

OECD Science, Technology and Industry Working Papers
2025/10

Acquisitions and their effect on start-up innovation: Stifling or scaling?

Marius Berger,

Sara Calligaris,

Andrea Greppi,

Dmitri Kirpichev

https://dx.doi.org/10.1787/b4efd3ab-en

OECD

OECD Science, Technology and Industry Working Papers

OECD Working Papers should not be reported as representing the official views of the OECD or of its member countries. The opinions expressed and arguments employed are those of the authors. Working Papers describe preliminary results or research in progress by the author(s) and are published to stimulate discussion on a broad range of issues on which the OECD works. Comments on Working Papers are welcomed, and may be sent to Directorate for Science, Technology and Innovation, OECD, 2 rue André-Pascal, 75775 Paris Cedex 16, France.

© OECD 2025

Attribution 4.0 International (CC BY 4.0)
This work is made available under the Creative Commons Attribution 4.0 International licence. By using this work, you accept to be bound by the terms of this licence (https://creativecommons.org/licenses/by/4.0/).
Attribution – you must cite the work.
Translations – you must cite the original work, identify changes to the original and add the following text: In the event of any discrepancy between the original work and the translation, only the text of original work should be considered valid.
Adaptations – you must cite the original work and add the following text: This is an adaptation of an original work by the OECD. The opinions expressed and arguments employed in this adaptation should not be reported as representing the official views of the OECD or of its Member countries.
Third-party material – the licence does not apply to third-party material in the work. If using such material, you are responsible for obtaining permission from the third-party and for any claims of infringement.
You must not use the OECD logo, visual identity or cover image without express permission or suggest the OECD endorses your use of the work.
Any dispute arising under this licence shall be settled by arbitration in accordance with the Permanent Court of Arbitration (PCA) Arbitration Rules 2012. The seat of arbitration shall be Paris (France). The number of arbitrators shall be one.

Acquisitions and Their Effect on Start-up Innovation: Stifling or Scaling?

Marius Berger,[1] Sara Calligaris,[1] Andrea Greppi,[1] and Dmitri Kirpichev[1]

This paper highlights a critical issue in the innovation ecosystem – whether acquisitions of start-ups by incumbent firms foster or stifle innovation. Using a unique firm-level dataset covering 60 countries for the period 2001-2021, the study finds that acquisition targets are highly innovative before the deal, and acquirors are generally innovation-oriented firms. Acquired start-ups are also technologically close to their acquirors and often share the same industries and countries, suggesting potential market synergies. However, post-acquisition, start-up patenting declines without a corresponding increase in the acquiror's innovation activity, raising concerns that such deals may serve anti-competitive purposes rather than enhancing innovation.

[1] OECD Directorate for Science, Technology and Innovation

Keywords: start-ups; acquisitions; innovation.

JEL codes: D22, L26, O31, O32.

Acknowledgements

The report is a deliverable to the project “Building a Robust Innovative entrepreneurship ecosystem for a Digital and Green Economy” (BRIDGE) financed under Work Programme Horizon Europe – 2021-2022 Horizontal support expenditure for Horizon Europe and Euratom Programmes under grant no. LC-01965673.

The authors would like to thank Valentina Di Girolamo, Erik Canton and Julien Ravet (DG RTD) for their support throughout this project and for their insightful feedback on an earlier version of the report.

The authors also thank the participants at the Working Party on Industrial Analysis (WPIA), the Committee on Industry, Innovation, and Entrepreneurship (CIIE), Ana Paola Costa, Mika Maliranta, as well as participants at the OECD Work-In-Progress, CEMFI, ZEW Mannheim, and INSEAD/Collège de France seminars for their comments and suggestions, Antoine Dechezleprêtre, Hélène Dernis, Guy Lalanne for their important contributions to this project, Charles Parry for his excellent research assistance, and Shai Somek and Charles-Édouard Van De Put for technical assistance.



Funded by
the European Union

Table of contents

Acknowledgements 4

Executive Summary 7

1 Introduction 9

2 Literature review 14
- Characteristics of firms involved in acquisitions 14
- The impact of acquisitions on innovation 15

3 Data 17
- Dataset 17
- Descriptive statistics 20

4 What kind of firms engage in acquisitions? 24
- Methodology 24
- Acquisition of targets 26
- Acquirors 29
- How are acquiror and start-up pairs formed? 31

5 How does acquisition affect innovation? 33
- Methodology 33
- Acquired start-ups 35
- Acquirors 39
- Potential underlying channels 42

6 Conclusions 47

Endnotes 49

References 56

Annex A. Supplementary material 62

Annex B. Robustness and Extensions 63
- A description of VC-funded acquired start-ups 63
- Ex-ante heterogeneity in acquired start-ups across regions and sectors 64
- Heterogeneity across acquirors in ex-ante characteristics 65

Estimating the effect of acquisitions on innovation using propensity score matching 65
Estimating the effect of acquisitions on innovation using an exogenous shock 67
Causal analysis using withdrawn bids for acquirors 68
Heterogeneous ex-post responses by technological proximity 69
The impact on citation flows 70
Ex-post heterogeneity 71

Tables

Table 3.1. Descriptive statistics: acquired versus non-acquired start-ups. 21
Table 3.2. Descriptive statistics: acquired start-ups before and after acquisition. 22
Table 3.3. Descriptive statistics: acquirors versus other investors. 22
Table 4.1. The effect of patents, their quality, and VC stocks on the probability of being acquired. 27
Table 4.2. Heterogeneity of the effect of holding a patent on the likelihood of acquisition across acquired start-ups. 28
Table 4.3. The effect of patents and their quality on the probability of acquiring a start-up 30
Table 4.4. The effect of technological and market overlap on the likelihood of pair formation. 32
Table 5.1. The effect of acquisitions across acquirors with different patenting levels and alternative measures of innovation. 43
Table 5.2. The impact of acquisitions on the target's patent filings across industries and countries 45

Table A A.1. Descriptive statistics of the acquisition sample 62
Table A B.1. The effect of patenting activity and VC stocks on the likelihood of acquisition 63
Table A B.2. Heterogeneity across acquirors. 65
Table A B.3. Propensity score estimation and balance test 66
Table A B.4. Balance checks across exogenously withdrawn and successful bids 67
Table A B.5. Ex-post effects on the number of filed patents by start-up targets by technological proximity with the acquiror. 69

Figures

Figure 1.1. The evolution of start-up and non-start-up acquisitions. 9
Figure 5.1. The effect of the acquisition on the patent filings of acquired start-ups. 36
Figure 5.2. The effect of the acquisition on the patent filings of acquired start-ups using withdrawn bids. 37
Figure 5.3. The effect of acquisitions on the patent quality of acquired start-ups. 38
Figure 5.4. The effect of acquisitions on the patent filings of acquirors. 41
Figure 5.5. The effect of acquisitions on the patent filings of acquirors using withdrawn bids 42
Figure 5.6. Correlation between number of acquisitions and different measures of patent quality 44

Figure A B.1. The innovation premium across regions and sectors. 64
Figure A B.2. Bias reduction in observable characteristics across treatment and control start-ups 66
Figure A B.3. The effect of acquisitions on patenting activity using propensity score matching 67
Figure A B.4. Event study of the patent flow across acquired start-ups and start-ups with exogenously withdrawn bids 68
Figure A B.5. The effect of acquisitions on the patent quality of acquirors 68
Figure A B.6. The impact of acquisitions on target and acquiror citations 70
Figure A B.7. The effect of acquisitions on the patenting activity of targets and acquirors in the EU 71

Executive Summary

Start-ups are young and small players that can have a big impact on the economy. A vast literature has shown their key role as drivers of employment creation, output growth, and *radical innovations* (i.e., innovations with the potential to bring about processes of creative destruction to the market). Their growth and success rely on a complex ecosystem that includes access to venture capital and supportive regulatory frameworks.

A key feature of this ecosystem is the availability of viable exit options for investors and founders. A common exit strategy, especially in markets and periods where alternative options (e.g., IPOs) are limited, is acquisition by an established firm. For incumbents, acquiring start-ups is often a strategic means to access the target's novel technologies and innovation capabilities. This paper explores the growing prevalence of start-up acquisitions by established firms and assesses their implications for innovation.

Accessing start-ups' innovations through acquisitions may allow established firms to realise synergies and foster economic efficiency. However, it may also stifle competition and dampen innovation. Existing studies are increasingly showing the negative impact of M&A on innovation, often focusing on specific countries, sectors, or time periods. While studies focusing on publicly listed companies and single-country settings have captured most of the attention, studies focusing specifically on start-ups and in a global context are still limited. Start-ups are key players of the innovation dynamics, are inherently different from publicly listed companies, and present specificities that might make the impact of acquisitions differ substantially from the one that emerged from prior literature.

This paper provides an integrated and updated assessment by leveraging a comprehensive and unprecedented firm-level cross-country dataset covering start-ups, their acquisitions, and patent applications across 60 countries over the past two decades. It explores two key questions. First, which start-ups and established companies engage in acquisitions? Second, how do acquisitions impact the subsequent innovation performance of both parties?

The key findings are the following:

1. Start-ups and incumbents with more and higher-quality patents are more likely to be involved in acquisitions.
2. Following an acquisition, start-ups experience a substantial decline in the number and the quality of their patenting activity, without a corresponding increase in innovation from the acquiror.
3. The negative impact of patenting is more pronounced when the acquiror and target operate in the same geographical area or industry, suggesting potential anti-competitive motives.

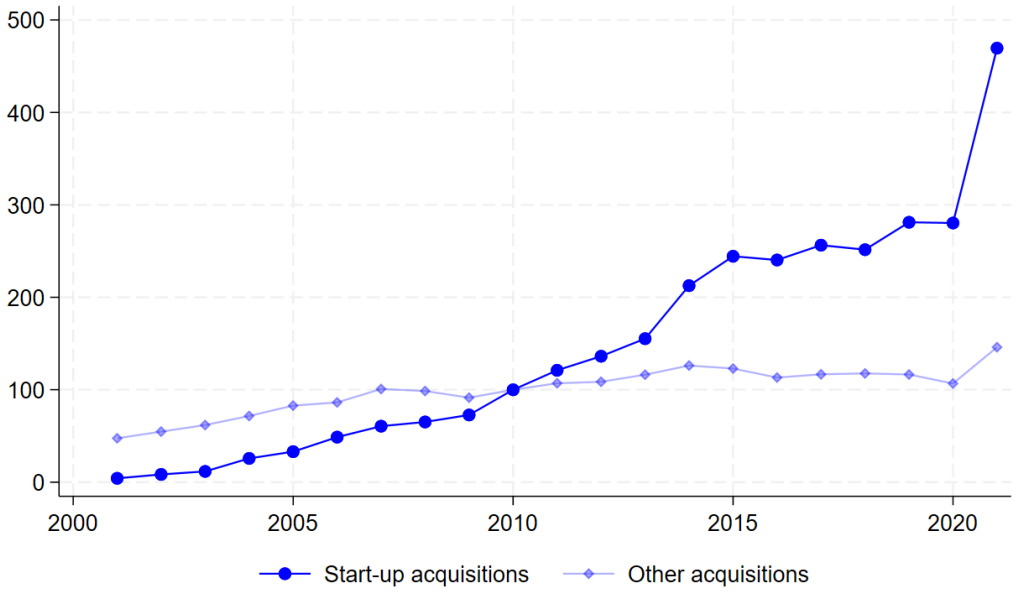
In the context of increasing industry concentration and declining business dynamism, this study supports the view that start-up acquisitions often stifle innovation. This has important policy implications. Start-ups often escape antitrust scrutiny due to their relatively small market shares, yet their acquisition by incumbents can have long-term consequences, including increased market concentration and reduced technological progress. While the prospect of acquisition can incentivise start-up entry and innovation, a balanced policy approach is needed. Policymakers should integrate forward-looking antitrust enforcement

with measures that promote innovation and its diffusion, lower entry barriers, and enhance the scalability of new firms. At the same time, a key element in supporting the development of start-up technologies is encouraging venture financing by ensuring efficient exit strategies for investors. Policymakers should therefore promote the availability of alternative exit options, reducing excessive dependencies on large established companies. This strategy is essential to sustaining the dynamic benefits of innovation while mitigating the potential adverse effects of acquisitions on industry dynamism.

1 Introduction

Start-ups play a crucial role in driving technological advancement and economic development. Despite their small size, these companies account for a disproportionate amount of job creation (Haltiwanger, Jarmin and Miranda, 2013[2]), output growth (Haltiwanger, Jarmin and Miranda, 2017[3]), and innovation (Kortum and Lerner, 2000[4]). More importantly, start-ups are often the source of *radical* innovations (Schnitzer and Watzinger, 2022[5]) that lead to creative destruction, fostering competition, benefitting consumers, and enhancing productivity growth (Gans, H. and Stern, 2002[6]; Akcgit and Kerr, 2018[7]).

Figure 1.1. The evolution of start-up and non-start-up acquisitions.



Note: The figure shows the change in the number of acquisitions of start-ups and incumbent firms (i.e. not start-ups) relative to 2010. Start-ups are firms that applied for their first patent or raised their first VC financing between 2001 and 2021 and did so before reaching ten years of age. Incumbent firms are all firms not respecting these criteria.
Source: OECD calculations based on OECD/STI Start-ups Database, PATSTAT, and Orbis M&A data.

Innovation- and growth-oriented start-ups have increasingly attracted the interest of established companies in recent decades. Figure 1.1 shows that these companies have substantially increased their stakes in start-up companies through acquisitions. Acquisitions are transactions in which a company buys a majority stake in a target company to gain control and decision-making power over its operations. Relative to 2010, these kinds of transactions have increased five-fold, surpassing substantially those of other firms (i.e. not start-ups), which have increased approximately 50%. Other authors also have noted the shift of exit strategies from IPOs to acquisitions in the last decades (Ederer and Pellegrino, 2023[8]). Several factors can account for such trends. For instance, firms might have increasing incentives to engage in acquisitions to take advantage of economies of scale following the rise of intangible assets in the last decades (Atalay,

Hortacsu and Syverson, 2014[9]). Likewise, financial and monetary motives like portfolio diversification and search-for-yield can also account for these patterns (Alexandridis, Antypas and Travlos, 2017[10]; Bellavitis, Fisch and Vismara, 2023[11]), particularly in a context where the cost of risk is low. Despite several alternative explanations associated with the observed trends, this paper focuses on the role of *innovation motives*.

The increasing interest of companies in start-ups may reflect a fundamental shift in the process of scientific discovery and corporate innovation (Arora, Belenzon and Patacconi, 2017[12]; Arora, Belenzon and Sheer, 2021[13]) in times when it is becoming increasingly challenging to create novelties (Bloom et al., 2020[14]). Acquiring stakes in young, innovation-driven companies may be a strategy of established firms to gain access to radical innovations, thereby providing a way to deal with declining research productivity and reflecting a more efficient way of organising their research and innovation process. Innovation can be potentially boosted through the technological diffusion that might take place between companies (Bloom, Schankerman and Van Reenen, 2013[15]), the access to complementary assets that allow scaling up technologies (Rhodes-Kropf and Robinson, 2008[16]; Bena and Li, 2014[17]), or the relaxation of financial and other constraints that allow the acquired company to run its operations more smoothly (Didier et al., 2021[18]), among others.

At the same time, increasing stakes of established firms in start-ups coincide with some concerning trends over the past two decades, such as rising industry concentration (Bajgar et al., 2023[19]; Calligaris et al., 2024b[20]), declining business dynamism (Calvino, Criscuolo and Verlhac, 2020[21]; Calligaris et al., forthcoming[22]), and a declining share of disruptive innovations (Park, Leahey and Funk, 2023[23]). Some consider that these aggregate patterns can be partly explained by the increasing stakes of large companies in start-ups. Cunningham, Ederer, and Ma (2021[24]) show that established firms acquire other companies to discontinue their innovative projects, thereby preserving market power and maintaining their dominant status quo. Other authors argue that the prospect of being acquired may trigger start-up entry and innovation (Fons-Rosen, Roldán-Blanco and Schmitz, 2022[25]), but may also be internalised by start-ups, who increasingly develop projects that are more likely to appeal to incumbents and lead to acquisitions rather than pursuing promising projects that could potentially disrupt the market (Warg, 2022[26]).

