within the operational period starting from the date of incorporation. Therefore, our sample consists of legally operational Orbis firms worldwide that receive 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 applying for 2.4 million patents with at least one equivalent at the EPO/USPTO/JPO and receiving 9 million citations, including 3 million citations in the first 3 years of priority as presented in Table 2. Although this sample includes 36% of all patenting firms, they account for more than two-thirds of raw patents and almost three-quarters of raw citations.[12]

[12] These figures result from comparing column 1 in Table 2 to column 1 in Table 1

Figure 1: Patenting and firm participation in patenting activity trend over the period



Notes: This figure presents the yearly data coverage on patents and firms engaging in patent activity, over the period 2007-2018, after addressing multiple counts of patents due to patent equivalents. The left-hand side axis represents the number of patents, while the right-hand side axis represents the number of firms, both in thousands.

Table 2: Estimating sample patent data coverage

	(1) Raw data	(2) Clean data	(3) EPO/USPTO/JPO	(4) Cited
Nbr. Patents	12,784,653	3,618,124	2,405,275	980.579
Nbr. 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 in Orbis IP after data cleaning. Columns are organized as follows: (1) presents raw data, (2) presents coverage after addressing multiple counts due to patent equivalents, (3) clean data for the sub-sample of patents with at least one equivalent at the EPO/USPTO/JPO., and (4) the subset of patents from column (3) that received at least one citation within the first 3 years of priority, excluding self-citations.

2.3 Descriptive statistics

We report firms' BG affiliation and their corresponding patenting activity over the period in Table 3. On the one hand, only around 11% of our sample is part of a BG, with 2% as parents and 9% as affiliates. However, despite their small share, these firms dominate more than 60% of all innovation activities measured by the number of patents and citations, with parents alone representing approximately 40%. This is consistent with the concentration of knowledge within BGs as studied by Belenzon and Berkovitz [2010]. In contrast, around 70% of our sample consists of standalone firms that never join a BG at any point in time, accounting for only a quarter of the innovation activity. The remaining 19% of our sample consists of firms that change their status between standalone and part of a BG (either as an affiliate or a parent).

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

	(1) Firms	(2) Patents	(3) Citations	(4) Patents	(5) Citations
Sample		Full		EPO/USPTO/JPO & Cited	
Nbr.	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: This table summarizes the distribution of firms according to their BG affiliation dynamics and participation in patenting activity over the period 2007-2018. Columns (2) and (3) include all patenting activity after data cleaning, while columns (4) and (5) include patenting activity in one of the 3 leading patent offices (EPO/USPTO/JPO) that receive at least one cross-citation within the first 3 years of priority.

The distribution of firms in our sample and their patenting activity are suggestive of the existence of an innovation premium that Business Groups leverage. We document this premium in Table 4, which shows that, on average, a firm that is part of a BG (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 higher citations. These differences in means between the two samples are statistically significant at the 99% confidence level.

Within the sample of standalone firms, we observe 17,722 firms that get acquired by BGs over our period, including 7.6% that get acquired more than once. We focus on 15,493 firms that are acquired only once over the period to simplify the analysis with a single treatment.[13] Acquisitions in our sample are observed in 87 2-digit NACE industries. These acquisitions are predominantly found in high-tech industries such as Research and Development, Manufacture of computer,

[13] The total number of firms acquired once over the period is 16,354, however we exclude 861 acquired standalone firms for which the 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: This table summarizes firm patenting activity by BG affiliation over the period 2007-2018. The differences in means, between the 2 samples, are significant at 99 confidence level.

electronic and optical products, Manufacture of machinery and Wholesale Trade (except motor vehicles) (see Appendix A1). Appendix B presents descriptive statistics indicating that acquired standalone firms, on average, tend to be younger, larger in terms of revenue and employment, and possess higher assets and liabilities compared to their peers that were never acquired. This evidence suggests that BGs cherry-pick young well-performing firms.

3 Empirical Analysis

In this section, we document novel evidence concerning the link between innovation and BGs' strategic acquisition behaviours. First, we confirm a finding already established in the literature [Wu and Chung, 2019]: the higher the level of innovation of standalone firms, the greater the probability of them becoming part of a BG. Second, we examine the innovation trajectory of acquired standalone firms. We find that BGs tend to acquire standalone firms that exhibit an upward trend in innovation performance before acquisition, compared to other non-acquired firms. However, post-acquisition, these firms experience a significant deterioration in their innovating activity, on average. Third, considering that BGs may have various motives driving their acquisition of firms, we analyze potential defensive/expansionary acquisition behaviours exhibited by BGs. We explore the patent portfolios of acquired firms and their acquiring BGs pre-acquisition. We focus more precisely on their respective technological scopes. Results show that the average deterioration in innovation activity shown by acquired standalone firms is driven specifically by firms with a patent portfolio particularly similar to the one of the headquarter. Fourth, we find that these effects are particularly pronounced for acquisitions occurring in markets characterized by high concentration and increasing average age of leading firms. These findings are consistent with the defensive behaviour of acquiring competing high-performing standalone firms, and the expansionary behaviour of acquiring firms with complementary technological spaces.

3.1 Standalone patenting and probability of acquisition

In Table 5, we study the relationship between the innovation activity of standalone firms and their probability of being acquired by a BG. To achieve this, we examine both citations and patents. Specifically, 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. For both measures, we examine their value at a specific point in time (Panel A of Table 5) as well as their accumulation over a specific time span (Panel B). In the analysis, denoting a generic firm as *i* and *t* as a generic year, and ignoring fixed effects, column 1 of Panel A in Table 5 presents the results of the following econometric specification:

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

where $Acquired_{i,t}$ is a dummy variable that takes the value one if firm *i* becomes part of a BG in year *t*, and $ln(Citations{+}1)_{i,t-1}$ is (the log of) firm's *i* number of citations received in year *t-1* (plus one). Estimates include firm and year fixed effects, allowing us to exploit the within-firm variation in the data. The sample for this estimation includes all standalone firms acquired once or never acquired (our control group) in the period of analysis (2007-2018).

Column 1 indicates that a higher number of citations is associated with a greater likelihood of a firm getting acquired by a BG. Column 2 replicates the analysis of the first column using an explanatory variable based on the number of patents, rather than citations. Results confirm that when firms increase their patenting activity they are more likely to be acquired by a BG.

In columns 3 and 4 of Panel A, we restrict the analysis to only firms with at least one citation or one patent in the period *t-1*. Results are also confirmed in these sub-samples of firms. 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 5 focuses on the lagged citation/patent stock of firms. The cumulative stock of citations or patents obtained in the previous three years *(t-3,t-1)* are used as explanatory variables in columns 1 and 2, respectively. In columns 3 and 4, the analysis is replicated in the sub-samples of firms with at least one citation or one patent in the period *(t-3,t-1)*.