While there is mounting evidence of the impact of acquisitions on the innovation of established acquisition targets – still yielding mixed results (Stiebale and Reize, 2011[27]; Bena and Li, 2014[17]; Haucap, Rasch and Stiebale, 2019[28]; Cunningham, Ederer and Ma, 2021[24]) – evidence for start-ups is still limited. However, these companies differ from established companies and merit closer examination. Start-ups are typically small, hold negligible market shares, and may not yet have commercialised any product. As a result, they tend to have limited or no market power. While such companies may not pose an immediate competitive threat to incumbents, and the static gains from acquiring them – such as increased pricing power or access to substitute products – may be limited, their long-term potential is substantial. On the one hand, start-ups are often focused on developing new technologies; thus, their acquisition may allow established firms to scale these innovations more effectively or strengthen their competitive advantage. On the other hand, these same start-ups may represent a longer-term competitive threat to incumbents' business models. For these reasons, the motives for acquiring start-ups and the consequences of such acquisitions on innovation may differ significantly from those involving more mature firms. Understanding these trade-offs in the start-up context is essential for policymakers seeking to design effective innovation and competition policies (European Commission, 2024[29]).

The present study provides a comprehensive overview of how acquirors and their start-up targets have evolved across a broad set of countries over the last decades. In particular, it focuses on two key aspects of start-up acquisitions. First, it explores the characteristics of both start-ups and their acquirors, with an emphasis on their innovation activities. Second, it examines the impact of these acquisitions on the subsequent innovation performance of both acquirors and start-up targets.

To answer these questions, this paper develops a comprehensive and unprecedented dataset gathering cross-country evidence on start-ups, their interactions with established firms, and their innovation activities. The analysis combines information from various sources to build a unique dataset providing a thorough picture of the global start-up landscape over the past two decades. The foundation for this data set is the OECD/STI Start-ups Database, which harmonises information from Crunchbase and Dealroom, two commercial data providers with information on start-ups and their ecosystems. Combining the two allows for a much broader coverage of start-up companies across different geographies with respect to the existing literature, helping to overcome criticism on the bias towards the United States of using Crunchbase alone (Dalle, den Besten and Menon, 2017[30]). This paper considers start-ups as young firms oriented toward innovation and growth.[1] The start-up data are further augmented with information from Orbis M&A, a global database on mergers, acquisitions (M&A, henceforth), and minority stake investments, as well as from PATSTAT, a widely used source of information on patents maintained by the European Patent Office (EPO). The final sample covers more than 90 000 start-ups from 60 countries and more than 200 3-digit industries, and approximately 18 000 acquisitions. The analysis covers start-up acquisitions during the period 2001-21. The large, cross-country sample gathered for the analysis represents a key contribution of the paper.

The paper conducts three exercises to characterise the companies engaging in acquisitions. First, it focuses on characterising the acquired start-ups by comparing them to non-acquired start-ups within the same industries and countries. It finds that acquired start-ups are more likely to have prior innovations (measured through patent applications) than non-acquired start-ups. Among start-ups holding at least one patent over the sample period, having more innovations and of higher quality (measured through their 5-year forward citations) further increases the likelihood of acquisition. This positive effect of patent ownership on acquisition probability is particularly strong for younger start-ups and for those acquired across industries or countries.

Second, the paper focuses on the characteristics of acquirors, showing that acquisitions are related to incumbents' innovation performance as well. Comparing acquirors to other incumbents that actively engage with start-ups through means other than acquisitions (i.e., minority stake investments), the paper shows that acquirors are more innovation-oriented. They are not only more likely to hold patents, but also have more of them, and of better quality. On the one hand, this may suggest that incumbents need some level of absorptive capacity (i.e., a base level of technology) to acquire start-ups and effectively benefit from the interactions with them. On the other hand, it may also suggest that innovation leaders (i.e. incumbents with a larger patent stock) engage more in start-up acquisitions to enlarge their knowledge portfolio, and perhaps to suppress the potentially most disruptive and innovative competitors. These channels are still to be explored.

Third, the paper examines how the joint characteristics of start-ups and incumbents are related to the likelihood of an acquisition, focusing on the role of market overlap and the technological closeness of target-acquiror pairs. To answer this question, random pairs of start-ups and incumbent acquirors are formed and compared to the actual acquisition pairs that are observed in the data. The findings show that having similar technologies (i.e., publishing patents in similar technological fields) is associated with a higher likelihood of engaging in an acquisition. Likewise, acquiror-target pairs that share an industry or geography are also more likely to be observed.[2] Finally, the evidence indicates that technological proximity is more relevant when acquisitions occur across industries. These findings allow for multiple interpretations. First, incumbents may use acquisitions to expand into new industries while leveraging technological synergies with their existing businesses. Second, acquirors may seek to acquire start-ups within the same industry but with different technologies to eliminate potential competition, particularly if the start-up develops a more efficient way to produce the same product as the incumbent firm.

Next, the paper examines how acquisitions affect the subsequent innovation performance of both targets and acquirors. This is done using state-of-the-art econometric techniques that address the key challenge of endogeneity – namely, the fact that acquisitions are not random events and may be influenced by

unobserved factors related to innovation. The main approach relies on a difference-in-differences (DiD) framework, which estimates the impact of an acquisition by comparing changes in innovation outcomes over time between acquired start-ups (or acquirors) and a suitable control group. To improve upon standard DiD techniques, the paper adopts the recent estimator proposed by de Chaisemartin and D'Haultfoeuille (2024[31]). This estimator offers two main advantages. First, it corrects for biases that arise in settings with staggered treatments (i.e. treatments that take place at different points in time, like acquisitions) (de Chaisemartin and D'Haultfoeuille, 2023[32]). Second, in the case of start-ups, it allows to estimate the impact of acquisitions by comparing acquired and not-yet-acquired start-ups, alleviating concerns about the inherent differences – as highlighted in the first part of the paper – across acquired and never-acquired start-ups. Lastly, in the case of acquirors, the method also accounts for variation in the intensity of the treatment (i.e. the number of acquisitions by each acquiror). This represents a substantial improvement over earlier studies that focus only on "isolated acquisitions" (i.e. acquisitions that are not followed or preceded by other acquisitions). By including "serial acquirors," who are responsible for a large share of total acquisitions and innovation, the analysis provides a broader and more realistic description of acquisition activity and its implications for innovation with respect to previous literature.

Second, this estimation procedure is combined with the identification strategy proposed in Seru (2014[33]), who compares the innovation performance of acquired targets with targets that received an acquisition bid that was eventually withdrawn for reasons unrelated to innovation. Orbis M&A provides information on withdrawn bids involving start-ups, and online news are surveyed to ensure that the bids were withdrawn for reasons unrelated to innovation (e.g. failure to comply with the liquidity requirements of regulatory bodies). As argued by Seru (2014[33]), the targets of exogenously withdrawn bids represent a good counterfactual for what would have happened to the innovation activity of acquired start-ups if the acquisition had not been realised. Under this framework, the selection into acquisition can be considered "as good as random" and the results can be regarded as causal.

The main findings reveal a substantial decline in the innovation performance of start-ups following an acquisition. This decline is mostly explained by start-ups that stop patenting altogether after being acquired. Importantly, this decline in the innovation rate is not offset by an increase in follow-on innovation by the acquirors. Likewise, the start-ups that continue patenting experience a decline in the quality of their patents. The quality of the patents is measured through their citations-weighted patent flows and the average radicalness of their patent portfolio, which captures the ability of a patent to take existing technologies and apply them to entirely new fields. Similarly, no offsetting impact is found on the quality of the patent portfolio of their acquirors. Therefore, the combined evidence points to a negative impact of start-up acquisitions on innovation.

This worsening in the innovative performance can be interpreted in different non-mutually exclusive ways. The paper concludes by performing different exercises to provide suggestive evidence of the potential channels that might be at play. For example, once acquired, start-ups might decide not to patent all new inventions and pursue other ways to protect them, like increased secrecy around the innovation process. Alternatively, upon acquisition, the innovation activity might decrease because start-ups may shift to a subsequent phase of the innovation process, either starting to commercialise products or integrating innovations into their production processes. The literature also highlights that a large portion of start-ups enter the market primarily to patent ideas that complement those of incumbents and, once they achieve a buyout, they lack further incentives to continue innovating (*innovation-for-buyout*) (Fons-Rosen, Roldán-Blanco and Schmitz, 2022[25]; Warg, 2022[26]; Serrano, 2019[34]). Finally, it may also be that established firms acquire start-ups to subsequently shut down their innovation efforts to stifle future competition (*killer acquisitions*) (Cunningham, Ederer and Ma, 2021[24]).

Among the different channels explored, the analysis shows that the reduction in patenting experienced by acquired start-up following the acquisition is stronger in transactions that happen within the same industry and country. These are transactions in which acquirors might feel the threat of the start-up and acquire it to stifle future competition. This finding is in line with the *killer acquisition* hypothesis and with a growing

body of evidence (Cunningham, Ederer and Ma, 2021[24]; Altomonte, El-Mallakh and Sonno, 2024[35]). No supporting evidence is found for the other channels explored.

Importantly, the alternative channels explored in the paper are not mutually exclusive and do not cover all possible scenarios, so they must be interpreted with caution. Likewise, the aggregate findings also hide many layers of heterogeneity. Further research will be necessary to establish more robust evidence on the channels driving the observed results. For instance, it cannot be excluded that neither the start-up nor the acquiror is actively looking to decrease the start-up's patenting activity, but this decrease occurs because of inefficiencies associated with the transition from two independent entities into one united corporation.

Regardless of the underlying cause, the findings indicate a clear decline in innovation following acquisitions. While some argue that acquisitions can be positive for innovation by fostering synergies and accelerating technological advancements, others contend that they can harm innovation, particularly for the acquired firms. The findings of the paper support the latter view, confirming previous findings (Cunningham, Ederer and Ma, 2021[24]; Altomonte, El-Mallakh and Sonno, 2024[35]) in the specific context of start-ups. This outcome has significant policy implications and calls for careful consideration of the potential long-term effects of M&As on innovation. A decline in innovation post-M&A could undermine industry dynamism and technological progress, making it essential to incorporate innovation impacts into the regulatory review of such transactions. Due to their relatively small scale and less established presence in product markets, start-up acquisitions often escape antitrust scrutiny (OECD, 2020[1]). Nevertheless, their acquisitions can profoundly impact the long-run competitiveness in product markets. At the same time, the prospect of acquisition and the possibility of a profitable exit for start-up founders incentivise start-up entry and innovation. This calls for a balanced approach to start-up acquisitions that integrates forward-looking antitrust enforcement with measures that promote innovation and its diffusion, lower entry barriers, and enhance the scalability of new firms. At the same time, the evidence presented below calls for policymakers to promote the availability of alternative exit options for start-ups, reducing excessive dependencies on large established companies.

This paper proceeds as follows. Section 2 discusses a review of the relevant literature, while Section 3 describes the different data used in the analysis. Sections 4 and 5 provide evidence, respectively, on the characteristics of firms engaging in acquisitions, and on their consequences on innovation performance. Finally, section 6 concludes and describes the next steps of the project.

2 Literature review

This paper builds on a broad body of literature that explores the factors driving firms' acquisitions, as well as their impact on innovation. This section first reviews the literature characterising firms that engage in or are the target of acquisitions, and then the studies exploring the ex-post effects of acquisitions on innovation measures.

Characteristics of firms involved in acquisitions

Both theoretical and empirical contributions have explored the characteristics of companies involved in an acquisition; however, most of them do not focus specifically on start-ups and their acquirors.

The theoretical contributions predict a positive impact of innovation on the likelihood of being acquired. For example, Phillips and Zhdanov (2013[36]) show that small firms (such as the start-ups on which this paper focuses) may decide to innovate more when they can sell out to larger firms. Along the same lines, other authors have argued that the prospect of getting acquired may constitute an incentive for start-ups to innovate and enter the market (Cabral, 2021[37]; Fons-Rosen, Roldán-Blanco and Schmitz, 2022[25]; Eisfeld, 2024[38]; Dijk, Moraga-González and Motchenkova, 2024[39]). Larger firms, in turn, often find it more convenient or less risky to access innovation through acquisition rather than developing innovation internally (Phillips and Zhdanov, 2013[36]; Weiss, 2023[40]).

An empirical portrait of the characteristics of acquired firms has already been developed in various settings. Consistently with the theoretical predictions outlined above, most of the literature confirms that being an active developer of technologies (either through R&D or patents) increases the probability of being acquired (Hoberg and Phillips, 2010[41]; Phillips and Zhdanov, 2013[36]; Bena and Li, 2014[17]; Altomonte, El-Mallakh and Sonno, 2024[35]). These papers use data from publicly listed companies in COMPUSTAT and Orbis. As the coverage of privately held and small companies is generally worse than that of publicly listed companies in these datasets, studies focusing on start-ups' selection into acquisitions are limited. Some exceptions include a series of studies exploiting the Crunchbase dataset. Breschi, Lassébie, and Menon (2018[42]) study the selection of Crunchbase firms into acquisitions using a cross-country sample. They show that firms founded by inventors are more likely to either receive VC or be acquired. Consistently, Eisfeld (2024[38]) shows in a structural model that these firms innovate to get acquired. Along the same lines, Wang (2018[43]) and Alezra and Berquier (2024[44]) show that Crunchbase companies innovate in the technological fields of their acquirors.[3,4]

The selection of incumbents into acquisitions has produced more mixed results in the literature. For instance, Zhao (2009[45]) and Bena and Li (2014[17]) focus on acquirors included in the COMPUSTAT dataset – and, thus, publicly listed in the market – that perform isolated acquisitions (i.e., acquirors that do not acquire more than one firm in a given window). The former shows that these acquirors have similar levels of innovation, as proxied by patent counts when compared to other publicly listed firms, while Bena and Li (2014[17]) show that they have a higher level of patents.[5] A notable shortcoming of these studies is the restriction to isolated acquisitions, excluding companies that engage in acquisitions year after year, despite that these companies account for a disproportionate share of the overall M&A activity. An exception that includes serial acquirors is Hsu et al. (2021[46]), who leverage cross-country firm-level information from

firms in Worldscope to show that more innovative acquirors are more likely to pursue cross-border deals, especially if they are located in low-innovation countries.

The impact of acquisitions on innovation

An extensive literature has also explored the impact of M&A activities on innovation performance. Theoretically, scholars have argued that these interactions can have ambiguous effects on innovation. On the positive side, some research suggests that innovations may be more valuable in the hands of incumbents, as they might have greater resources to scale them up (Cabral, 2018[47]; Letina, Schmutzler and Seibel, 2021[48]). Moreover, small firms may benefit from the additional resources gained through these interactions, as they help overcome financial and other constraints (Fumagalli, Motta and Tarantino, 2020[49]; García-Santana et al., 2024[50]). On the other hand, a prominent strand of literature highlights the potential for incumbents to suppress future competition through acquisitions (Cunningham, Ederer and Ma, 2021[24]). Once incumbents gain control of a target company, they may restrict the start-ups' innovation to prevent their ideas from threatening their dominant position. New ideas can depreciate the value of existing ones, reducing the new entity's incentives to innovate (Federico, Langus and Valletti, 2017[51]; Denicolo and Polo, 2021[52]; Cavenaile, Celik and Tian, 2021[53]; Weiss, 2023[40]). From the target's perspective, start-ups might also innovate with the goal of being acquired, and once that objective is achieved, they may shift to more incremental innovation or cease innovating altogether (Fons-Rosen, Roldán-Blanco and Schmitz, 2022[25]; Weiss, 2023[40]).

This question has also been extensively investigated empirically, and in line with the ambiguous theoretical predictions, mixed results have emerged. Recent industry-specific studies have traditionally supported the *killer acquisition* hypothesis. Notably, Cunningham, Ederer, and Ma (2021[24]) analyse the pharmaceutical industry in the US and find that acquired drug projects are less likely to be developed when they overlap with the acquiror's product portfolio, especially when the acquiror's market power is large due to weak competition or distant patent expiration. Haucap, Rasch, and Stiebale (2019[28]), also analysing the pharmaceutical industry, identify a causal negative effect on the innovation of the merged entities and their rivals, as measured through patent counts. Gautier and Lamesch (2021[54]) and Affeldt and Kesler (2022[55]) focus on acquisitions by GAFAM firms and show that the target companies' products are usually discontinued after the acquisition. Finally, de Barsy and Gautier (2024[56]) show that the patents of firms acquired by GAFAM experience a temporary increase in the citations by their acquiror's patents.

Other studies closely related to this analysis include Zhao (2009[45]), Bena and Li (2014[17]), and Sevilir and Tian (2010[57]), all of which address similar questions using COMPUSTAT data for the US. Zhao (2009[45]) compares the innovation activities of acquirors to those of acquirors that initiated acquisition negotiations but ultimately withdrew. She finds that successful acquirors tend to increase their innovation activity relative to acquirors with unsuccessful bids post-transaction. Sevilir and Tian (2010[57]) follow a similar approach, showing that firms engaging more in M&A tend to patent more after acquisitions.[6] Bena and Li (2014[17]) – building on the methodology introduced by Seru (2014[33]) – compare the joint innovation of targets and acquirors whose acquisitions were completed versus those withdrawn for reasons exogenous to innovation.[7] While they find no overall effect on innovation, they show that pairs experience an improvement in their innovation performance post-acquisition when there is technological overlap between the target and the acquiror.

Another set of studies exploiting both information on publicly listed and privately held companies also gathered mixed evidence. Altomonte, El-Mallakh and Sonno (2024[35]) study the effect of acquisitions by business groups in the cross-country Orbis database, showing that the patenting activity of target companies declines, on average, after the acquisitions. The result is strongly driven by targets with similar technologies to their acquirors. In a single-country study, Stiebale and Reize (2011[27]) exploit a representative panel of small and medium-sized German firms and causally show that acquisitions by

foreign companies harm the German target's innovation. Similarly, Stiebale (2016[58]), using Amadeus data for European companies, shows that while the targets of cross-border acquisition experience a decline in innovation post-acquisition, the overall innovation performance of the merged entity increases substantially. The author provides evidence that the results are driven by the relocation of innovation from the target to the acquiror's country. Lastly, Farre-Mensa, Liu, and Nickerson (2022[59]) exploit US patent data, focusing on patent acquisitions of first-time inventors (which they call start-ups). They causally show that inventors whose patents get acquired by another company substantially decrease their innovative output following this event.

With respect to this literature, the contributions of this paper are manyfold. First, and most importantly, it offers a comprehensive analysis of the relationship between acquisition and innovation, focusing specifically on start-ups. Exploring both the ex-ante characteristics and the post-deal effects on both sides of the acquisition delivers indeed a complete picture of the dynamics. Likewise, most of the prior literature leverages either datasets entirely focusing on publicly listed companies or datasets that are substantially biased towards them. The focus on start-ups is motivated by their importance in developing innovation and new technologies.[8] Second, this paper leverages a richer cross-country dataset, addressing the gap in prior literature that largely centres on US companies. By incorporating data from both developed and emerging economies, the paper captures broader trends in the start-up ecosystem that may not apply to the US alone. Lastly, unlike previous studies that typically limit analysis to single-time acquirors, this paper includes "serial acquirors" – firms that engage in multiple acquisitions over time. Thanks to newly developed econometric methods, this analysis provides insights into the behaviour and performance of firms that frequently acquire start-ups. Understanding the characteristics and performance of these firms is extremely relevant when looking at innovation, as often firms at the innovation frontier engage in more than one start-up acquisition.

3 Data

This paper combines several data sources for its analysis, covering start-ups, their financing events, and innovation activities. This section presents the different data sources used in the analysis, detailing how these data have been cleaned and linked for joint use. It concludes by presenting some descriptive statistics on the final sample used in the subsequent analysis.

Dataset

Data on start-ups are obtained from the OECD/STI Start-ups Database. This database combines data from Crunchbase and Dealroom, considered by investors and analysts among the most comprehensive sources of information on start-up activity in the US and Europe, respectively.[9] Data are collected from various sources like public news, company filings, domain and trade registries, and investor portfolios, among others. Crunchbase was founded in 2005 and Dealroom in 2013, but they contain retrospective information with a sufficiently large coverage from the early 2000s. These commercial datasets are combined, curated, cleaned, and harmonised within the Productivity, Innovation, and Entrepreneurship (PIE) Division of the Science, Technology, and Innovation (STI) Directorate at the OECD to create a unique and comprehensive dataset on the worldwide start-up ecosystem.

Information on start-up acquisitions and other financial interactions with incumbent companies is provided by Orbis M&A, part of the Orbis platform from Moody's Analytics. Previously known as Zephyr, this commercial dataset compiles information on M&A deals from media, press releases, financial reports, and administrative filings. It includes both domestic and cross-border M&As, covering deals involving target and acquiring firms across all industries. It offers global deal coverage from 2001, with European deals available from 1997. In this paper, acquisitions are defined as transactions between incumbent and start-up companies in which the incumbent acquires more than a 50.01% stake in the start-up.[10]

To characterise the innovative portfolios of the companies in the data, this study resorts to PATSTAT Global – Autumn 2023 Edition. This dataset is a snapshot of the bibliographic and legal events database of the European Patent Office (EPO) as of Autumn 2023. It contains detailed data on patents filed, published, and cited at the European and US patent offices.[11] Further information on the details of patent data is provided below.

To provide suggestive evidence on the possible channels driving the decline in patenting activity found after an acquisition takes place, additional variables from Orbis vintage 2022 and the OECD/STI IP Database are used to complement the analysis. The first database allows tracking the evolution of the financial statement variables – and specifically firm-level sales and productivity (henceforth, TFP) – of privately and publicly held firms using information from unconsolidated balance sheet data.[12] The second database allows tracking of the filing of new trademarks following the acquisition (standardised within the intellectual property office and year) from the OECD/STI IP Database. This database covers all trademarks registered at the EIPO (European Intellectual Property Office), the JIPO (Japanese Intellectual Property Office), and the USPTO (United States Patent and Trademark Office).

Finally, the different datasets have been merged relying on the links available at the OECD/STI MicroData Lab. The links across datasets rely on a string-matching procedure that takes information about the

companies – such as their names, countries, addresses, websites, or any other information available – to generate measures of similarity between pairs of companies across datasets. Pairs with similarity measures above a certain threshold are then assigned a unique identifier across datasets.[13] At the end of this procedure, firms belonging to the OECD/STI Start-ups Database, Orbis M&A, and PATSTAT are uniquely linked across the three different databases.

Identifying innovative start-ups

The paper focuses on innovative start-ups involved in M&A activity, where start-ups are regarded as young, innovation-driven, and growth-oriented firms. To ensure the analysis captures relevant start-ups, the OECD/STI Start-ups Database is further refined based on the following three criteria:

1. The firm appears in the OECD/STI Start-ups Database and has been linked to Orbis M&A,
2. The firm received the first venture capital financing round or filed its first patent between 2001 and 2021,
3. The firm was less than 10 years old at the time of its first relevant event (either the financing round or patent filing).

The reasoning behind the three criteria is as follows. The first criterion ensures all start-ups included in the sample have M&A information, making it possible to determine whether they have been acquired or not.[14] By restricting the sample to matched observations across datasets, the analysis avoids uncertainty regarding the acquisition status of non-matched start-ups. Additionally, the OECD/Start-ups Database lacks key information – like the companies' industries, which is obtained from the Orbis M&A dataset – that is leveraged extensively in the analysis. The second criterion narrows the sample to innovation-driven start-ups, in line with existing literature, where innovative start-ups are those securing early-stage financing or filing patents (or both) (Fons-Rosen, Roldán-Blanco and Schmitz, 2022[25]; Ederer and Pellegrino, 2023[8]).[15] Finally, the last criterion ensures the dataset captures actual start-ups rather than established companies.[16] Overall, these additional constraints aim at refining the start-up sample to focus exclusively on innovation- and growth-oriented start-ups, filtering out other types of young or small enterprises, and mature established companies.

The narrow and rigorous definition used to define start-ups plays a crucial role in the analysis, as it guarantees that all the start-ups in the sample are comparable and attenuates selection concerns. The specific thresholds used in criteria 2 and 3 are as close as possible to the existing literature (Fons-Rosen, Roldán-Blanco and Schmitz, 2022[25]; Ederer and Pellegrino, 2023[8]), even if they remain somewhat arbitrary. For this reason, extensive robustness checks have been performed throughout the different exercises carried out in this paper to assess whether any of these arbitrary choices drive the results. The findings through the paper remain qualitatively unchanged even when these conditions are not imposed.

Identifying acquirors and other investors

Acquirors and the companies against which they will be compared (i.e. the control group) are identified as all companies involved in either a majority or a minority stake deal with the start-ups in the sample, respectively. Thus, the sample of acquirors and their control group includes companies listed in the Orbis M&A database either as acquirors or as investors through minority stake investments of the above-mentioned start-ups' sample. Focusing solely on companies that interact with start-ups and distinguishing between those that acquire and those that provide other sources of funding ensures that the companies included in the sample are comparable, mitigating selection concerns in the analysis.

Final sample

The final sample considered in the analysis includes 93 855 start-ups across 60 countries, active in 204 3-digit NACE Rev. 2 industries within the manufacturing and market services sectors.[17] In addition, countries with less than 50 companies are dropped. Similar country and industry restrictions are applied on the side of actual and potential acquirors, resulting in a sample of 156 681 companies active in 217 3-digit NACE Rev. 2 industries and 74 countries. The time horizon included in the analysis considers all acquisitions of start-ups from 2001 to 2021. For more information on the sample composition by industries and countries, see Table A A.1 in Annex A.

The dataset presents a series of improvements over prior literature. First, the sample of acquired firms is larger than most of the papers mentioned above studying the relationship between start-up acquisitions and innovation. In particular, the sample covers 17 732 acquired start-ups.[18] Second, the global coverage of start-ups in this dataset is a major advancement, as most of the existing literature on start-ups is heavily biased towards the US.

Key innovation variables

To characterise a firm's innovative performance, the paper uses patent data. While patents are an imperfect proxy for innovation and capture only a portion of the overall innovation efforts developed by firms, they are a very widely established measure to proxy for innovation (Basberg, 1987[60]). Several alternative measures of innovation are leveraged in the paper.

First, the number of inventions filed by each firm is computed. This is measured by counting the annual number of DOCDB patent families each firm files. A DOCDB family consists of patents filed in different patent offices that cover the same invention, and the filing date of the earliest patent in the family is used as the invention's date of inception.[19] The annual amount of patent filings of a firm is then standardised according to the total number of inventions filed in each patent authority, WIPO technological class, and year and then summed across patent authorities and WIPO classes to have a standardised measure at firm-year level.[20] This standardisation accounts for variations in patenting practices across technologies, countries, and time. The flows will be used to assess the yearly post-acquisition performance of start-ups and acquirors. In addition, the stock will be used to characterise the start-ups and their acquirors at the moment of acquisition, reflecting their past innovative trajectory. To calculate the stock of inventions, standardised invention flows are aggregated at the firm level, with an initial stock starting in 1973 (to account for pre-sample inventions) and depreciating annually at a rate of 15%. The technological-class-specific invention stocks are also recorded to assess the technological proximity between companies (discussed further below).

Second, a quality-weighted measure of patenting activity is computed by weighting the number of inventions filed by each firm with the 5-year forward citations (excluding self-citations).[21] Because each patent within the same DOCDB family often includes several publications, the average 5-year forward citations across patents in the same DOCDB family is used to compute the citations-weighted count of inventions at the family level. Then, this measure is again standardised and aggregated for each firm similarly to the unweighted flows and stocks. This measure aims at better capturing the relevance of each filed invention and is traditionally interpreted as a sign of the quality of the patent (Squicciarini, Dernis and Criuscolo, 2013[61]). While the simple patent count measure includes information from patent offices all around the world, information on citations is restricted to those patents applied in the EPO and USPTO.

Third, the average radicalness of the patent portfolio of the company is created. The radicalness of a patent is defined as the ability of an invention to create something completely different from what already exists (Squicciarini, Dernis and Criuscolo, 2013[61]). This paper uses the definition of radicalness given by Shane (2001[62]), who proposes to compute the radicalness of a patent as the share of 4-digit IPC classes (i.e. the technological sub-classes that compose the WIPO fields) that a patent cites but is not classified in. This

captures the idea of taking a series of technologies and creating something new from them rather than following the same technological path. To compute the average radicalness of the patent portfolio, the average radicalness of each invention is computed as the average across the applications of the same DOCDB family. Then, this measure is further averaged across patents to generate a firm-year-specific measure of radicalness. The latter captures the average radicalness of the yearly patent flow. Finally, the average radicalness of the patent portfolio is, therefore, a weighted average of the radicalness of the current patent flow and the past patent stock.

Finally, measures of patent proximity between pairs of firms are constructed to capture the technological overlap. In other words, this variable aims at capturing whether firms patent inventions in similar technological fields, as defined by the WIPO classification. Following Jaffe (1986[63]), each firm *i* is characterised by a 1x35 vector of patent stocks F_i across the 35 WIPO technological fields.[22] Then, the measure of technological proximity between firms *i* and *j* is given by the cosine similarity between their vectors of patent stocks as

$$\text{Technological Proximity}_{ij} = \frac{F_i F_{j'}}{\sqrt{(F_i F_{i'})(F_j F_{j'})}},$$

where the measure is bounded between 0 and 1: firms publish in orthogonal WIPO fields when it is equal to 0, and identical ones when it is equal to 1.

Another important variable used in the analysis is the amount of venture capital (VC) raised by start-ups. While patents proxy for the innovative outcomes of the company, the amount of VC capital can be used as a proxy for the input to the innovation process – similarly to what is usually done with R&D expenditures. This variable is important to characterise acquisition targets, as start-ups are likely building their patent portfolio through R&D expenditures, which are typically financed through their funding rounds. In the early stages of a firm's life cycle, revenues are often minimal or non-existent, making external funding a primary source of capital for innovation (Dickinson, 2011[64]). In essence, while patents reflect the tangible results of innovation, VC funding provides the financial backing necessary to drive the development of new ideas, technologies, and products. Therefore, the VC stock will proxy these innovative inputs in this setting. The reasoning is that higher financing needs correlate with high R&D-intensity (Didier et al., 2021[18]).

Descriptive statistics

This section presents descriptive statistics on the final sample assembled for the analysis. First, the section compares acquired and non-acquired start-ups. Then it compares acquired start-ups before and after an acquisition. Finally, it delves into the differences between acquiring and non-acquiring incumbents.

The upper panel of Table 3.1 presents descriptive statistics for non-acquired start-ups, while the lower panel is for acquired ones. First, the table shows that acquired startups are, on average, more innovative than those in the control group. The first and second lines in each panel show the distribution of the number of patents filed by each firm over the sample period. In the first row, all firms in each of the two samples are used, while the second row focuses on start-ups that file a patent during their life cycle. Acquired firms are more likely to file a patent, as reflected by the difference in the mean value of the first line between the upper and lower panels. However, the patent portfolio is similar across patent-holding start-ups as shown in the second row. In the third and fourth lines, an equivalent exercise shows the distribution of patents filed by each firm, where each patent is weighted by its 5-year forward citations. As seen in the third line, acquired start-ups present patents that are substantially more cited. The fourth line shows that these differences across groups hold for patent-holding start-ups. The differences in patenting quantity and quality are smaller when comparing the second and fourth line of each panel to the first and the third line, suggesting that the main difference between acquired and non-acquired start-ups is on the extensive margin (having a patent or not), rather than on the intensive margin (citation weighted and unweighted

number of patents among patent-holding companies). This can also be seen in the proportion of firms that drop from the sample when restricting it to only patent-holding firms, i.e. all those start-ups that are in the sample because they received VC but never applied for a patent. While the number of start-ups from the first to the second row decreases by more than two-thirds in the upper panel, it only decreases by approximately one-half in the lower panel.

Table 3.1. Descriptive statistics: acquired versus non-acquired start-ups.