Taken together, these pieces of evidence confirm that an increase in firms' citation levels and/or patent counts at a specific point in time, as well as an increase in their cumulative patent stock over a given period, is associated with a higher likelihood of acquisition by a BG.[14]

[14] In Appendix C, we demonstrate 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 non-cited patents does not change our findings, as detailed in Table A4.

Table 5: Standalone patenting and 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: This table includes all standalone firms i acquired once or never acquired over 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-years forward count of citations received for patents by firms i in year t-1. Log(Patents+1) (i,t-1): number of patents by firm i in year t-1. Log(Citations+1) (i,t-3,t-1): sum of citations received for patenting activity over the period t-3 to t-1. Log(Patents+1) (i,t-3,t-1): number of patents by firm i over the period t-3 to t-1. Column (3) includes the sub-sample of firms that receive at least one citation in year t-1, and column (4) includes the sub-sample of firms that have at least one patent in year t-1. Standard errors are clustered at firm-level and reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

3.2 Effect of acquisition on patenting activity

In this section, we conduct a Two-Way Fixed Effects Difference-in-Differences (TWFE DID) analysis with staggered treatment to compare the innovation performance of acquired firms to that of never-acquired standalone firms.[15]

The treatment group comprises standalone firms that were acquired only once during the period analyzed. In contrast, the control group consists of standalone firms that were never acquired.[16] Firm and year fixed effects are consistently included.[17]

Figure 2 illustrates a disruption in the innovation activity trend of acquired firms, subsequent to their acquisition, in terms of citations and patents. Their innovative performance is improving over time, reaching its highest level in the omitted pre-acquisition year (Pre -1), aligning with the evidence presented in Section 3.1. This disruption occurs in both the number of citations and patents, although is much stronger for citations. In fact, post-acquisition, these firms are cited less frequently compared to both their own previous standards and the average performance of never-acquired standalone firms. However, the positive trend in patenting slows down post-acquisition, i.e. the growth rate in number of patents decreases and the yearly number of patents stabilizes around the level of patenting in the year pre-acquisition (Pre -1). [18]

To explore further the mechanism, Figure 3 disentangles between effects observed on cited and non-cited patents. This figure demonstrates that the stabilization effect observed post-acquisition in terms of the number of patents produced (as shown in the right panel of Figure 2) is, in fact, the outcome of two opposing forces. Specifically, the right panel of Figure 3 confirms that there is no differential effect before and after the acquisition for non-cited patents. In other words, the production of non-cited patents maintains its positive trend throughout the entire period, and the acquisition does not alter this dynamic. Conversely, the positive trend in the production of cited patents pre-acquisition is sharply interrupted post-acquisition, at which point we observe a complete reversal in the trend, becoming negative and significant.

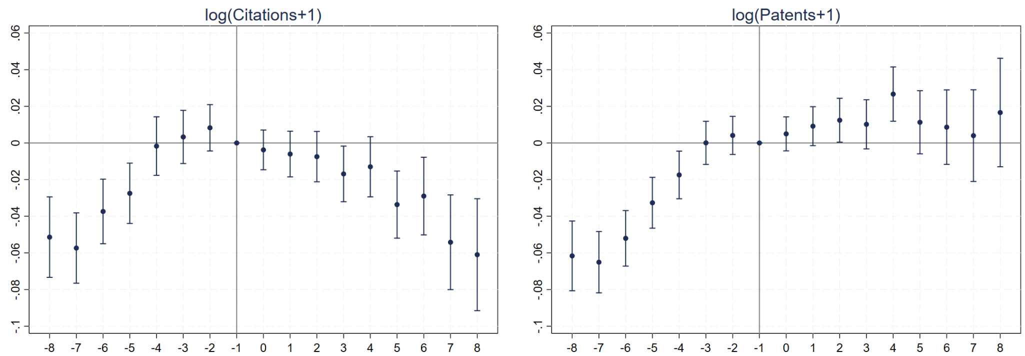
[15] Refer to Appendix E for the estimated equation.

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

[17] For the sake of graphical representation, we plot only the 8 years before and after acquisition. However, column 1 of Table A5 in Appendix E presents all the regression coefficients depicted in Figure 2.

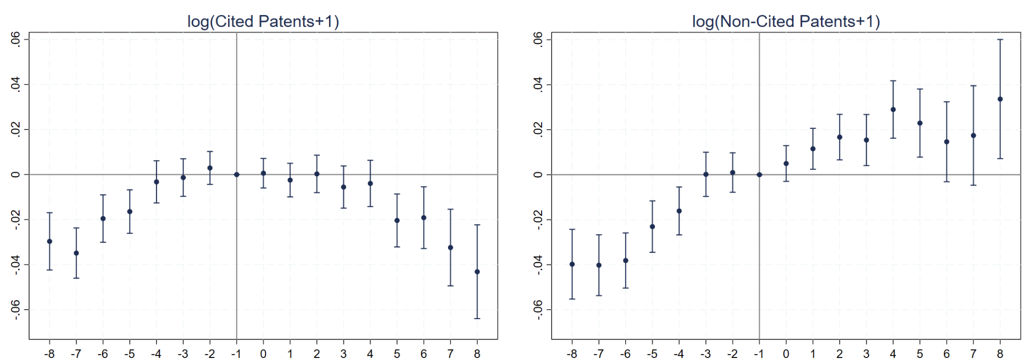
[18] Figure A1 in Appendix D replicates Figure 2 implementing the method proposed by Borusyak et al. [2024]. Reassuringly, results are perfectly consistent.

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



Notes: These figures plot estimates of the effect of the acquisition on acquired firms with respect to the year of acquisition. Regression includes acquisition period dummies for the sample of acquired firms excluding acquisition period -1 (Pre -1). Standard errors are clustered at firm-level and confidence intervals are presented at 95%. Column 1 of Table A6 in Appendix E shows the regression coefficients plotted in this figure.

Figure 3: The effect of acquisition on patenting activity of acquired firms: cited and not cited patents



Notes: These figures plot estimates of the effect of the acquisition on acquired firms with respect to the year of acquisition. Regression includes acquisition period dummies for the sample of acquired firms excluding acquisition period zero (Post 0). Standard errors are clustered at firm-level and confidence intervals are presented at 95%.

3.3 The role of patents' technical similarity

We now delve further into the innovation performance of firms post-acquisition, looking at the similarity in domains of their innovation activities with respect to the acquiring BG. In particular, we investigate how a potential overlap in the technological class of the acquired firm and the BG might impact post-acquisition innovation dynamics, building on the discussions from the previous section.

Figure 4 displays up to 16 regression coefficients of the period dummies – seven before and nine after the acquisition – by the level of portfolio similarity between the acquiring BG and acquired firm.[19] The left panel focuses on the number of citations as the dependent variable, while the right panel examines the number of patents (both logged and incremented by one unit). The year before the acquisition, which applies to all firms, is the omitted period. Specifically, we investigate whether the average decline in innovation activity among acquired standalone firms is more pronounced for those with a patent portfolio similar to their acquiring BG. This would be a situation that mimics a defensive acquisition of a firm competing in the same innovation space. In contrast, we also analyze whether acquired standalone firms with a different portfolio scope exhibit a smaller post-acquisition decrease in innovation performance. This would mirror an expansionary acquisition, where the BG acquires a firm in a distant innovation space.[20] These estimations include firm and year fixed effects, thereby accounting for any firm-specific or aggregate technological changes (see estimated equation in Appendix E).[21]

The results in Figure 4 reveal that, on average, there is a decline in innovation for firms innovating within the same technological class as the acquiring BG. For firms with divergent portfolios, instead, innovation continues to grow post-acquisition. Specifically, five years post-acquisition, acquired firms with similar portfolios experience a 30% decrease in the number of citations, compared to the year before acquisition and to non-acquired firms. Whereas, those with distinct portfolios experience a more than 10% increase in citations relative to the year before acquisition and non-acquired firms. Regarding patent numbers, firms with similar portfolios show a decrease of almost 15% five years post-acquisition, and firms with different technology portfolios see a 20%

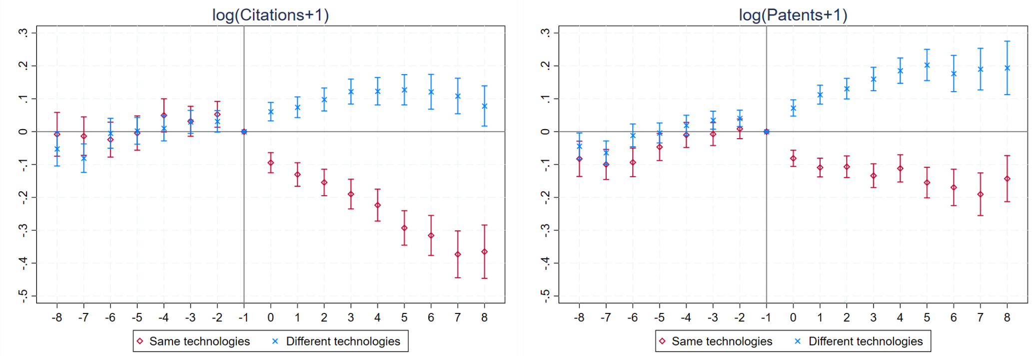
[19] Our sample includes a maximum of 11 years pre-acquisition and 10 years post-acquisition, and we exclude the period -1, i.e. the year before the acquisition. For symmetry the figures display only the coefficients from -8 to +8, but all period dummies are incorporated into the regression, as detailed in Table A5 in Appendix E.

[20] We consider the overlap in technological classes in the patent portfolio of the acquired firm and the acquiring BG. Further explanations on how we create these two groups is discussed in Appendix F.

[21] Note that the sample of firms included in this analysis is limited to firms and groups for which we observe a pre-period technological portfolios. The results are in any case robust to the replication of this analysis using the similarity of the 2-digit NACE industry (Same/Different industry).

increase.[22]

Figure 4: Acquisition and similarity in innovation areas



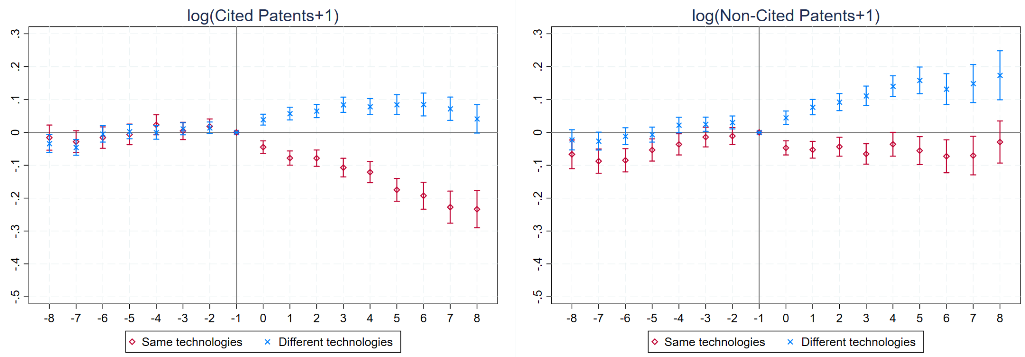
Notes: These figures display estimates illustrating the effect of the acquisition on acquired firms with respect to the year of acquisition and the technological class alignment between the acquired firm and the acquiring BG. The omitted period is the period before the acquisition (Pre -1). *Treated-SameTechnologies* (*Treated-DifferentTechnologies*) refer to acquisitions with a level of patent portfolio particularly similar (different) in technologies of acquired firms and acquiring BG. Details in Appendix F. Standard errors are clustered at firm-level and confidence intervals are presented at 95%. Table A6 in Appendix E shows the regression coefficients plotted in this figure.

Similar to Section 3.2, we distinguish between the dynamics of cited and non-cited patents, this time incorporating the Same/Different technology characterization into the analysis. Both the left and the right panels of Figure 5 confirm that the positive trends of cited and non-cited patents are maintained, before and after acquisitions, for standalone firms acquired by BGs differing in terms of technological class. In other words, standalone firms acquired by groups specialized in different areas of knowledge (thus, less likely to be competitors), sustain the positive trend of their patenting activities for both cited and non-cited patents. Conversely, when examining the patenting dynamics of standalone firms acquired by BGs particularly similar in terms of technological class (and, therefore, more likely to be competitors), we observe that the positive trend in patenting activity pre-acquisition is diminished for non-cited patents (as shown in the right panel of Figure 5). Additionally, it is significantly interrupted, turning into a negative trend post-acquisition for cited patents (as depicted in the left panel). Hence, BGs tend to display a defensive behaviour only with respect to particularly innovative (cited) patents in the same technological class. Importantly, all these effects are also confirmed when employing a different grouping method. Specifically, Appendix G demonstrates that all the evidence described so far is corroborated if we use, instead of the categorization based on Same/Different technology, a grouping of standalone firms that distinguishes between acquired firms active in the Same/Different industry

[22] Refer to Table A6 in Appendix E for detailed coefficients.

as the acquiring BG.