Panel A. Never acquired					
	N	Mean	P25	P50	P75
Patents	76 123	2.1	0	0	1
Patents (only patenting start-ups)	22 535	7.0	1	2	6
Citations-weighted patents	76 123	58.4	0	0	0
Citations-weighted patents (only patenting start-ups)	22 535	197.5	0	7	42
Venture capital	76 123	16.8	0.0	0.6	5.6
Venture capital (only with VC)	49 411	25.9	0.7	2.9	13.0
Panel B. Acquired					
	N	Mean	P25	P50	P75
Patents	17 732	3.5	0	0	2
Patents (only patenting start-ups)	8 035	7.7	1	2	6
Citations-weighted patents	17 732	101.9	0	0	8
Citations-weighted patents (only patenting start-ups)	8 035	224.6	1	12	68
Venture capital	17 732	11.7	0.0	0.0	5.0
Venture capital (only with VC)	8 383	24.9	1.3	5.8	21.0

Note: This table presents descriptive statistics on non-acquired and acquired startups in the upper and lower panel, respectively. It shows different moments of the distribution of a selected number of innovation measures that include the mean, the first, the second, and the third quartiles, as well as the number of observations in each panel. The innovation measures include the number of patents, the citation-weighted patents, and the venture capital, all aggregated over the sample period for each company.
Source: OECD calculations based on Orbis M&A, OECD/STI Start-ups Database, and PATSTAT.

Next, Table 3.1 focuses on the amount of VC raised by start-ups. While the average amount of VC is higher for non-acquired start-ups, acquired ones raise similar VC amounts when the sample is restricted to firms with a strictly positive amount. This can be explained by the acquisition event: acquired firms infrequently raise capital through VC rounds since they draw funds from the corporate parent and internal capital market (only 400 start-ups raise additional VC after being acquired). The median start-up company in the sample gets acquired when it is seven years old. If a company is acquired early on, it is less likely it will resort to VC financing. Nevertheless, those who have time to raise funds before the acquisition, on average, obtain similar financing to control group start-ups, corroborating their innovative profile.

Table 3.2 performs a similar exercise but looks only at acquired start-ups and compares the pre- and post-acquisition period (excluding the acquisition year itself) in the upper and lower panels, respectively. As can be seen, most of the patenting takes place before the acquisition, while it decreases substantially after, both when looking at simple and citation-weighted patents.[23]

Table 3.2. Descriptive statistics: acquired start-ups before and after acquisition.

Panel A. Before acquisition					
	N	Mean	P25	P50	P75
Patents	17 623	2.4	0	0	1
Patents (only patenting start-ups)	8 013	5.3	1	2	5
Citations-weighted patents	17 623	93.5	0	0	6
Citations-weighted patents (only patenting start-ups)	8 013	205.5	0	9	58
Panel B. After acquisition					
	N	Mean	P25	P50	P75
Patents	15 182	1.1	0	0	0
Patents (only patenting start-ups)	7 038	2.3	0	0	1
Citations-weighted patents	15 182	8.5	0	0	0
Citations-weighted patents (only patenting start-ups)	7 038	18.3	0	0	0

Note: This table presents descriptive statistics on acquired startups before and after the acquisition in the upper and lower panel, respectively. It shows different moments of the distribution of a selected number of innovation measures that include the mean, the first, the second, and the third quartiles, as well as the number of observations in each panel. The innovation measures include the number of patents, the citation-weighted patents, and the venture capital, all aggregated over the period before and after the acquisition for each company (excluding the year of the event).
Source: OECD calculations based on Orbis M&A, OECD/STI Start-ups Database, and PATSTAT.

The descriptive evidence reported in these two tables offers preliminary insights into the main findings of the paper. In the next sections, econometric analysis is performed to provide more robust results of the suggestive evidence highlighted in this subsection, regarding both the differences between acquired and non-acquired start-ups and the effects of acquisitions on start-up innovation performance.

Table 3.3. Descriptive statistics: acquirors versus other investors.

Panel A. Never acquire					
	N	Mean	P25	P50	P75
Patents	145 561	4.2	0	0	0
Patents (only patenting start-ups)	13 772	44.0	1	3	11
Citation-weighted patents	145 561	38.1	0	0	0
Citation-weighted patents (only patenting start-ups)	13 772	394.9	0	4	40
Number of minority stakes	145 561	3.4	1	1	2
Panel B. Acquire					
	N	Mean	P25	P50	P75
Patents	11 120	18.3	0	0	1
Patents (only patenting start-ups)	3 492	59.7	1	4	15
Citation-weighted patents	11 120	392.7	0	0	0
Citation-weighted patents (only patenting start-ups)	3 492	1 250.0	1	19	186
Number of acquisitions	11 120	1.3	1	1	1

Note: This table presents descriptive statistics on non-acquiring and acquiring incumbents in the upper and lower panel, respectively. It shows different moments of the distribution of a selected number of innovation measures that include the mean, the first, the second, and the third quartiles, as well as the number of observations in each panel. The innovation measures include the number of patents and the citation-weighted patents, all aggregated over the sample period for each company. Similarly, it reports the distribution moments of the number of minority stakes in start-ups for non-acquiring companies and the number of acquisitions for acquiring ones.
Source: OECD calculations based on Orbis M&A, OECD/STI Start-ups Database, and PATSTAT.

Finally, Table 3.3 focuses on the acquirors and their respective control group (i.e. firms that finance start-ups but do not acquire them). It presents descriptive statistics similar to Table 3.1 distinguishing between those that acquire start-ups and those that do not. Acquirors are substantially more innovative than companies that do not acquire start-ups across all patent measures considered. In all cases, the density of each patent measure for acquirors is shifted to the right with respect to the distribution presented by companies that invest in start-ups through minority investments. The last row of each panel shows that, on average, acquirors acquire more than one start-up in the sample period, and not-acquiring companies also engage with several start-ups through minority stake investments. The last row of the bottom panel also shows that most of the acquirors (more than 75% of them) are involved in only one acquisition. Given that the number of acquisitions is 17 902 and more than 75% of the 11 120 acquirors buy only one start-up, it follows that there are very few companies undertaking many acquisitions, the so-called “serial acquirors”.

4 What kind of firms engage in acquisitions?

This section characterises the companies in the dataset at the moment of acquisition, to understand whether target and acquiror firms have some key characteristics that distinguish them from other companies, with a focus on its innovation characteristics.

Methodology

The analysis below explores how the probability of acquisition depends on target or acquiror characteristics, and how the probability of a pairing depends on their joint attributes. In other words, this section answers the questions: (i) who the acquisition targets are, (ii) who the acquirors of start-ups are, and (iii) how targets-acquirors pairs are formed.

As mentioned in the previous section, the sample of start-ups is composed of firms that receive the first VC investment or apply for the first patent between 2001 and 2021 and are less than 10 years old at that time. Among these, the sample of acquired start-ups (treated targets) includes all the start-ups that were acquired between 2001 and 2021. These constitute approximately 20% of the start-ups in the final sample. The rest of the start-ups (i.e. non-acquired start-ups in the sample who received at least a VC or filed a patent) represent the so-called control group. The analysis will compare the treated targets to the start-ups in the control group to understand if acquired start-ups have systematically different characteristics than non-acquired ones.

On the acquiror side, the sample comprises firms that, according to Orbis M&A, invested in the sample of start-ups either through a majority or a minority stake investment. The analysis compares firms acquiring majority ownership in a start-up (i.e. treated companies or, equivalently, acquirors) with those that engage with start-ups through minority stakes (i.e. non-acquiring firms). The latter group serves as the control group in the analysis of acquirors.

A linear probability model is used to answer the first two questions addressed in this section. The specification uses the cross-sectional variation in the data (i.e. it compares the levels of innovation across firms) to analyse how the innovation activity affects the probability of being acquired (acquiring).

Specifically, the following linear probability regression is considered:

$$1\{\text{Acquisition}\}_{\text{it}} = \alpha_{sct} + \beta * \text{Innovation characteristics}_{\text{it}-1} + \varepsilon_{it},$$

Equation 1

where the dependent variable is a dummy that equals 1 if an acquisition takes place for a target (acquiror) *i* at year *t,* and 0 otherwise; α_{sct} is a set of 3-digit NACE Rev. 2 industry (*s*)-country (*c*)-year (*t*) fixed effects; and $\text{Innovation charactertistics}_{\text{it}-1}$ captures the different patent-related measures of innovation as well as the VC stocks for company *i* at time *t-1*, as discussed in detail below. This specification exploits cross-sectional variation by comparing the levels of the variables of interest between acquired and non-acquired

start-ups (respectively acquirors and non-acquiring companies in the case of acquirors) within the same country-industry-year. It allows determining whether higher values of the explanatory variables – their innovation characteristics – are associated with a higher probability of being acquired (resp. acquiring). The configuration of fixed effects allows controlling for all unobservable characteristics that are common to all start-ups (resp. acquirors) within the same country-industry-year. When looking at start-ups, the specification includes the age of the start-up as a control variable.

Equation 1 exploits a repeated cross-section to identify the parameters of interest. Acquired start-ups are considered in the sample only in the year of acquisition, while the control group firms are considered multiple times. Specifically, acquired start-ups are compared potentially against the same set of control group start-ups over time for a limited number of periods. In particular, non-acquired start-ups are considered in the control group only up to 10 years before and after the first VC investment or 6 years before and after the first patent (depending on which one happened first).[24] This choice is also made to mitigate potential concerns about attrition of the start-up sample. In other words, this ensures that comparisons are not made against firms that exited the market, as the data are not well-suited to analyse exit dynamics, or against more established firms that grow during the sample period.[25]

Finally, to answer the question on pair formation, the paper employs a specification that identifies the pair characteristics that increase the likelihood of a deal, following a methodology proposed by Bena and Li (2014[17]). Fictitious pairs – representing potential but unrealised deals – are generated to serve as a comparison against actual transactions. By calculating various pair-specific explanatory variables for all cases, the analysis contrasts these variables between real and fictitious deals. This comparison helps identify the characteristics that increase the likelihood of a pair engaging in a deal.

The set of fictitious deals is built by matching each acquired target to three potential acquirors from the control group of acquirors, and each actual acquiror to three start-ups from the control group, i.e. start-ups that were not acquired.[26] These matches are formed in two ways. First, the analysis randomly matches targets and acquirors. Second, the analysis matches acquirors to targets that have similar VC stocks and age as the acquired start-ups. This matched sample guarantees that acquired and non-acquired start-ups do have similar *observable* characteristics other than the explanatory variables of interest and therefore makes the two groups of start-ups more comparable. In particular, start-ups are divided into four age groups (0-2, 3-5, 6-10, and more than 10 years old) and three VC levels (no VC raised, VC raised below and above the median VC level in the same industry and country). Then, the fictitious deals are built drawing control group start-ups that match the same age and VC category as the actual acquired start-up.

Specifically, the following linear probability specification is considered:

$$1\{\text{Pair is formed}\}_{ijt} = \alpha_{d(i,j)} + \beta_1 * \text{Technological Proximity}_{ijt-1} + \beta_2 * \text{Cross} - \text{Industry}_{ij} + \beta_3 * \text{Cross} - \text{country}_{ij} + \varepsilon_{ijt},$$

Equation 2

where $1\{\text{Pair is formed}\}_{ijt}$ is a dummy variable that takes the value 1 if a deal takes place between target *i* and incumbent *j* at time *t*, and 0 otherwise, and $\alpha_{d(i,j)}$ represents a "menu-of-deals" fixed effect. By construction, each menu of deals is composed of seven deals: the actual one and six fictitious ones (i.e. three by matching the actual target to three potential acquirors and three by matching the actual acquiror to three potential targets). Simply put, the specification is informative about which deal is more likely to happen out of each set of seven deals. This fixed effect ensures that the variation exploited in the regression comes solely from comparing actual deals with their *matched* fictitious counterparts.

$\text{Technological Proximity}_{ijt-1}$ is the primary focus of this specification. It measures technological proximity à la Jaffe (1986[63]), assessing the overlap across technological classes of the patent portfolios of companies *i* and *j*. As explained in the previous section, this variable captures the similarity in innovation portfolios of

two firms, allowing to determine whether acquisitions primarily occur between firms with similar technologies or between those developing innovations in distinctly different areas. Since it is only possible to build this measure for patenting firms, this analysis is restricted to pairs in which both sides have patents. $\text{Cross} - \text{Industry}_{ij}$ is an indicator that takes value 1 if *i* and *j* are in different 3-digit industries, and $\text{Cross} - \text{Country}_{ij}$ is an indicator that takes value 1 if *i* and *j* are in different countries. These variables will inform whether pairs are more likely to happen within the same country and industry, or whether acquisitions are also used to expand into new markets.

Importantly, since this identification strategy relies heavily on the fictitious matches for each target and acquiror, the analysis draws the randomly matched sample 100 times and reports the results of the 100 iterations to corroborate its robustness to the selection of the fictitious pairs. For each simulation, different random pairs are formed.

Acquisition of targets

Table 4.1 reports the results of Equation 1 when looking at the acquisition of targets. The explanatory variables of interest are four alternative patent-related measures of innovation outcomes (one for each column), and the amount of VC received over the last three years before the acquisition, as a proxy for innovation inputs. The row labelled “mean dependent variable” reports the average probability of being acquired in the sample used in each column; this variable is used as a reference point for interpreting the magnitude of the results.[27] Likewise, the row labelled “premium” showcases the ratio between the coefficient of interest and the mean dependent variable expressed in percentages. The first column shows that having (at least) a patent increases the probability of being acquired: for start-ups that did not secure any VC funding, having a patent before the acquisition increases the probability of being acquired by 0.84 p.p., which is approximately 35% of the average probability of being acquired (2.4%).[28] Also, the amount of VC funds raised in the last three years before the acquisition is positively associated with the acquisition event. The positive association between VC funds and the probability of acquisition can be interpreted in different ways. On the one hand, firms that raised more VC funds can be more attractive to the acquiror since other investors already showed interest in their potential. On the other hand, prior literature shows that there exists a correlation between R&D-intensive firms and higher financing needs (Didier et al., 2021[18]). Therefore, firms raising more funds can potentially be more R&D-intensive as well.

Column 2 restricts the sample to those companies that hold a patent at some point during the sample period and exploit the intensive margin of innovation outcomes (i.e. the number of patents held) rather than the extensive margin (whether firms held a patent or not).[29] The positive coefficient indicates that the probability of being acquired increases with the number of patents held by the start-ups. This column, focusing only on patenting start-ups, reinforces the result of Column 1. However, there are substantial differences in the magnitude of the premium between extensive and intensive margins. In Column 2, the premium represents the effect of a change from a patent stock of 0 to a standardised patent stock equivalent to the average patent stock across start-ups in the sample. The difference in the premia between Column 1 and Column 2 might suggest that the first patenting event is more relevant for the prospect of acquisition than the subsequent ones. This set of results is similar to those reported by Bena and Li (2014[17]). Using a sample with patenting and non-patenting firms, they show that target companies have more patents and R&D expenditures than firms in the control group within their industries. Also, in their analysis the differences are smaller when restricting to only patent-holding companies (specifically, they find non-statistically significant differences, while this paper finds that they decrease substantially). The findings reported Table 4.1, in line with those reported by Bena and Li (2014[17]), reinforce the idea that the extensive margin is more relevant than the intensive one.[30]

Table 4.1. The effect of patents, their quality, and VC stocks on the probability of being acquired.

	(1)	(2)	(3)	(4)
$\text{Has a patent}_{t-1}$	0.0084***			
	(0.0006)			
$\log(1 + \text{Patent stock}_{t-1})$		0.0405***		0.0340**
		(0.0112)		(0.0132)
$\log(1 + \text{Citations} - \text{weighted patent stock}_{t-1})$			0.0155***	
			(0.0043)	
Radicalness_{t-1}				-0.0025
				(0.0022)
$\log(1 + \text{VC stock}_{t-1})$	0.0006***	0.0005***	0.0005***	0.0005***
	(0.0000)	(0.0001)	(0.0001)	(0.0001)
Only patent-holding start-ups	No	Yes	Yes	Yes
Observations	557 191	197 194	197 194	126 288
R-squared	0.059	0.079	0.079	0.074
Mean dep. variable	2.4	2.6	2.6	2.6
Premium	34.9	0.9	1.3	-4.2

Note: The table shows the results of Equation 1. Column 1 shows the effect of a dummy variable that takes the value 1 if start-up *i* had a patent at time *t-1* on the probability of being acquired (extensive margin). Columns 2 and 3 reflect the effect of the patent stock and the citation-weighted patent stock, respectively, among firms that ever held a patent during the sample period (intensive margin). Column 4 reflects the effect of the radicalness of the patent portfolio of the start-up, controlling for the size of the portfolio. All columns include, as a control variable, the VC stock defined as the amount of VC funds secured over the last three years before the acquisition. The row mean dep. variable reports the unconditional probability of being acquired in the relevant sample in percentages. The premium shows the change in the probability of being acquired from having a patent in the first column, from increasing the stock from 0 to the average patent stock in the second and third columns, and from increasing the radicalness from 0 to the average radicalness in the fourth column, over the mean dependent variable expressed in percentages. All regressions control for the firm's age and industry-country-year fixed effects. *: p-value < 10%, **: p-value < 5%, *: p-value < 1%.
Source: OECD calculations based on data from PATSTAT, OECD/STI Start-ups Database, and Orbis M&A.