Figure 5: The effect of acquisition on patenting activity of acquired firms by technology: cited and not cited patents



Notes: These figures display estimates of the effect of the acquisition on acquired firms with respect to the year of acquisition and the technological class of the acquired firm with respect to the acquiring BG. The omitted period is the period before the acquisition (Pre -1). Same Technologies (Different Technologies) refer to acquisitions with a level of patent portfolio particularly similar (different) in technologies of acquired firms and acquiring BG. Details in in Appendix F. Standard errors are clustered at firm-level and confidence intervals are presented at 95%.

3.4 The role of market concentration and appropriability

Table 6 further explores the defensive behaviour exhibited by acquiring BGs, and described in the previous section. In particular, we check whether competitive conditions influence BG strategies in acquiring innovative firms. First, we gather data on the Herfindahl-Hirschman Index (HHI) for every industry in our sample in 2001, as a pre-period year.[23]. Panel A reveals that when a standalone firm is acquired in a particularly concentrated market (*Treated-High HHI*), a significant decrease in the number of citations is observed post-acquisition, alongside an overall increase in the number of patents, although this increase is predominantly driven by non-cited patents.[24] In contrast, acquisitions occurring in less concentrated markets (*Treated-Low HHI*) lead to an increase in the number of patents for both cited and non-cited patents. These results align well with the analysis presented in previous sections, as we would expect markets with potentially higher

[23]We retrieve the HHI based on market shares of firms at country-industry-year from the CompNet database. Market shares of each firm are squared and the resulting numbers summed by country-industry-year. We then construct the index at industry-level in 2001, by taking the average across countries

[24]We consider industries to be highly concentrated (*High HHI*) if the average HHI of the industry, at the NACE 2-digit level, is greater than or equal to the median level. Conversely, we consider industries to be slightly concentrated (*Low HHI*) if the average HHI of the industry, at the NACE 2-digit level, is lower than the median level.

market power to more easily encourage defensive behaviours toward potentially risky competitors.

Panel B of Table 6 examines the relationship between the average age of leading firms in an industry and their defensive behaviour. We hypothesize that markets with an increasing average age of leading firms indicate these firms are consolidating their market share, facilitating defensive actions.[25] Conversely, a decreasing average age suggests that younger, often smaller, firms are making significant market inroads. Our findings support these hypotheses: in contexts with an increasing average age of leading firms (*Treated-Increasing age top 8*), there is a reduction in citations and an uptick in non-cited patents. Meanwhile, markets with a decreasing average age of leading firms (*Treated-Decreasing age top 8*) appear to stimulate innovation, as evidenced by increases in both citations and notably cited patents.

The findings in sections (3.1, 3.2, 3.3, and 3.4) collectively suggest a pattern of defensive acquisition behaviour targeting high-performing standalone competitors. Specifically, the evidence indicates a decline in innovation activity of acquired firms within technological areas potentially competitive to BGs, in concentrated markets, and in contexts marked by an increasing average age of leading firms – environments where such behaviours can be more readily implemented.

Finally, one might wonder what happens to the BG after acquisition, such as whether it increases its knowledge productivity and/or overall performance in terms of profit and/or size. In Appendix H, we show that we do not find an effect on the overall number of citations of acquiring BGs post-acquisition, also if we differentiate among BGs acquiring a standalone firm with a complement tech portfolio. However we are able to document an increase in BG turnover and employment post-acquisition. Due to the limitations of this analysis, we present these last findings as preliminary anecdotal evidence, and emphasize the need for more detailed investigation into this specific aspect in future research.

4 Conclusion

In conclusion, this paper offers an examination of the intricate relationship between innovation and strategic acquisition behaviours within BGs. Through empirical analysis leveraging newly assembled datasets based on Orbis Intellectual Property and Ownership databases, alongside additional balance-sheet information, we have delved into the nuanced dynamics surrounding BG acquisitions and their impact on innovation activity of acquired firms.

[25] We analyze the dynamic of the average age of leading firms using balance sheet turnover data from 2001-2007, focusing on the top 8 firms by market share, following standard practices in the literature.

Table 6: Market concentration and ease of knowledge appropriability

	(1)	(2)	(3)	(4)
Dep. Variable	Citations(i,t)		Patents(i,t)	
Sample	All	All	Cited Patents(i,t)	Non-Cited Patents(i,t)
Panel A: By HHI				
Post × Treated-High HHI	-0.0185**	0.0275***	-0.0022	0.0322***
	(0.007)	(0.007)	(0.004)	(0.006)
Post × Treated-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 B: By age growth				
Post × Treated-Increasing age top 8	-0.0199***	0.0106*	-0.0050	0.0159***
	(0.007)	(0.006)	(0.004)	(0.005)
Post × Treated-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: This table presents the Two-Way Fixed Effects Difference-in-Differences (TWFE DID) estimation results on the effect of acquisition on innovation of acquired firms by the level of industrial concentration (Panel A) and by age growth of the top 8 leading firms in terms of market share (Panel B). The sample includes the acquired standalone firms (treated group) and non-acquired standalone firms (control group), over the period 2007-2018. Citations(i,t): 3-years forward count of citations received for patents by firms i in year t-1. Log(Patents+1) (i,t-1): number of patents by firm i in year t-1. In each panel, the treated group is divided into 2 sub-groups depending on the position of the firm with respect to: the median level for the average HHI at NACE 2-digits (Panel A) and the growth in age of the top 8 firms in the industry. Post × Treated-High (Low) HHI is a dummy variable equal to one for acquired firms in a highly (slighlty) concentrated industry, during the post-acquisition period, 0 otherwise. Post × Treated-Increasing age top 8 (Decreasing age top 8) HHI is a dummy variable equal to one for acquired firms with a growing (decreasing) age of the 8 leading firms, during the post-acquisition period, 0 otherwise. Standard errors are clustered at firm-level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Our findings contribute significantly to the existing literature by shedding light on several critical aspects that have remained under-explored. Firstly, we confirm the well-established phenomenon that standalone firms exhibiting higher levels of innovation are more likely targets for BG acquisitions. This underscores the strategic importance of innovation in driving acquisition decisions within the corporate landscape.

Secondly, our study highlights a worrisome trend of deterioration in innovative activities among acquired firms post-acquisition. This suggests that while BGs may seek to incorporate innovative capabilities through acquisitions, the assimilation process may inadvertently stifle the innovative momentum of the acquired entities.

Moreover, we distinguish between defensive and expansionary motives underlying BG acquisitions, demonstrating how the alignment of patent portfolios between acquirers and acquired firms influences post-acquisition innovation dynamics. This nuanced understanding enriches our comprehension of the strategic rationale behind BG acquisition strategies.

Overall, our research underscores the multifaceted nature of the relationship between innovation and strategic acquisitions. By providing empirical evidence and insightful analyses, we offer valuable insights for policymakers, corporate strategists, and researchers seeking to understand and navigate the complex interplay between innovation dynamics and corporate acquisition strategies in contemporary markets. Moving forward, further exploration of these dynamics is essential to inform strategic decision-making and foster innovation-driven growth within business groups and the broader economy.

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Appendix

A Acquisitions by industry

In the clean data, we observe 17,722 firms that get acquired over our period including 7.6% that get acquired more than once. We focus on 15,493 firms acquired only once, excluding 861 acquired standalone firms for which the industry information is missing. Acquisitions in our sample are observed in 87 2-digit NACE industries listed below, 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: Decomposition of acquisitions by industry

NACE code	Description	Nbr. Acquisitions
46	Wholesale except motor vehicles	1337
72	Scientific R&D	1325
26	Manufacture of computer, electronic, optical prod	1291
28	Manufacture of machinery and equipment n.e.c.	1269
62	Computer programming, consultancy	851
71	Architectural and engineering	743
25	Manufacture of fabricated metal prod	621
32	Other manufacturing	618
27	Manufacture of electric equipment	542
20	Manufacture of chemicals products	476
82	Office admin, office support and other business support	432
22	Manufacture of rubber and plastic	418
74	Other professional, scientific and technical activities	401
21	Manufacture of basic pharmaceutical products	385
29	Manufacture of motor vehicles, trailers	338
70	Activities of head offices; consultancy	334
47	Retail except motor vehicles	320
64	Financial intermediation	319
58	Publishing	255
43	Specialised construction	200
10	Manufacture of food	163
86	Human health activities	147
23	Manufacture of non-metallic mineral products	143
30	Manufacture of other transport equipment	139
24	Manufacture of basic metals	129
61	Telecommunications	121
63	Information services	117
77	Rental and leasing activities	114
68	Real Estate activities	110
13	Manufacture of textiles	110
96	Other personal service activities	102
45	Wholesale, retail and repair of motor vehicles	100
35	Electricity, gas, steam and air conditioning supply	100
33	Repair and installation of machinery	96
66	Other financial activities	83
17	Manufacture of paper products	80
69	Legal and accounting	76
73	Advertising and market research	73
31	Manufacture of furniture	73
41	Construction of buildings	69
52	Warehousing and support for transportation	65
16	Manufacture of wood, cork, straw and plaiting	63
42	Civil engineering	61
18	Printing and reproduction of recorded media	51

NACE code	Description	Nbr. Acquisitions
9	Mining support service activities	50
14	Manufacture of wearing apparel	42
49	Land transport and via pipelines	39
1	Crop and animal production	37
59	Multimedia services	37
38	Waste collection, treatment and disposal activities	34
81	Services to buildings and landscape	30
85	Education	29
11	Manufacture of beverages	28
56	Food and beverage services	26
80	Security services	22
93	Sports activities and amusement	20
55	Accommodation	14
36	Water collection, treatment and supply	13
6	Extraction of crude petroleum and natural gas	13
19	Manufacture of coke and refined petroleum products	12
65	Insurance	11
7	Mining of metal ores	11
15	Manufacture of leather and related	11
78	Employment activities	11
60	Programming and broadcasting activities	11
3	Fishing and aquaculture	10
75	Veterinary activities	10
79	Travel services	9
8	Other mining and quarrying	9
12	Manufacture of tobacco	9
90	Creative, arts and entertainment activities	8
94	Activities of membership organisations	8
37	Sewerage	8
88	Social work activities without accommodation	7
95	Repair of computers and personal and household goods	7
92	Gambling and betting activities	6
98	Undifferentiated goods and services of households	6
50	Water transport	5
51	Air transport	5
84	Public administration and defence	5
53	Postal and courier activities	4
39	Remediation activities and other waste management services	4
2	Forestry and logging	4
91	Libraries, archives, museums and other cultural activities	3
87	Residential care activities	3
99	Activities of extraterritorial organisations	1
5	Mining of coal and lignite	1

Notes: This table summarizes the number of standalone firm acquisitions we observe in our sample by industry classified at NACE 2-digits. We exclude firms that get acquired more than once over the period, for a total of 15,493 acquisitions included in this table and in the empirical analysis.

B Additional descriptive statistics

To understand how different standalone firms that get acquired are with respect to standalone firms that are never acquired, we regress a set of 5 firm-level characteristics on an acquired dummy that equals one if a standalone firm is eventually acquired for all pre-acquisition periods, and zero if the firm is never acquired by a BG. The chosen dependent variables are age, employment, turnover, assets and liabilities. The regression also includes year fixed effects and all other 5 firm characteristics not taken as a dependent variable in the regression. We exclude post-acquisition periods for the acquired firms to avoid capturing a difference driven by the effect of the acquisition. Data coverage is significantly reduced when balance sheet data is included. Table A2 reports results for the sample of 4243 acquired standalone firms and 24651 never acquired standalone firms for which we observe the firm-level data. It shows that firms that get acquired are on average younger, bigger, have higher assets and liabilities compared to their never acquired peers. This evidence suggests that BGs cherry-pick young well-performing firms.

Table A2: Acquired firms' premia

Dep. Variable	(1) Age (i,t)	(2) Employment (i,t)	(3) Turnover (i,t)	(4) Assets (i,t)	(5) 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: This table documents differences in standalone firm characteristics between acquired (pre-acquisition period) and never acquired. All dependent variables are at the firm-year level with an added unit and logged. Eventually acquired (i) is a firm-level dummy that equals one if a standalone firm is eventually acquired for all pre-acquisition periods, 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 include 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 firm-level and reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

C Additional evidence on knowledge and acquisition

In Table A3, we disentangle the intensive margin of the correlation highlighted in Table 5 by substituting the explanatory variable in equation (1) with two dummy variables, each one indicating whether the firm received a number of citation below or equal to the median (*Citations Low*), or above the median (*Citations High*) of citations.Therefore, in columns 1 and 2 of Table A3, Panel A, ignoring fixed effects, we estimate the following specification, where the control group is non-cited firms in year t-1:

$$Acquired_{i,t} = \sigma + \eta \; Citations\ Low_{i,t-1} + \rho \; Citations\ High_{i,t-1} + e_{i,t} \tag{2}$$

Results show that the result is mainly driven by firms in the higher quantile of citations. This is true also if we look at different categories of knowledge innovation intensity in terms of the number of patents. Replicating the same dummy analysis with patents, we see that firms with above the median level of number of patents (*Patents High*) are more likely to be acquired with respect to firms below the median (*Patents Low*) and firms without any patent. These results hold also if we restrict the analysis to firms with at least one citation or patent, columns 3 and 4 of Table A3. Results are also confirmed when we look at the stock of citations/patents, instead of the flow, i.e. Panel B.