The last two columns in Table 4.1 present similar exercises with a focus on the patent stock quality, restricting to start-ups with at least one patent over the sample period. In particular, Column 3 uses the citations-weighted patent stock as a dependent variable, while Column 4 uses the average radicalness of the patent stock (controlling for the unweighted patent stock to control for the size of the patent portfolio). The findings show that the patent stock of acquired companies is more cited than that of non-acquired start-ups, but it is, on average, equally radical. The premium of the citations-weighted patent stock is higher than that of the unweighted patent stock, indicating that not only is the number of patents relevant for acquisition, but also their relevance.[31]

Table 4.2 provides a better understanding of start-up targets by investigating possible heterogeneities across different dimensions. All these exercises are estimated relying on the cross-sectional framework of Equation 1. The first column examines how the impact of having a patent varies across age categories. Relative to start-ups younger than 3 years (the reference category for the table), the interaction term "Has a patent x Age" shows that having a patent significantly increases the probability of being acquired for start-ups aged 3–5 years and those aged 6-10 years. However, this effect becomes slightly negative for start-ups older than 10 years. Therefore, there is an inverted U-relationship between having a patent and the start-up's age, suggesting that patents are more relevant for companies at ages 3 to 10. For start-ups without VC funding and between 3 and 10 years old, having a patent can increase the likelihood of being acquired by approximately 50% with respect to the average probability of being acquired.[32] For start-ups older than 10 years, instead, the premium of having a patent is statistically lower than for start-ups younger than 3 years.

Table 4.2. Heterogeneity of the effect of holding a patent on the likelihood of acquisition across acquired start-ups.

		Age	Across industries	Within industries	Across countries	Within countries
		(1)	(2)	(3)	(4)	(5)
$\text{Has a patent}_{t-1}$		0.0040**	0.0078***	0.0016***	0.0043***	0.0051***
		(0.0017)	(0.0005)	(0.0004)	(0.0003)	(0.0005)
$\text{Age x Has a patent}_{t-1}$						
	3-5	0.0073***				
		(0.0019)				
	6-10	0.0078***				
		(0.0018)				
	+10	-0.0040*				
		(0.0022)				
$log(1 + VC\ stock_{t-1})$		0.0006***	0.0003***	0.0003***	0.0002***	0.0005***
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Observations		540 637	535 417	530 615	529 858	536 179
R-squared		0.0609	0.0630	0.0374	0.0622	0.0554
Mean dep. variable		2.5	1.7	0.9	0.7	1.8
Premium		16.2	46.7	18.1	57.5	28.7

Note: The table shows the results of Equation 1 exploiting heterogeneity across start-ups. All columns show the effect of a dummy variable that takes the value 1 if start-up *i* had a patent at time *t-1* on the probability of being acquired (extensive margin). All columns include the VC stock defined as the amount of VC funds secured over the last three years before the acquisition. Column 1 allows the effect of having a patent to vary across age categories by interacting "Has a patent" with age category dummies, where the category from 0 to 2 years old is the reference category. For this column, the non-interacted age category coefficients are not reported for the sake of clarity, but they are included in the regression. Columns 2 and 3 only include acquisitions that happen across and within 3-digit NACE Rev. 2 industries, respectively. Columns 4 and 5 only include acquisitions that happen across or within countries, respectively. The control group never changes. The row mean dep. variable reports the unconditional probability of being acquired in the relevant sample in percentages. The premium shows the change in the probability of being acquired from having a patent over the mean dependent variable multiplied by 100 (i.e. the ratio between the coefficient on "Has a patent" over the row "Mean dep. variable" multiplied by 100). Notice that this implies that the first premium reflects the premium for companies with ages 0 to 2. All regressions control for the firm's age and industry-country-year fixed effects. *: p-value < 10%, **: p-value < 5%, *: p-value < 1%.
Source: OECD calculations based on OECD/STI Start-ups Database, Orbis M&A, and PATSTAT data.

The next two columns explore if having a patent affects the probability of being acquired differently depending on whether the acquisition occurred within the same 3-digit NACE industry or across different industries. Specifically, the treated start-ups in the second column only include those that have been acquired by a company active in a different industry, while the third column only includes start-ups acquired by a company active in the same industry. In both columns, acquired start-ups within and across industries are compared against the baseline control group of non-acquired start-ups. The result shows that having a patent increases the average probability of being acquired by more than 45% the average probability of being acquired when acquisitions happen across industries (for firms that did not raise any VC funds). Meanwhile, the premium of having a patent when acquisitions happen within the industry decreases to 16% of the average probability of being acquired. Similarly, the fourth and fifth columns perform a similar exercise disentangling among acquisitions that happened across or within countries. While having a patent increases the likelihood of acquisition by more than half the value of the baseline average probability (third column) when acquisitions happen across countries, this premium decreases to one-fourth of the average probability when acquisitions happen within countries.[33]

In Table A B.1 in the Annex, further heterogeneity exercises comparing start-ups across regions (EU versus USA) and sectors (active in high versus low digital intensive sectors) are provided. The evidence

shows that EU targets are more likely to have a patent, while US targets are more likely to raise more VC funds before the acquisition. At the same time, while having a patent yields a similar premium across high- and low-digital-intensity sectors, raising VC funds is strongly correlated with the acquisition event for targets in high-digital-intensity sectors but not in low-digital-intensity ones.

Overall, the evidence in this subsection indicates that start-ups with more patents are systematically more likely to be acquired. This aligns with the existing literature suggesting that acquisitions are often driven by innovation motives. However, several other mechanisms could explain this pattern. First, patents may serve as a quality signal, reassuring investors about a start-up's technological strength, commitment to innovation, and long-term viability. Second, patents can reduce information asymmetries, giving acquirors clearer insights into a start-up's technological direction, potential market applications, or competitive edge. This is particularly relevant in industries where due diligence is complex or start-ups are acquired before commercialisation. Beyond signalling, patents may also hold direct strategic value. They can provide legal protections that strengthen a company's market position, making a start-up more attractive for defensive acquisitions – where an acquiror seeks to prevent competitors from accessing key technologies. Additionally, patents might indicate that a start-up possesses specialised knowledge, research capabilities, or technical talent that an acquiror seeks to integrate into its operations. Importantly, the importance of patents appears to be amplified in situations of greater uncertainty. When start-ups are younger and have yet to establish a track record, or when acquisitions occur across industries or countries – where information asymmetries between the acquiror and target are larger – patents seem to be a more critical factor in acquisition decisions.

Acquirors

Following the same steps discussed in the previous subsection, the analysis now shifts the focus to the acquirors engaging in start-up acquisitions. The results are reported in Table 4.3. Specifically, the first four columns (Columns 1-4) show the estimated coefficients of Equation 1 where the dependent variable is a dummy for acquisition. The next four columns (Columns 5-8) use instead the log of the cumulative number of acquisitions per year for each acquiror as a dependent variable, restricting to those acquirors with at least one acquisition. This choice is motivated by the presence of serial acquirors, i.e., those that acquire more than once in the sample period, as reported in Table 3.3. Thus, Columns 5-8 are estimated using the Poisson pseudo-maximum likelihood estimator, which allows to deal with discrete outcome variables and leveraging the intensity of M&A activity on the acquiror side.[34]

The first four columns highlight the innovative profile of acquirors. At the bottom of the table, the row "Mean dependent variable" reports the average probability for incumbents to acquire a start-up, and it is again used to interpret the coefficients. The premium in these regressions is computed similarly to the previous exercises. Column 1 shows that acquirors that filed a patent are more likely to acquire a start-up than those that did not.[35] Second, Column 2 restricts to those acquirors that filed a patent (approximately 12% of incumbents), and shows that the previous result also holds at the intensive margin: the more patents an acquiror holds, the higher the probability of making an acquisition. Third, Column 3 shows that the latter result also holds when accounting for the quality of the patent stock, indicating that incumbents with higher quality patents – proxied by the citations-weighted stock of patents - have higher probabilities of acquisition. Finally, Column 4 includes the measure of the radicalness of the patent stock of the acquiror, together with the unweighted patent stock to control for the size of the patent portfolio. Similarly to the start-ups' case, acquirors do not present a differential radicalness relative to non-acquiring companies with patents.

The next four columns (Columns 5-8) show that these results also hold when looking at the log of the cumulative number of yearly acquisitions as a dependent variable for acquirors with at least one acquisition. In these columns, the coefficients show the incidence rate ratio, i.e. the multiplier associated with a unit increase in the predictor variable.[36] In these specifications, the mean dependent variable shows

the average cumulative number of acquired start-ups, while the premia is the expected increase in the cumulative number of acquired start-ups for a unit increase in the dependent variable, expressed in percentages (i.e. the incidence rate ratio minus one multiplied by a hundred). The same patterns hold when exploiting the intensive margin of acquisitions: having a patent substantially increases the cumulative count of acquired start-ups. Having more of these patents and of better quality also substantially increases the count.

Table A B.2 in the Annex B shows a similar exercise to that of Table 4.3 exploiting differences across acquisitions that happen across and within industries and countries. The patent premium is still stronger when acquisitions happen across industries or countries.

Table 4.3. The effect of patents and their quality on the probability of acquiring a start-up

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{Has a patent}_{t-1}$	0.0154***				1.4417***			
	(0.0002)				(0.0315)			
$\log(1 + \text{Patent stock}_{t-1})$		0.0276***		0.0290***		1.2025***		1.2016***
		(0.0029)		(0.0036)		(0.0764)		(0.0788)
$\log(1 + \text{Citations} - \text{weighted patent stock}_{t-1})$			0.0259***				1.3032***	
			(0.0013)				(0.0581)	
Radicalness_{t-1}				-0.00233				0.8626*
				(0.0018)				(0.0708)
Estimation	LP	LP	LP	LP	Poisson	Poisson	Poisson	Poisson
Only patent-holding acquirors	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	2 992 702	268 715	268 715	167 583	10 761	3 727	3 727	3 179
R-squared	0.051	0.098	0.099	0.104	0.077	0.092	0.096	0.094
Mean dep. variable	0.5	1.9	1.9	1.9	1.5	1.9	1.9	1.9
Premium	322.7	3.1	8.1	-4.8	44.2	20.3	30.3	-13.7

Note: The table shows the results of Equation 1. Columns 1-4 use as a dependent variable a dummy variable that takes the value 1 if acquiror *i* acquired a start-up at time *t* and are estimated using a linear probability model. Columns 5-8 use the cumulative number of acquired start-ups by acquiror *i* at time *t* as a dependent variable and are estimated using a Poisson model, restricting to those acquirors with at least one acquisition. Columns 1 and 5 show the effect of a dummy variable that takes the value 1 if acquiror *i* had a patent at time *t-1* on the probability of acquiring (extensive margin). Columns 2 and 3 reflect the effect of the patent stock and the citation-weighted patent stock, respectively, among firms that ever held a patent during the sample period (intensive margin). Columns 6 and 7 are the equivalent using the continuous dependent variable. Columns 4 and 8 reflect the effect of the radicalness of the patent portfolio of the acquiror, controlling for the size of the portfolio. The row mean dep. Variable in Columns 1-4 reports the unconditional probability of being acquired in the relevant sample in percentages, while in Columns 5-8 reports the unconditional average number of acquired start-ups in the relevant sample in percentages. The premium shows the change in the probability of being acquired from having a patent in Columns 1 and 4, from increasing the stock from 0 to the average patent stock in Columns 2 and 6, and Columns 3 and 7, respectively, and from increasing the radicalness from 0 to the average radicalness in the Columns 4 and 8, over the mean dependent variable expressed in percentages. All regressions control for industry-country-year fixed effects. *: p-value < 10%, **: p-value < 5%, *: p-value < 1%.
Source: OECD calculations based on data from PATSTAT, OECD/STI Start-ups Database, and Orbis M&A.

All in all, the evidence suggests not only that acquirors choose start-ups that are actively engaging in innovation activities, but also that acquirors are more innovation-oriented than other companies. This might suggest that incumbents need a base level of absorptive capacity to acquire start-ups and benefit from their technological infrastructure. Alternatively, it could indicate that technological leaders engage in acquisitions to prevent disruptive start-ups from growing.

How are acquiror and start-up pairs formed?

After having established that both acquisition targets and acquirors are more likely to hold patents before the acquisition event, this subsection studies the role of market and technology overlap in pair formation. In particular, this analysis leverages the framework described in Equation 2 to assess whether industry, country, and patent similarities are important dimensions in pair formation. As explained above, this specification exploits differences across the actual business deals and fictitious pairs.

Columns 1 and 3 of Table 4.4 show the median coefficients resulting from one hundred iterations of Equation 2 using two different samples: Column 1 uses the randomly formed pairs, while Column 3 the "matched sample" of fictitious deals. In Column 3, the specification also includes the "menu-of-deal" fixed effect and, therefore, exploits variation within each acquiror-target pair. The standard errors are the standard deviation of these coefficients across the different iterations.

The coefficients of "Technological proximity" show a positive relationship between a formed pair and their technological proximity: acquisitions are more likely when the patent stocks of the acquiror and targets exhibit greater similarity across technological WIPO fields. This suggests that acquisitions might be strongly motivated by technological reasons and can serve as a means for acquirors to access the innovations developed by start-ups. By the same token, the next two coefficients show that pairs are less likely to be formed when the actors do not share industries or countries.

These results are consistent with Hoberg and Phillips (2010[41]) who show that acquisitions are more likely to happen when companies share broad product similarities, which they show to be higher between companies within the same 3-digit industries. Similarly, these results align with those of Bena and Li (2014[17]), who found that pairs with a higher product market relatedness and technological overlap are more likely to be formed in a sample with cross-industry pairs. These findings hint that product market overlaps and technological synergies are important components in start-up acquisitions.

Columns 2 and 4 of Table 4.4 zoom into the heterogeneous role of technological proximity, using the same samples of Columns 1 and 3, respectively. The baseline specification is expanded to include an interaction term between the technological proximity variable and both a cross-industry and a cross-country dummy. The results show that technological proximity plays a more relevant role when pairs are formed across industries: if the pair is cross-industry, it becomes more important for the companies to have patents in related technologies (the opposite being true for countries).

This result directly speaks to the result of Bena and Li (2014[17]). In their paper, the authors find that, while technological overlap and product market relatedness both increase the likelihood of pair formation, their interaction has a negative effect. They argue, along the lines of Hoberg and Phillips (2010[41]), that as firms have closer substitutes, gains in an acquisition will only stem from acquiring firms with differentiated technologies. Assuming that industries proxy well for product markets (Hoberg and Phillips, 2010[41]; Calligaris et al., 2024b[20]), the same logic applies in this paper. First, acquirors that choose to expand in new industries might find it beneficial to acquire companies with similar technologies to leverage their existing knowledge and create synergies. Second, a different technology might be of interest to the acquirors, as it might signal that the start-up can either compete more efficiently or produce a more differentiated product, prompting the acquisition in both cases.

Table 4.4. The effect of technological and market overlap on the likelihood of pair formation.

	(1)	(2)	(3)	(4)
$\text{Technological proximity}_{t-1}$	0.5526***	0.6134***	0.4877***	0.4954***
	(0.0140)	(0.0567)	(0.0079)	(0.0224)
$\text{Cross} - \text{industry}$	-0.3313***	-0.3700***	-0.2629***	-0.2841***
	(0.0171)	(0.0192)	(0.0076)	(0.0086)
$\text{Cross} - \text{country}$	-0.1824***	-0.1431***	-0.0733***	-0.0577***
	(0.0120)	(0.0130)	(0.0050)	(0.0052)
$\text{Technological proximity}_{t-1}$ x $\text{Cross} - \text{industry}$		0.1137**		0.0645***
		(0.0496)		(0.0204)
$\text{Technological proximity}_{t-1}$x $\text{Cross} - \text{country}$		-0.1950***		-0.0769***
		(0.0454)		(0.0199)
Fictitious pairs	Random	Random	Matched	Matched
Menu-of-Deals FE	No	No	Yes	Yes
Observations	23 835	23 835	6 776	6 776
Deals	3 405	3 405	968	968
R-squared	0.2639	0.2650	0.2744	0.2821

Note: The table shows the results of 100 iterations for Equation 2 estimated using a linear probability model. The coefficient in the table is the median value of the specified coefficient, and the standard errors are the standard deviation of these coefficients across the simulations. The dependent variable is a dummy variable that takes value 1 if the deal took place and 0 otherwise. Technological proximity is the measure of technological closeness à la Jaffe (1986[63]), cross-industry is a dummy variable that takes the value 1 if the target and acquiror pair are in different 3-digit NACE Rev. 2 industries, and cross-country is a dummy variable that takes the value 1 if the target and acquiror pair are in different countries. The row labelled Sample indicates whether the pairs were formed randomly or matched the start-ups on the VC and age level of the acquired start-up. Columns 3 and 4 include menu-of-deals fixed effects. *: p-value < 10%, **: p-value < 5%, *: p-value < 1%.
Source: OECD calculations based on OECD/STI Start-ups Database, Orbis M&A, and PATSTAT.

5 How does acquisition affect innovation?

The previous sections showed that innovation motives can be a key factor in a company's decision to pursue start-up acquisitions. Acquirors with strong patent portfolios are indeed more likely to engage with start-ups that exhibit early signs of innovation activity. Furthermore, acquisitions tend to occur more frequently when the patent portfolios of the acquiror and target exhibit greater similarity. This result reinforces the idea that acquiring a start-up's innovation might be a driving force behind the acquisition decision. A natural question arises: how do these interactions impact the innovation performance of both the acquiring and the acquired after the deal is completed?

Methodology

To answer this question, a difference-in-differences (DID, henceforth) estimator strategy is employed. Specifically, this estimator traditionally compares the outcome of interest (patenting activity) of treated units (acquired start-ups or acquirors) with the outcome of interest of control group units (non-acquired start-ups or non-acquiring companies) before and after the treatment (acquisition). The DID estimator is unbiased as long as the differences in the outcome of interest would have remained constant between treated and control groups in the absence of the treatment (Abadie, 2005[65]). In this specific setting, it means that the coefficient of interest is properly estimated if, in the absence of an acquisition, the differences in patenting activity between treated and non-treated firms observed in the pre-acquisition phase would have remained constant over time.

In practice, a widely used method to estimate the so-called average treatment effects is to use two-way fixed effects (TWFE) regressions to get an estimate of the DID estimator.[37] However, recent research shows that the use of TWFE to estimate average treatment effects requires additional assumptions on the nature of the treatment for the estimator to be unbiased (Borusyak, Jaravel and Spiess, 2024[66]). Specifically, the treatment effect should be constant over time and across treated units – an assumption that is hardly met in this setting.[38] On the one hand, firms are treated at different points in time; on the other, the effect of the treatment is likely to vary across both periods and firms (e.g. acquirors purchasing different numbers of start-ups).

As a response to this problem, a plethora of estimators that avoid these biases have been developed.[39] Among the many estimators proposed to deal with staggered treatments with heterogeneous effects (Callaway and Sant'Anna, 2021[67]; Sun and Abraham, 2021[68]; Borusyak, Jaravel and Spiess, 2024[66]; de Chaisemartin and d'Haultfoeuille, 2021a[69]), this paper relies on the methodology developed by de Chaisemartin and D'Haultfoeuille (2024[31]), as it best accommodates all the necessary cases present in the data.[40] First, it enables estimation with both binary and staggered treatments. These are particularly relevant when analysing start-up targets, as they are usually acquired only once (binary) but in different years (staggered). Second, it also accommodates discrete staggered treatments, which is relevant in the case of acquirors, as some of them engage in multiple start-up acquisitions.

Unlike the traditional DID estimator, this methodology also provides unbiased estimates without requiring a never-treated control group by exploiting variation between treated and not-yet-treated units. As shown in the previous section, firms with more patenting activity are more likely to be acquired. This selection bias makes it challenging to accurately and causally identify the effect of acquisition on patenting activity by comparing treated and never-treated start-ups, as they are inherently different in terms of patenting performance. Other factors beyond the acquisition itself might be correlated with the different innovation performance observed after the acquisition. For instance, acquirors might target companies that have completed the development of their technologies and are ready for commercialisation, so they stop patenting. By comparing never-acquired to acquired start-ups, one would obtain a negative effect of the acquisition on patenting. However, the decline cannot be causally attributed to the acquisition event, as it would have happened in its absence too. To address this selection bias, the main specification restricts the control group to not-yet-treated companies, i.e. companies that will be acquired (will acquire) but have not yet been acquired (have not yet acquired). By focusing only on treated firms, the analysis focuses on a more comparable sample, alleviating these concerns. Additionally, the announcement date of the acquisition is used instead of the completion date to control for anticipation effects that might bias the estimates.

Formally, the cumulative effect of an acquisition on the innovative activity for a company *i* that gets treated in the period F_i and the period $F_i + l$ is computed as

$$\mathrm{DID}_{\mathrm{i,l}} = \mathrm{Innovation}_{\mathrm{i},\mathrm{F_i}-1+\mathrm{l}} - \mathrm{Innovation}_{\mathrm{i},\mathrm{F_i}-1} - \frac{1}{\mathrm{N}^{\mathrm{i}}_{\mathrm{F_i}-1+\mathrm{l}}} \sum_{\mathrm{i}':\mathrm{D_{i'},1}=\mathrm{D_{i,1}},\mathrm{F_{i'}}>\mathrm{F_i}-1+\mathrm{l}} \mathrm{Innovation}_{\mathrm{i}',\mathrm{F_{i'}}-1+\mathrm{l}} - \mathrm{Innovation}_{\mathrm{i}',\mathrm{F_{i'}}-1}, \quad \textbf{Equation 3}$$

where $\mathrm{Innovation}_{\mathrm{i},\mathrm{F_i}-1+\mathrm{l}}$ is the innovation outcome of the company *i* in the period $F_i - 1 + l$ and $D_{i,1}$ is the level of treatment for the same company in the first period of the sample. The first difference of Equation 3 is simply the difference in the innovation outcome between the period of interest and the last period before the acquisition takes place. The second term is the average of this outcome across all firms *i'* that start with the same baseline treatment and have kept that treatment from period 1 to $\mathrm{F_i} - 1 + \mathrm{l}$. Simply put, the estimator compares the differential impact of the acquisition on a company that underwent an acquisition against companies that had the same treatment path over the sample period and were not treated. These company-level estimates are then averaged across all firms to obtain the *l*-specific coefficients necessary for the event study plots shown below.

Moreover, the analysis aims to provide further causal analysis by combining the staggered DID estimation with the approach suggested by Seru (2014[33]), which relies on withdrawn bids. A causal interpretation of the coefficients would require information on the counterfactual trajectory of patenting activity of acquired firms had they not undergone acquisition. Seru (2014[33]) argues that firms subject to acquisition bids subsequently withdrawn for reasons unrelated to innovation serve as an appropriate counterfactual, as long as these acquisitions have been withdrawn for reasons exogenous to innovation. For instance, a negative development of the target's technology can lead to the withdrawal of the bid and a differential impact across acquired companies and those with withdrawn bids. Instead, if the withdrawal is exogenous to these causes, the assignment of companies to acquisition can be considered as good as random. Thus, this strategy rules out selection concerns and provides a causal interpretation of the acquisition's impact on innovation outcomes. Following this rationale, the analysis below examines the post-withdrawal performance of start-ups with withdrawn bids compared to never-acquired start-ups and contrasts this difference with the performance difference between acquired start-ups and never-acquired start-ups after acquisition. In other words, the analysis exploits a triple DID estimator to address endogeneity concerns by comparing the ex-post-performance of start-ups with withdrawn and successful bids vis-à-vis never-acquired start-ups.[41]

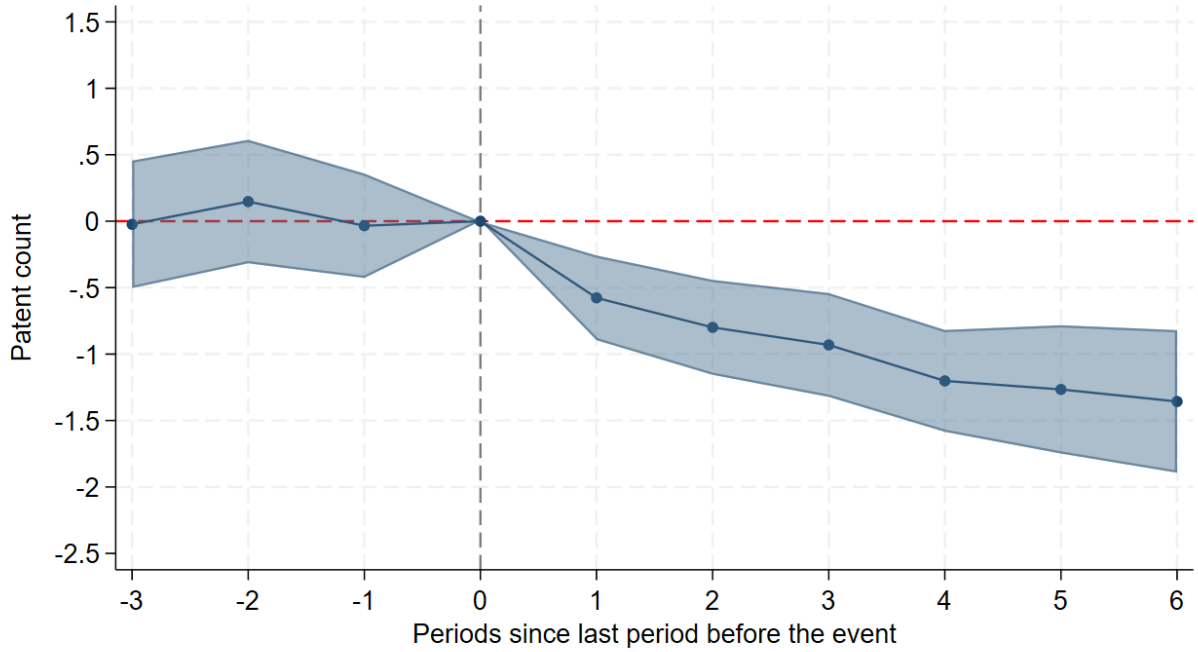
The Orbis M&A database identifies 457 withdrawn bids in the sample of countries and years covered in the analysis. To determine whether the discontinuation of these transactions happened for reasons unrelated to the innovation performance of the target, online news on the withdrawn acquisitions have been surveyed. The different reasons for withdrawal have been classified, and only the ones that are exogenous to innovation strategies have been selected. Namely, the exercise regards as exogenous with respect to innovation performance those acquisitions withdrawn due to competing bids (and not followed by another acquisition), macroeconomic conditions, or objections by regulatory bodies.[42] Those related to differences in opinions about the valuation of companies, growth strategies, or disagreements among owners are left out as they could potentially correlate with the innovative performance of companies. This leaves 122 bids for start-ups that were withdrawn due to reasons exogenous to innovation, spanning 14 countries and 46 3-digit NACE Rev. 2 industries.[43] In this exercise, the regressions are only performed on those country-industry combinations for which there is at least one withdrawn bid. This leaves 6 725 acquired start-ups and 5 091 acquirors active in these country-industry combinations.[44] On the acquiror side, acquirors are restricted to single-time acquirors, i.e. acquirors that engage only with one start-up acquisition, to control also for acquisitions of other incumbent firms.[45] The sample of exogenously withdrawn acquisitions is restricted to companies involved only in the withdrawn deal, without any other acquisition of start-ups or other incumbent firms.

Acquired start-ups

This subsection looks at the innovation performance of start-ups after the acquisition. Figure 5.1 presents the baseline DID estimates. It shows the average treatment effects of acquisitions on the flow of patent counts using as a control group the not-yet-treated companies, i.e. companies that will be acquired but have not yet been acquired. Each plotted coefficient represents the change in the difference in patenting flows between not-yet-acquired and acquired companies, comparing the period before the acquisition (normalised to *t=0* in the graph) with the period of interest, *t*. In addition, the variable of interest has been normalised by the average number of patents filed by acquired start-ups before the acquisition to ease the interpretation of the standardised flows. Therefore, a point estimate of *x* at time *t* should be interpreted as a change in the difference of patenting flows between acquired and not-yet-acquired start-ups between *0* and *t*, equivalent to *x* times the unconditional average patent flow.[46]

The figure shows that while the difference in patenting performance between control and treated groups follows a similar trend before the acquisition, the number of patents filed by acquired start-ups decreases relatively more after the acquisition. This evidence points to a negative effect of acquisition on the innovation performance of targets (Stiebale and Reize, 2011[27]; Stiebale, 2016[58]; Cunningham, Ederer and Ma, 2021[24]; Altomonte, El-Mallakh and Sonno, 2024[35]). In terms of magnitude, the decrease is not only statistically significant but also economically sizable. The difference in the standardised flow of yearly patent filings decreases by approximately 1.5 times the unconditional average yearly flow over the time horizon considered.

Figure 5.1. The effect of the acquisition on the patent filings of acquired start-ups.



Note: Figure 5.1 shows the evolution of the differences in the number of applied inventions using the methodology proposed by de Chaisemartin and D'Haultfoeuille (2024[31]). It shows the evolution of the differences in patent filings between acquired and not-yet-acquired start-ups. The dependent variable is expressed as a percentage of its unconditional average. Each coefficient plotted represents the change in the difference in patenting flows between the corresponding treatment (acquired start-ups) and control group companies (not-yet-acquired companies), comparing the period before the acquisition (normalised to t=0 in the graph) with the period of interest, t. The year of acquisition is considered the announcement date. Coefficients are standardised in the year before the announcement of the acquisition. All specifications include 3-digit NACE Rev.2 industry-country-specific linear trends and firm fixed effects.

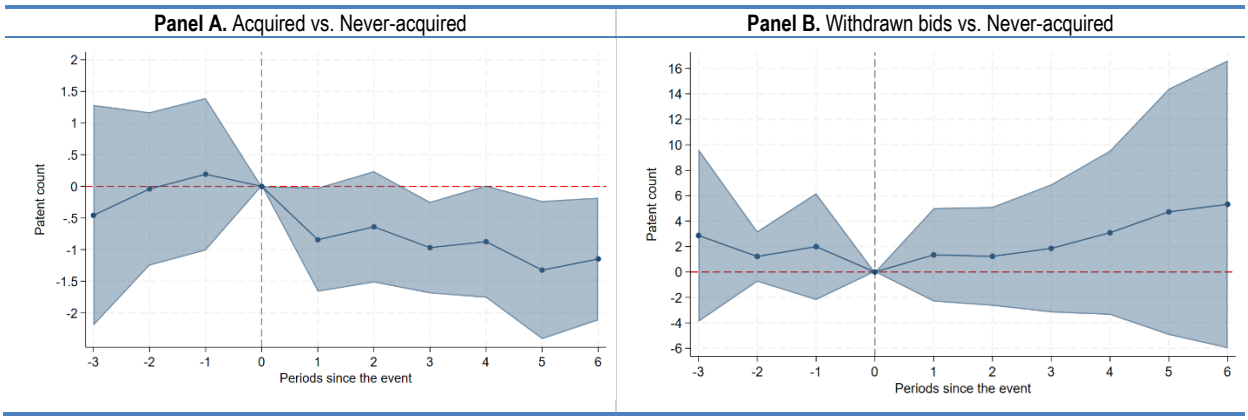
Source: OECD calculations based on OECD/STI Start-ups Database, PATSTAT, and Orbis M&A.