Table A4 expands upon the findings presented in Table 5 by examining the potential differential impact of cited and non-cited patents. Specifically, we replicate the analysis conducted in Table 5, distinguishing between the heterogeneous effects of cited (columns 1 and 3) and non-cited (columns 2 and 4) patents. Panels A and B delve further into the heterogeneous effects by considering the stock of patents from 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 not particularly influenced by either subgroup. We observe a positive and significant effect in all combinations examined.

Table A3: Standalone firms' 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: This table includes all standalone firms i acquired once or never acquired over the period 2007-2018. Acquired (i,t): dummy equals 1 if firm i is acquired by a BG in year t, zero otherwise. Citations Low (High) (i,t-1): a dummy variable equals to 1 if the 3-years forward count of citations received for patents by firms i in year t-1 is below or equal (above) the median. Patents Low (High) (i,t-1): a dummy variable equals to 1 if the number of patents by firms i in year t-1 is below or equal (above) the median. Column (3) includes the sub-sample of firms that receive at least one citation in year t-1, and column (4) includes the sub-sample of firms that have at least one patent in year t-1. Standard errors are clustered at firm-level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Standalone firms' 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(Non-Cited 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(Non-Cited 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

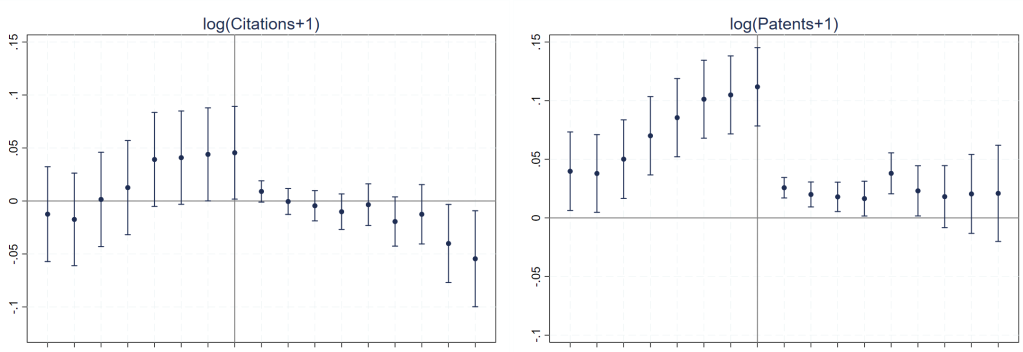
Notes: This table includes all standalone firms i acquired once or never acquired over the period 2007-2018. Acquired (i,t): dummy equals 1 if firm i is acquired by a BG in year t, zero otherwise. Log(Cited Patents+1) (i,t-1): number of cited patents by firm i in year t-1. Log(Non-Cited Patents+1) (i,t-1): number of non-cited patents by firm i in year t-1. Log(Cited Patents+1) (i,t-3,t-1): number of cited patents by firm i over the period t-3 to t-1. Log(Non-Cited Patents+1) (i,t-3,t-1): number of non-cited patents by firm i over the period t-3 to t-1. Columns (3) and (4) includes the sub-sample of firms that have at least one patent in year t-1. Standard errors are clustered at firm-level and reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

D Borusyak et al. [2021]

In this section, we replicate the analysis presented in Figure 2, as discussed in Section 3.2, but we adopt the approach for conducting difference-in-differences analysis with staggered treatment as proposed by Borusyak et al. [2024].

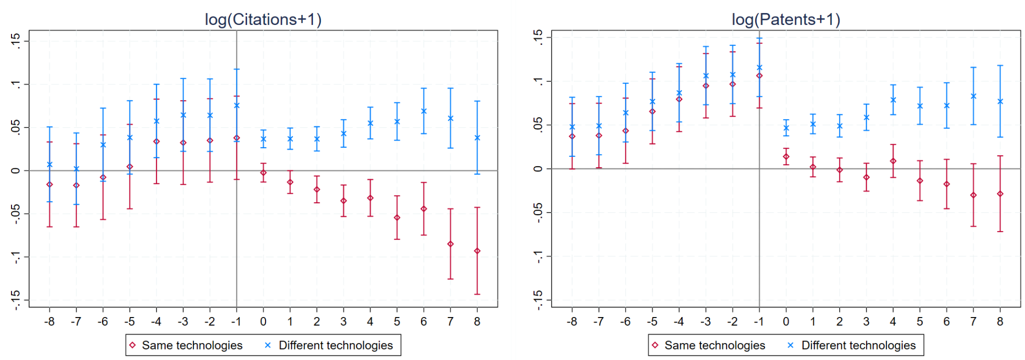
Figures A1 and A2 reaffirm the findings illustrated in Figure 2 and 4, respectively. Prior to acquisition, acquired firms outperform non-acquired firms in terms of innovation, as measured by both the number of citations and patents. However, following acquisition, they receive fewer citations and generate fewer patents compared to their own pre-acquisition performance and the average performance of non-acquired firms. In essence, post-acquisition, acquired firms not only underperform in innovation relative to their previous standards but also lag behind the average performance of never-acquired standalone firms. This effect is particularly pronounced when the acquired firm has a patent portfolio in the same technological space as the acquiring BG, hence, reinforcing the defensive strategy. Figure 4 illustrates the effect of the acquisition on acquired firms by technological class alignment between the acquired firm and the acquiring BG from difference-in-differences estimation à la Borusyak et al. [2024]. Estimating the effect of acquisition for each sub-sample (with similar patent portfolio and with different patent portfolio) is not allowed in this setting. Thus, we estimate the effect of acquisition on each sub-sample separately and combine results for on citations in the left panel and on patents in the right panel, for easier comparison.

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



Notes: These figures show the results on the effect of acquisition on acquired firms patenting activity from difference-in-differences estimation à la Borusyak et al. [2024], accounting for the staggered nature of the treatment (acquisitions). Confidence intervals are presented at 95%.

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



Notes: These figures illustrate the effect of the acquisition on acquired firms by technological class alignment between the acquired firm and the acquiring BG from difference-in-differences estimation à la Borusyak et al. [2024]. Since interactions are not allowed in this setting, we estimate the effect of acquisition on the sub-sample of acquired firms with similar patent portfolio and the sub-sample with different patent portfolio, separately. We combine results on citations in the left panel and on patents in the right panel. Confidence intervals are presented at 95%.

E Additional Tables

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

E.1 Acquisitions and acquired firms' innovation

Equation (3) documents in detail the estimation equation of Figure 2, while Table A5 presents the coefficients of the same figure. Excluding fixed effects, the equation estimated is as follows:

$$Y_{i,t} = \theta + \sum_{t=-11}^{+10} \delta_t \, T_{i,t} + e_{i,t} \tag{3}$$

where, $Y_{i,t}$ represents the measure of innovation: (i) number of citations, (ii) number of patents, (iii) number of cited patents, and (iv) number of non-cited patents; logged and incremented by one unit. $T_{i,t}$ indicates period-specific (and firm-specific, as we re-scale all the years with respect to the firms-specific acquisition year) dummies. The estimation includes firm and year fixed effects. Thus, the coefficients δ_t, for t ranging from -11 to 10, indicate the average effect, with respect to the year before acquisition, on the outcome variable Y.