Subsequently, the analysis performs the causal exercise outlined above relying on exogenously withdrawn bids. Specifically, Panel A of Figure 5.2 shows the evolution of the difference in patent filings between acquired companies and those that were never acquired, restricting the sample to those industries and countries for which there is, at least, one withdrawn bid. Likewise, Panel B of Figure 5.2 shows the evolution of the difference in patent filings between companies that received a bid but were withdrawn for reasons exogenous to innovation and those that were never acquired. The difference in coefficients between the coefficients of the two figures effectively yields a triple DID estimator, comparing the evolution of acquired start-ups to that of start-ups with withdrawn bids – all relative to never-acquired start-ups (Olsen and Moen, 2022[70]).[47]

Panel A corroborates the negative effect on the patent flow found in Figure 5.1. The effect persists when comparing the patenting performance of acquired and never-acquired start-ups. Panel B compares the differences between start-ups with withdrawn bids to never-acquired start-ups before and after the withdrawal of the bid. In both exercises, the sample is restricted to countries and industries with at least one withdrawn bid. While acquired start-ups experience an overall decline in Panel A, the effect of the bid withdrawal on the start-ups in Panel B does not seem to be statistically different from zero. The difference between both coefficients yields the triple DID estimate of the effect of a successful bid with respect to a withdrawn bid, after controlling for selection and endogeneity. Since the effect on the withdrawn bids is not statistically significant as suggested by Panel B, the estimate of Panel A yields effectively the differential

impact on patenting performance between acquired start-ups and those start-ups that received an acquisition bid but the latter was withdrawn for reasons unrelated to innovation.

Figure 5.2. The effect of the acquisition on the patent filings of acquired start-ups using withdrawn bids.



Note: Figure 5.2 shows the evolution of the differences in the number of applied inventions using the methodology proposed by de Chaisemartin and D'Haultfoeuille (2024[31]). Panel A shows the evolution of the differences in patent filings between acquired and never-acquired start-ups, restricting to those countries and industries for which at least one withdrawn bid takes place. Panel B shows the evolution of the differences in patent filings between start-ups that received acquisition bids but were withdrawn for reasons exogenous to innovation and never-acquired start-ups. In all panels, the year of acquisition is considered the announcement date. The dependent variable is expressed as a percentage of its unconditional average. Each coefficient plotted represents the change in the difference in patenting flows between the corresponding treatment (acquired start-ups in Panel A, start-ups with withdrawn bids in Panel B) and control group companies (never-acquired start-ups), comparing the period before the acquisition (normalised to t=0 in the graph) with the period of interest, t. Coefficients are standardised in the year before the announcement of the acquisition. All specifications include 3-digit NACE Rev.2 industry-country-specific linear trends and firm fixed effects.
Source: OECD calculations based on OECD/STI Start-ups Database, PATSTAT, and Orbis M&A.

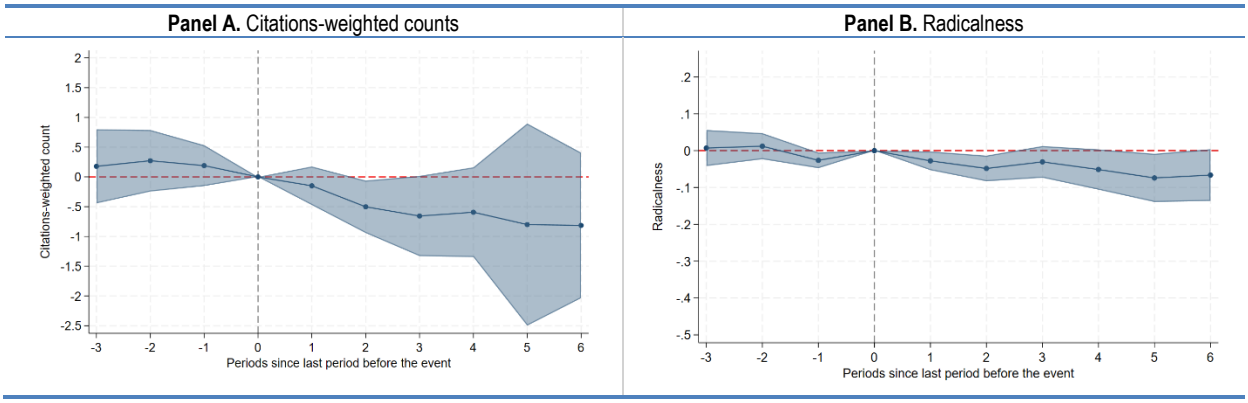
Several checks are performed to further validate the identification strategy using the exogenously withdrawn bids. These checks are important to provide evidence that start-ups receiving withdrawn bids represent a proper control group for acquired start-ups. In particular, Table A B.4 of Annex B shows the results of the regression specified in Equation 1, with a sample that includes only acquired start-ups in the moment of acquisition as treated units and start-ups whose bids were withdrawn in the moment of withdrawal as control group. The results indicate that the flow of patents and their citations are similar across acquired start-ups in the moment of acquisition and start-ups whose bids were withdrawn in the moment of withdrawal. Likewise, Figure A B.4 of Annex B shows the average patent flows of acquired start-ups and start-ups with withdrawn bids around acquisition or withdrawal. The evolution of the average patenting flows is identical across both groups before the announcement of an acquisition. However, acquired start-ups experience a decline in the patenting flow following an acquisition that is not as pronounced for start-ups whose bids were withdrawn. This evidence shows that – based on the observable characteristics – there are no systematic differences between start-ups that were acquired and those that experienced the bid withdrawal. Therefore, start-ups with withdrawn bids provide a meaningful comparison to what would have happened to the acquired start-ups had they not been acquired. Statedly differently, using this sample of acquired and withdrawn start-ups, the treatment assignment (acquisition) can be considered as good as random.

After establishing a causal and sizable decline in patent filings for acquired start-ups, the analysis shifts the focus to the quality of patented inventions. The steep decline found in Figure 5.1 is mainly explained by firms that stopped patenting following the acquisition event. Approximately half of the acquired start-ups filed patents before the acquisition, while approximately 10% continue to do so afterward.[48] For this

reason, the focus of the analysis will be the quality of the patents of the start-ups that continue patenting after the acquisition event.[49]

Figure 5.3 shows the DID estimates of the effect of the acquisition on the flow of citations-weighted patent filings and the average radicalness of the patent portfolio of the start-ups in Panels A and B, respectively. Particularly, the panels show the evolution of the differences in the two variables between acquired and not-yet-acquired start-ups after the acquisition, i.e. the baseline specification explained above.[50] Panel A shows that the citation-weighted flow of patents decreases substantially, meaning the newly filed patents by start-ups that continue patenting are less cited relative to the ones preceding the acquisition. Likewise, Panel B shows that the differences in the average radicalness of the patent portfolio also decrease by approximately 10% of the radicalness before the acquisition takes place. This evidence aligns with the theoretical and empirical literature that argues that acquirors might be more interested in developing incremental rather than radical innovation, as the former improves the commercialisation while the latter depreciates the value of their current patent portfolio (Cabral, 2018[47]; Weiss, 2023[40]).

Figure 5.3. The effect of acquisitions on the patent quality of acquired start-ups.



Note: Figure 5.3 shows the evolution of the differences in the quality of patents using the methodology proposed by de Chaisemartin and D'Haultfoeuille (2024[31]) restricting to those firms that patent after the acquisition. Panel A shows the evolution of the differences in the citations-weighted patent filings between acquired and not-yet-acquired start-ups. Panel B shows the evolution of the differences in the average radicalness of the patent portfolio between acquired and not-yet-acquired start-ups. In all panels, the year of acquisition is considered the announcement date. The dependent variable in Panel A is expressed as a percentage of its unconditional average. Each coefficient plotted represents the change in the difference in patenting flows between not-yet-acquired and acquired companies, comparing the period before the acquisition (normalised to t=0 in the graph) with the period of interest, t. Coefficients are standardised in the year before the announcement of the acquisition. All specifications include 3-digit NACE Rev.2 industry-country-specific linear trends and firm fixed effects.
Source: OECD calculations based on OECD/STI Start-ups Database, PATSTAT, and Orbis M&A.

The evidence above shows that acquisitions may negatively impact start-up innovation. Although acquired start-ups are more innovative and produce higher quality innovations before the acquisition, their innovation performance worsens afterward. However, it is not yet possible to draw definitive conclusions about the innovation performance without analysing the acquiror side. One possibility is that, upon acquisition, patenting activities are centralised in the parent company, which might, for example, start appropriating the innovations developed by the acquired start-up. In this case, some of the innovation outcomes of the start-ups would not be observed, potentially leading to misleading interpretations of the patterns observed in the figures above. This is what Stieable (2016[58]) suggests in the context of cross-border acquisitions. After conducting some robustness checks, the next subsection attempts to address this issue by performing the same analysis for acquiror companies.

Robustness exercises

As discussed throughout the text, several somewhat arbitrary choices have been taken to carry out the analysis, for example when selecting the sample, defining the variables, and choosing the methodologies. The robustness of the baseline results to these choices and assumptions is discussed below.

First, a series of robustness exercises focus on changing the outcome variable in the specifications exploited above. Particularly, the analysis alternatively uses (i) the count of patents, which refers to the unstandardised measures of patents and their citations, and (ii) a dummy variable that takes value 1 if a start-up files a patent in a specific period and 0 otherwise.

Second, another series of robustness analyses focuses on the sample under consideration. Specifically, the baseline specification is replicated by: (i) excluding start-ups in the financial sector; (ii) excluding start-ups acquired by incumbents in the financial sector; (iii) excluding start-ups selected because they filed their first patent but did not have a VC round in the relevant period (i.e. relaxing criterion 2 of the sample selection described in Section 3); and (iv) including start-ups that receive venture capital or file for the first patent at any age (i.e. removing criterion 3 of the sample selection described in Section 3).

Third, another set of robustness checks uses alternative estimators for the staggered DID framework (Sun and Abraham, 2021[68]; Callaway and Sant'Anna, 2021[67]; Borusyak, Jaravel and Spiess, 2024[66]). As motivated at the beginning of the section, the method developed by de Chaisemartin and D'Haultfoeuille (2024[31]) is chosen as the baseline in this paper as it best accommodates the set-up of the analysis. Nevertheless, all other methodologies convey the same findings.

The control group is also modified to ensure that the changes in the patenting activity are driven by treatment and not by other confounding factors. Specifically, the control group of not-yet-treated start-ups is substituted by (i) never-acquired start-ups (shown in Panel A of Figure 5.2), and (ii) start-ups that received acquisition bids, but the latter were withdrawn for reasons exogenous to innovation.[51] All results remain qualitatively unchanged in these exercises. Also, removing one reason for withdrawal from the bids at a time (i.e., excluding cases due to macroeconomic conditions, and considering only those due to competing bids or opposition from regulatory bodies) does not affect the results.

Along the same lines, a final robustness exercise performs a propensity score matching procedure to further refine the selection of the control group. This exercise is described in greater detail in Annex B. The methodology used in this exercise combines the de Chaisemartin and D'Haultfoeuille (2024[31]), estimation strategy with propensity score matching as in Guadalupe, Kuzmina, and Thomas (2012[71]), Haucap, Rasch and Stiebale (2019[28]) and Fons-Rosen et al. (2021[72]).[52] Specifically, the exercise is built in two steps. First, a logit specification is performed to compute the predicted likelihood of each firm to be acquired (the dependent variable being a dummy that takes the value 1 if an acquisition takes place and 0 otherwise). Then, the predicted probabilities are used as weights in the de Chaisemartin and D'Haultfoeuille (2024[31]) estimation procedure.[53] The independent variables in the first steps are again the age of the start-up and its VC stock level. The results of the propensity score estimation can be found in Panel A in Table A B.3. Panel B compares patenting flows between the treatment group and the propensity-score-weighted group of never-acquired start-ups, showing no statistically significant differences. Figure A B.3 shows the results of the DID estimation. The results are qualitatively and quantitatively similar to the main specification using not-yet-acquired start-ups as a control group.

Acquirors

As mentioned above, to unequivocally assert that acquisitions stifle innovation, the acquiror's innovation outcomes should not show any improvement following the event.

The analysis of the acquiror side follows the same rationale as the analysis of start-ups, although some additional assumptions must be imposed. These assumptions allow to exploit the different treatment intensities to which different acquirors are exposed. In other words, while in the case of start-ups, the comparisons were made between acquired and not-yet-acquired start-ups, comparisons in the case of the acquirors will be made between acquirors exposed to different intensities of the treatment (i.e. different numbers of acquired start-ups). This difference is imposed to accommodate the specificities of the acquirors set-up into the estimation strategy.

First, acquirors can be treated several times, even within the same period. To accommodate this nuance, the analysis defines the treatment as the cumulative number of start-ups acquired over time.[54] In the jargon of de Chaisemartin and D'Haultfoeuille (2024[31]), this allows for comparisons between treated firms and firms that are not yet treated with the same intensity.

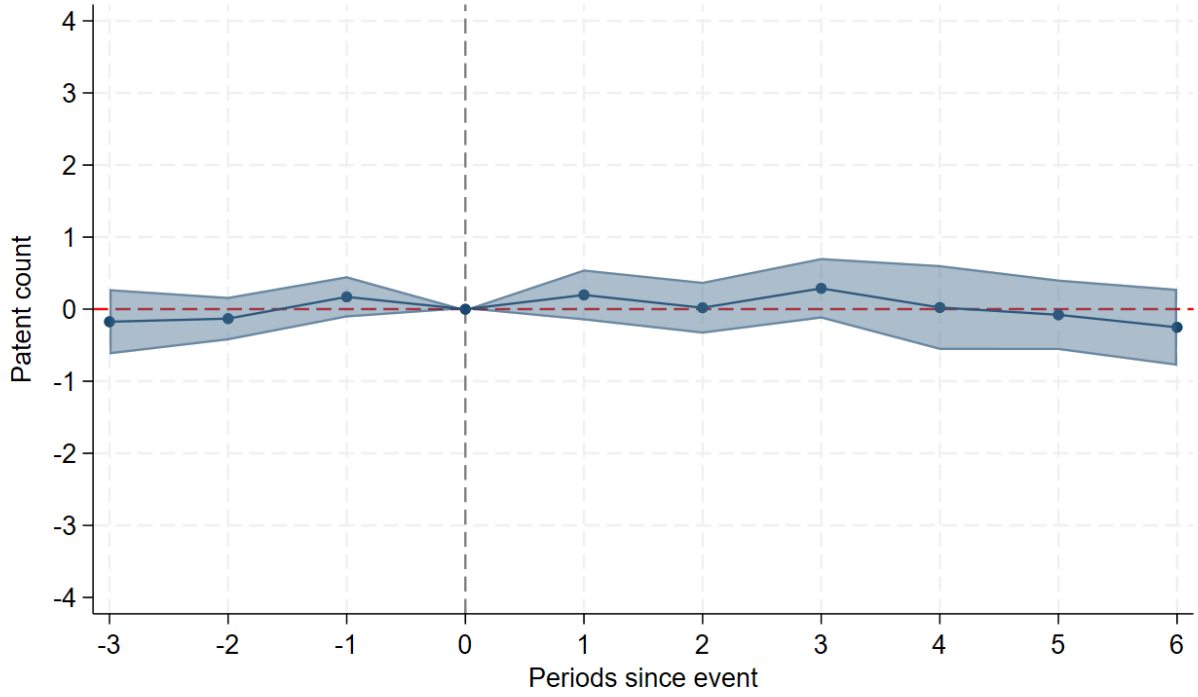
Second, the acquisitions of companies other than start-ups (i.e. acquired companies in Orbis M&A that have not been matched to the OECD/STI Start-ups Database) can contaminate the estimated treatment effects. For this reason, all regressions include the cumulative number of non-start-up companies acquired (i.e. acquisitions of companies reported in Orbis M&A that have not been matched to the OECD/STI Start-ups Database) as an additional control variable.