E.2 Acquisitions and acquired firms' innovation by technological similarity

Equation (4) documents in detail the estimation equation of Figure 4, while Table A6 presents the coefficients of the same figure. Excluding fixed effects, the equation estimated is as follows:

$$Y_{i,t} = \omega + \sum_{t=-11}^{+10} \gamma_t \, (T_{i,t} \times \textit{Treated-SameTechnology}_i) + \sum_{t=-11}^{+10} \eta_t \, (T_{i,t} \times \textit{Treated-DifferentTechnology}_i) + e_{i,t} \tag{4}$$

where, $Y_{i,t}$ represents either the number of citations or patents (both logged and incremented by one unit). $T_{i,t}$ indicates period-specific (and firm-specific, as we re-scale all the years with respect to the firms-specific acquisition year) dummies. The dummy variable $\textit{Treated-SameTechnology}_i$ takes the value one if the technological class of the acquired firm pre-acquisition closely matches that of the acquiring BG's. Conversely, the dummy variable $\textit{Treated-DifferentTechnology}_i$ indicates dissimilarity in technological class. Estimations consistently include firm and year fixed effects. Thus, the coefficients γ_t, for t ranging from -11 to 10, indicate the average effect, with respect to the year before acquisition, on the outcome variable Y for firms with a technology portfolio particularly similar to that of the acquiring BG. The η_t coefficients provide analogous effects for acquired standalone firms with differing technology portfolios.

Table A5: 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)	Non-Cited 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: This table includes all standalone firms i acquired once or never acquired over the period 2007-2018. Independent variables are dummies for the period with respect to acquisition with the omitted category being the year of acquisition (Pre -1). Standard errors are clustered at firm-level and reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A6: The effect of acquisition on patenting activity of acquired firms by petent portfolio similarity

Dep. Variable	(1) Citations(i,t)	(2) Patents(i,t)
Pre 11 × Treated-Same Tech	0.0773	-0.0907*
	(0.067)	(0.049)
Pre 10 × Treated-Same Tech	-0.0220	-0.1301***
	(0.047)	(0.037)
Pre 9 × Treated-Same Tech	-0.0492	-0.1302***
	(0.038)	(0.031)
Pre 8 × Treated-Same Tech	-0.0080	-0.0826***
	(0.034)	(0.027)
Pre 7 × Treated-Same Tech	-0.0136	-0.0997***
	(0.030)	(0.023)
Pre 6 × Treated-Same Tech	-0.0241	-0.0934***
	(0.027)	(0.022)
Pre 5 × Treated-Same Tech	-0.0043	-0.0466**
	(0.027)	(0.021)
Pre 4 × Treated-Same Tech	0.0495*	-0.0100
	(0.026)	(0.020)
Pre 3 × Treated-Same Tech	0.0316	-0.0075
	(0.023)	(0.018)
Pre 2 × Treated-Same Tech	0.0526***	0.0085
	(0.020)	(0.015)
Post 0 × Treated-Same Tech	-0.0945***	-0.0811***
	(0.016)	(0.013)
Post 1 × Treated-Same Tech	-0.1302***	-0.1091***
	(0.018)	(0.015)
Post 2 × Treated-Same Tech	-0.1544***	-0.1068***
	(0.021)	(0.017)
Post 3 × Treated-Same Tech	-0.1899***	-0.1339***
	(0.023)	(0.018)
Post 4 × Treated-Same Tech	-0.2235***	-0.1118***
	(0.025)	(0.021)
Post 5 × Treated-Same Tech	-0.2929***	-0.1549***
	(0.027)	(0.024)
Post 6 × Treated-Same Tech	-0.3157***	-0.1695***
	(0.031)	(0.028)
Post 7 × Treated-Same Tech	-0.3731***	-0.1904***
	(0.036)	(0.033)
Post 8 × Treated-Same Tech	-0.3650***	-0.1430***
	(0.041)	(0.036)
Post 9 × Treated-Same Tech	-0.3338***	-0.1232***
	(0.049)	(0.044)
Post 10 × Treated-Same Tech	-0.4237***	-0.1006**
	(0.059)	(0.051)
(...)	(...)	(...)
(...)	(...)	(...)
Pre 11 × Treated-Different Tech	-0.0553	-0.0943***
	(0.049)	(0.035)
Pre 10 × Treated-Different Tech	-0.0720**	-0.0934***
	(0.036)	(0.026)
Pre 9 × Treated-Different Tech	-0.0482	-0.0505*
	(0.032)	(0.026)
Pre 8 × Treated-Different Tech	-0.0523**	-0.0439**
	(0.027)	(0.020)
Pre 7 × Treated-Different Tech	-0.0807***	-0.0638***
	(0.022)	(0.018)
Pre 6 × Treated-Different Tech	-0.0049	-0.0114
	(0.023)	(0.018)
Pre 5 × Treated-Different Tech	0.0023	-0.0039
	(0.021)	(0.016)
Pre 4 × Treated-Different Tech	0.0103	0.0192
	(0.020)	(0.016)
Pre 3 × Treated-Different Tech	0.0297*	0.0349**
	(0.018)	(0.014)
Pre 2 × Treated-Different Tech	0.0312*	0.0405***
	(0.017)	(0.013)
Post 0 × Treated-Different Tech	0.0608***	0.0720***
	(0.014)	(0.013)
Post 1 × Treated-Different Tech	0.0743***	0.1126***
	(0.016)	(0.015)
Post 2 × Treated-Different Tech	0.0978***	0.1307***
	(0.018)	(0.016)
Post 3 × Treated-Different Tech	0.1220***	0.1601***
	(0.019)	(0.018)
Post 4 × Treated-Different Tech	0.1231***	0.1856***
	(0.021)	(0.020)
Post 5 × Treated-Different Tech	0.1274***	0.2028***
	(0.023)	(0.024)
Post 6 × Treated-Different Tech	0.1212***	0.1768***
	(0.027)	(0.028)
Post 7 × Treated-Different Tech	0.1085***	0.1902***
	(0.028)	(0.032)
Post 8 × Treated-Different Tech	0.0781**	0.1940***
	(0.031)	(0.041)
Post 9 × Treated-Different Tech	0.0999*	0.1909***
	(0.051)	(0.064)
Post 10 × Treated-Different Tech	1,227,095	1,227,095
	0.321	0.433
Year FE	Yes	Yes
Firm FE	Yes	Yes

Notes: This table includes standalone firms i acquired once over the period 2007-2018. Independent variables are dummies for the period with respect to acquisition with the omitted category being the year of acquisition (Pre -1). Standard errors are clustered at firm-level and reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

F Technological similarity of patent portfolios

In this appendix, we explain in detail the procedure used to establish an indicator of patent portfolio similarity between each acquired firm and the corresponding acquiring BG.

We observe technology classes associated to each patent applications according to the International Patent Classification (IPC). We rely on the World Intellectual Property Organization (WIPO) aggregation of IPC classes into 35 groups of technologies. First, we collect information on the WIPO classes of all patent applications linked to each acquired firm starting from the first year in our data, 2007, until the year before acquisition. Similarly, we collect the same information on all patent applications associated to the acquiring BG, whether applied for by the parent or an affiliate, from 2007 to the year before acquisition. Once we have this data, we 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 party. This results in reducing the sample significantly to 5,690 acquisitions (38.5%) since we don't consistently observe a patent application by each party in the pre-acquisition period.[26]

Second, we define the share of common technological classes between acquired firm i and acquiring BG j at year *pre 1* (the year before acquisition) $\textit{Share common classes}_{i,j,pre1}$ as number of common technological classes $\textit{Nbr. common classes}_{ij,pre1}$ over the total number of technological classes in the BG patent portfolio $\textit{Nbr. classes}_{j,pre1}$, as expressed in equation 5.

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

This share takes a value between zero and one. The value zero corresponds to a situation where there is no overlap between the scope of innovation of the acquired firm and the acquiring BG; i.e. the acquired firm is patenting in other technology space in comparison to the BG. The value one corresponds to a scenario where the acquired firm innovates in all analogous technological classes as the BG. Hence, this measure captures the level of competition/complementarity of the technological spaces in their patent portfolio.

This measure suffers from data truncation since we only observe data starting in 2007, which systematically generates a smaller patent overlap in patent portfolio for acquisitions in the early period compared to those that occur later in the period. This is true since for acquisitions happening later in the period, we observe more years in the pre-acquisition period allowing for more chances to observe a patent portfolio overlap in technological classes. In order to alleviate this bias in our measure, we consider the residual of a regression of the share of common classes, as

[26] This is in part driven by data truncation that we discuss later in this appendix.

previously defined, on the acquisition year fixed effect that should capture this systematic bias as follows:

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

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

Finally, we define acquisitions in same technologies as acquisitions with a level higher than or equal the median level of the adjusted share of common technological classes. While acquisitions in different technologies are acquisitions with a level of adjusted share of common technological classes below the median.

G The role of industries

In this section, we replicate the findings presented in Figures 2, 4, 3, and 5 using a Difference-in-Differences estimation.

Panel A of Table A7 corresponds to the analyses in Figures 2 and 4, whereas Panel B emulates the examination conducted in Figures 3 and 5.

Panel C, conversely, duplicates the analysis carried out in Section 3.3, albeit with a different classification of acquired firms. Specifically, whether the standalone firm is part of the same industry as the acquiring BG or not. The outcomes corroborate our descriptions in Figures 3 and 5, particularly that acquired standalone firms operating in the same industry as the acquiring BG exhibit a decline in the number of citations post-acquisition, a trend predominantly attributed to cited patents, while non-cited patents continue their positive trajectory even after acquisition. Conversely, the quantity of post-patent citations and new patents escalates if the acquired firm operates within the same industry as the acquiring BG, a pattern that holds for both cited and non-cited patents.

Table A7: Industry heterogeneity

	(1)	(2)	(3)	(4)
Dep. Variable	Citations(i,t)		Patents(i,t)	
Sample	All	All	Cited Patents(i,t)	Non-Cited Patents(i,t)
Panel A: Baseline				
Post × Treated	-0.0020	0.0226***	0.0023	0.0220***
	(0.005)	(0.004)	(0.003)	(0.003)
Obs.	1,302,739	1,302,739	1,302,739	1,302,739
R2	0.319	0.430	0.386	0.433
Panel B: By technological space				
Post × Treated-Same Tech	-0.1697***	-0.0866***	-0.0874***	-0.0237**
	(0.014)	(0.012)	(0.009)	(0.010)
Post × Treated-Different Tech	0.0825***	0.1122***	0.0590***	0.0765***
	(0.010)	(0.010)	(0.006)	(0.008)
Obs.	1,227,095	1,227,095	1,227,095	1,227,095
R2	0.321	0.432	0.389	0.436
Panel C: By industry				
Post × Treated-Same Industry	-0.0632***	-0.0030	-0.0256***	0.0165**
	(0.011)	(0.010)	(0.007)	(0.008)
Post × Treated-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
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Notes: This table includes the Two-Way Fixed Effects Difference-in-Differences (TWFE DID) estimation of the effect of acquisition on acquired firms, the control group being non-acquired standalone firms. Panel A presents the baseline estimation results. Panel B presents the effect for acquired firms with similar- and different- patent portfolio relative to the acquiring BG's. Panel C presents the effect for acquired firms within the same- and different- industry as the acquiring BG. Standard errors are clustered at firm level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

H Acquisitions' effect for Business Groups

This appendix presents preliminary evidence on the overall effect of standalone firms' acquisitions on both BGs affiliates' knowledge and performance. However, it is crucial to stress that this analysis requires comparing BGs before and after the acquisition of a standalone firm, keeping any other channel potentially impacting these outcomes constant. Therefore, we need to restrict our analysis to only BGs which do not acquire/sell any other affiliate in the year before and the year after the specific acquisition we want to study. Moreover, when we study balance sheet information together with innovation dimensions, the number of observations decreases even more. Therefore, the anecdotal evidence presented in this section must be taken with extreme caution and is intended to provide suggestive evidence for potential future research.

With the data at hand, focusing only on affiliates of acquiring BGs that undergo no change in composition, with the exception of the acquisition of a standalone firm, for at least 1-year post-acquisition, Table A8 we show that we do not detect any effect on the number of citations or patenting activity (columns 1 to 4) within-affiliate. Using two measures of affiliate performance, however, i.e. turnover and number of employees, we document an increase in profitability and size post-acquisition.

Table A8: Groups' effect

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	Citations(i,t)		Patents(i,t)		Turnover	Employment
Sample	All	All	Cited Patents(i,t)	Non-Cited Patents(i,t)	All	All
Post × Treated	-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: This table includes the estimation of the 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 composition, with the exception of the acquisition of a standalone firm, for at least 1 year pre- and 1 year post-acquisition. Post × Treated is a dummy equal to one for years post-acquisition for BG i, 0 otherwise. Standard errors are clustered at BG level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

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