Lastly, while start-ups are followed since their inception and only the first acquisition is considered, acquirors are more likely to be affected by previous start-up acquisitions - which are not observed. This happens because acquirors are often established old companies, whose M&A activity has started in years preceding those available in this analysis Thus, prior treatment effects can potentially contaminate those companies that have not yet acquired start-ups in the sample used. To deal with this concern, de Chaisemartin and D'Haultfoeuille (2024[31]) suggest implementing a *burn-in period.* This approach involves initiating the analysis few years after the start of the available data to ensure that comparisons are made among firms with similar treatment histories, thereby mitigating biases from unobserved prior treatments. As baseline, therefore, this exercise uses acquisitions from 2005 onwards, and alternative thresholds for the burn-in period have been tested, leaving the results unchanged.[55]

Likewise, the exercise exploiting the withdrawn bids requires some additional precautions in the case of the acquiror. Similarly to the start-up's case, the exercise will use the differences between acquiring and never-acquiring firms and compare them against the differences between acquirors that withdrew their bids with never-acquiring firms. However, withdrawn bids likely coexist with successful acquisitions on the acquiror side. Therefore, the sample of *withdrawn* acquirors is restricted to those with only one withdrawn bid and not successful bids during the sample period. By symmetry, the analysis of the differences between acquiring and never-acquiring firms also focuses only on single-time acquirors. Similarly to the start-up case, the analysis further restricts the sample to industries and countries with at least one observed withdrawn bid.

Figure 5.4 shows the DID estimates on the evolution of the differences in filed patents between acquiring and not yet acquiring (as many) acquirors. The panel shows no significant effects on the patent-count measures between acquirors with different treatment intensities. Figure 5.5 shows the result of the exercise using withdrawn bids, providing more causal evidence to this finding. Panel A shows the evolution of differences across acquiring and never-acquiring companies in those industries and countries with at least one withdrawn bid. Still, there are no differences in patent filings between both groups after the companies acquire a start-up. Finally, Panel B shows the evolution of the differences in patent filings between those acquirors with a withdrawn bid relative to never-acquiring firms after the bid withdrawal. Again, no differential evolution can be asserted from the findings.

Figure 5.4. The effect of acquisitions on the patent filings of acquirors.

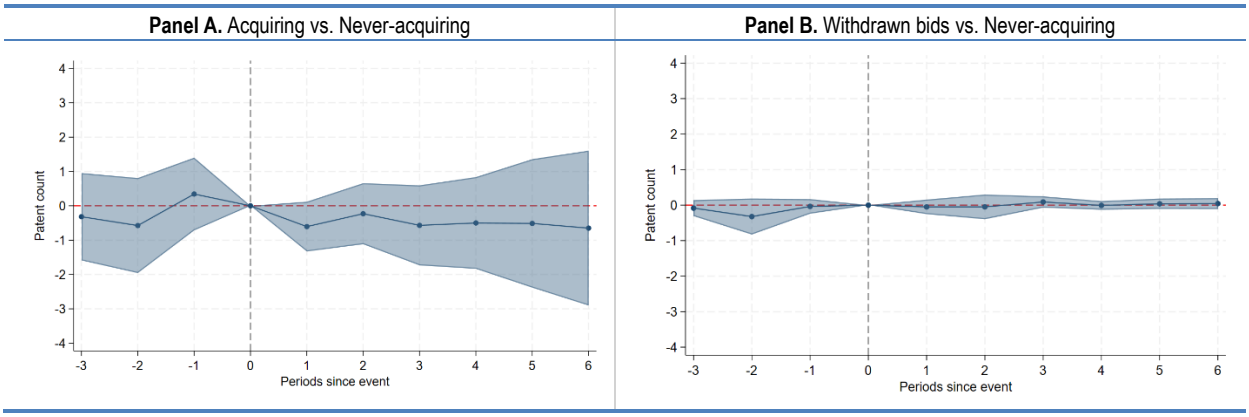


Note: Figure 5.4 shows the evolution of the differences in the number of applied inventions using the methodology proposed by de Chaisemartin and D'Haultfoeuille (2024[31]). It shows the evolution of the differences in patent filings between acquirors exposed to different intensities of the treatment (i.e. the number of start-up acquisitions). The year of acquisition is considered the announcement date. The dependent variable is expressed as a percentage of its unconditional average. Each coefficient plotted represents the change in the difference in patenting flows between the corresponding treatment (acquirors) and control group companies (acquirors with lower acquisition intensities), comparing the period before the acquisition (normalised to t=0 in the graph) with the period of interest, t. Coefficients are standardised in the year before the announcement of the acquisition. All specifications include 3-digit NACE Rev.2 industry-country-specific linear trends and firm fixed effects.
Source: OECD calculations based on OECD/STI Start-ups Database, PATSTAT, and Orbis M&A.

Lastly, Figure A B.5 looks at the effects of the treatment on the innovation quality measures of the acquirors. Panel A shows the impact on the citations-weighted patent flow, while Panel B shows the impact on the average radicalness of the patent portfolio. Panel A shows a decline in the citations-weighted patent flow, while Panel B shows no change in the radicalness of the patent portfolio. Therefore, the results suggest that there is – at minimum – no improvement in the quality measures of the acquiror.

All in all, the findings in this section corroborate studies that find a negative effect on the innovative activity of the merged pairs, as in Haucap, Rasch, and Stiebale (2019[28]). Contrary to Stiebale (2016[58]), this paper does not find that the acquirors' patenting activity compensates for the loss of activity in their targets.[56] Therefore, it is unlikely that the observed decline in target innovation is unlikely to result from a shift in patenting activities from the start-up to the corporate parent. Overall, the evidence reported thus far suggests that while acquirors largely target innovative start-ups, they do not catalyse subsequent innovation activity.

Figure 5.5. The effect of acquisitions on the patent filings of acquirors using withdrawn bids



Note: Figure 5.5 shows the evolution of the differences in the number of applied inventions using the methodology proposed by de Chaisemartin and D'Haultfoeuille (2024[31]). Panel A shows the evolution of the differences in patent filings between single-time acquirors and never-acquiring companies restricting to those countries and industries for which at least one withdrawn bid takes place. Panel B shows the evolution of the differences in patent filings between acquirors that issued an acquisition bid but were withdrawn for reasons exogenous to innovation and never-acquiring companies. In all panel, the year of acquisition is considered the announcement date. The dependent variable is expressed as a percentage of its unconditional average. Each coefficient plotted represents the change in the difference in patenting flows between the corresponding treatment (acquirors in Panel A, companies with withdrawn bids in Panel B) and control group companies (never-acquiring companies), comparing the period before the acquisition or withdrawal of the bid (normalised to t=0 in the graph) with the period of interest, t. Coefficients are standardised in the year before the announcement of the acquisition. All specifications include 3-digit NACE Rev.2 industry-country-specific linear trends and firm fixed effects.
Source: OECD calculations based on OECD/STI Start-ups Database, PATSTAT, and Orbis M&A.

Potential underlying channels

The evidence reported so far shows a decline in patenting activity of acquired start-ups, not offset by an increase in the patenting activity of their acquirors. Several explanations can be proposed to explain this outcome. This subsection provides *suggestive evidence* on the possible channels discussed above to understand whether some of them are more likely to apply.

The patenting activity of companies reflects not only their technological advancements but also their strategic behaviour (Veugelers and Schneider, 2018[73]; Chondrakis, Serrano and Ziedonis, 2025[74]). The target's patenting activity may decline because its intellectual property (henceforth, IP) strategy changes post-acquisition, opting for greater secrecy in the innovation process. In this case, actual innovation may not decline after the transaction, even if patent filings decrease. To explore this, the paper first investigates the heterogeneity across acquisitions performed by acquirors with different levels of patents, as this might reflect different IP strategies adopted by acquiring firms. Specifically, acquiring firms are categorised into two groups based on whether their number of filed patents is above or below the median.[57] Then, the sample of acquired start-ups is divided according to whether their acquiror was above or below the median number of patents filed. The patenting performance of these two groups of acquired start-ups is then analysed using the framework outlined in this section, and the results are reported in Columns 1 and 2 of Table 5.1, respectively. The first row of Table 5.1 shows the average ex-post effect of the acquisition on the patent flow of the target in the years following the event. The second and third rows show the test for the joint nullity of the ex-post effects and the pre-trends, respectively. In other words, the second row tests whether the differences across treatment (acquired) and control (not-yet-acquired) start-ups change after the acquisition. The third-row tests instead whether these differences were already changing before the acquisition period. Columns 2 of Table 5.1 shows that the effect of the acquisition on the target's patent flow is negative and statistically significant only for targets acquired by acquirors who patent frequently,

while it is not significant for start-ups acquired by low-patenting acquirors. This finding does not support the earlier hypothesis that low-patenting acquirors may follow a more secretive innovation strategy, leading them to patent less. Therefore, differential IP strategies do not seem to explain the observed reduction in patenting activity.

Alternatively, upon acquisition, the innovation activity might decrease because start-ups shift from the technological development to the commercialisation phase. First, the analysis looks at the evolution of trademarks registered by the start-ups, since trademarks are indicative of market entry efforts.[58] Column 3 uses as a dependent variable the standardised yearly flow of trademarks registered by the start-up (normalised by its average value).[59] There is a statistically significant negative and sizeable impact of the acquisition on registered trademarks, declining by approximately 50% of the average standardised trademark flow.[60] Second, start-ups might have started integrating their innovations into the production processes. Innovations developed by the start-ups could be incorporated into the acquiror's technology or create synergies with the existing assets, potentially leading to a productivity increase. Columns 4 and 5 show the effect of the acquisition on the target and the acquiror's TFP, respectively, using the restricted sample with Orbis information. In both cases, a statistically significant reduction in TFP is observed following the acquisition (approximately 4 and 8% for targets and acquirors, respectively).[61]

Furthermore, since patenting activity, productivity (Hall, 2011[75]) and trademarks (Mendonca, Santos and Mira, 2004[76]; Millot, 2009[77]) are all innovation-oriented measures, the consistent picture emerging from these different exercises suggests that there is an actual decline in innovation upon acquisition.

Table 5.1. The effect of acquisitions across acquirors with different patenting levels and alternative measures of innovation.

	Acquiror has patents below the median	Acquiror has patents above the median	Target's trademarks	Target's log(TFP)	Acquiror's log(TFP)
	(1)	(2)	(3)	(4)	(5)
Average effect on the variable of interest after acquisition	-0.9557 (0.6948)	-2.023*** (0.4937)	-0.4784*** (0.1148)	-0.0408 (0.0302)	-0.0813* (0.0507)
Test joint nullity of the effects (p-value)	0.1347	0.0009***	0.0000***	0.0014***	0.0022***
Test joint nullity of the pre-trends (p-value)	0.2800	0.3962	0.0074**	0.1467	0.1200

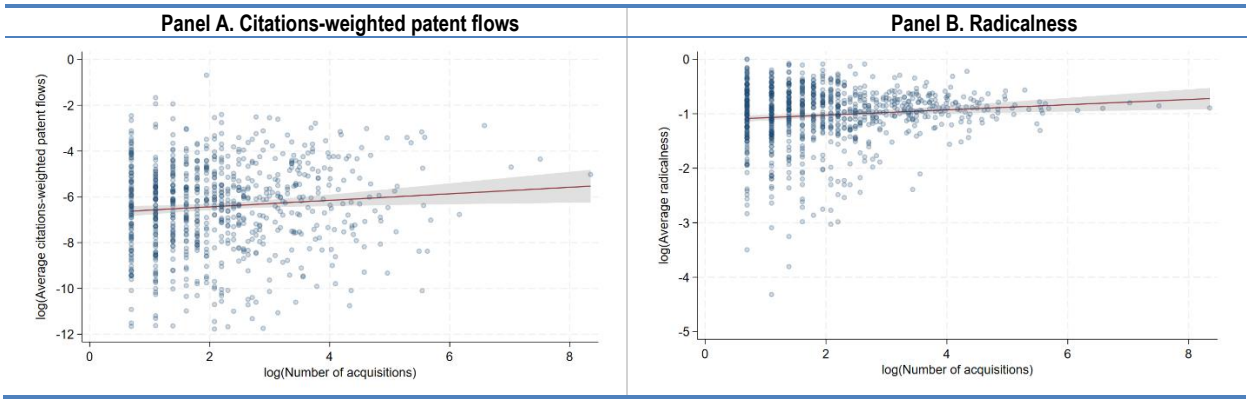
Notes: Table 5.1 shows the evolution of the differences in selected variables using the methodology proposed in de Chaisemartin and D'Haultfoeuille (2024[31]). Rows 2 and 3 represent the p-value of the test for the joint nullity of the effects and the pre-trends, respectively. Columns 1 and 2 estimate the effect of the acquisition on the differences in patent filings between acquired and not-yet-acquired start-ups across acquirors with patent stocks below and above the median, respectively. Column 3 estimates the effect of the acquisition on the differences in registered trademarks between acquired and not-yet-acquired start-ups. Columns 4 and 5 estimate the effect of the acquisition on the differences in TFP between acquired and not-yet-acquired start-ups, and acquirors exposed to different treatment intensities, respectively. In all columns, the year of acquisition is considered the announcement date. The dependent variable in Columns 1, 2, and 3 is expressed as a percentage of its unconditional average. Coefficients are standardised in the year before the announcement of the acquisition. All specifications include 3-digit NACE Rev.2 industry-country-specific linear trends and firm fixed effects.
Source: OECD calculations based on data from PATSTAT, Orbis, Orbis M&A, the OECD/STI IP Database, and the OECD/STI Start-ups Database.

Shifting to possible explanations reflecting an actual decline in innovation, another hypothesis is related to *innovation-for-buyout*. According to this view, start-ups strategically develop inventions to attract acquisition by established firms and, therefore, prioritise incremental advancements that align with those of established companies rather than pursuing disruptive breakthroughs. Once acquired, the start-up loses the incentive to innovate further, having already cashed out its benefits, and innovation declines. To explore whether target firms tailor their inventions to appeal to potential acquirors, the paper examines the

relationship between acquisition activity and patenting quality. Several papers show that start-ups tend to focus on more incremental (rather than disruptive) innovations when an acquisition becomes a more likely exit strategy (Fons-Rosen, Roldán-Blanco and Schmitz, 2022[25]; Wang, 2018[43]; Warg, 2022[26]; Weiss, 2023[40]). Therefore, one would expect to see lower patent quality (i.e. less disruptive innovations) in markets where acquisitions are more common. To assess this hypothesis, the paper uses the average citation-weighted patent count as a measure of patent radicalness, two measures of patent quality, as explained in Section 3.[62] Both measures are computed at the firm level for acquired start-ups before acquisitions and then averaged at the country–3–digit industry level.

Building on this reasoning, Panel A of Figure 5.6 shows the relationship between the number of acquisitions in a specific 3-digit industry and country and the average quality of patents held by the acquired start-ups, measured by the average 5-year forward citations of their pre-acquisition patents. Panel B shows the equivalent exercise using patent radicalness as the dependent variable.[63] The findings reveal a positive correlation between the number of acquisitions and the quality of the inventions of the acquired start-ups, whether measured by radicalness or citations-weighted patent counts. This does not confirm the predominance of the innovation-for-buyout hypothesis, as start-ups in markets with high acquisition activity do not seem to focus on more incremental innovation. Instead, acquisitions tend to occur more in markets where start-ups are more innovative, suggesting that innovation-for-buyout might not be the main reason explaining observed patterns.

Figure 5.6. Correlation between number of acquisitions and different measures of patent quality



Note: The figure shows the scatter plot between the (log) total number of acquisitions in a specific 3-digit industry and country and the (log) average citation-weighted number of patents of acquired companies before acquisition in a specific 3-digit industry and country. The predicted line in Panel A is given by y = -6.7239*** + 0.1424** X while the predicted line in Panel B is given by y=-1.1195*** + 0.0477*** X.
Source: OECD calculations based on PATSTAT, Orbis M&A, and OECD/STI Start-ups Database.

Finally, the analysis provides additional suggestive evidence for the killer acquisitions hypothesis by exploiting market heterogeneity. If this channel is at play, the decline in patenting activity should be more pronounced when firms operate in the same market – whether an industry or a geographical market – compared to when they do not. While there can be reasons to suppress competitors in other markets (e.g. expand into a market niche), the incentives for killer acquisitions are stronger when firms share the market.

To test this hypothesis, the analysis compares acquisitions occurring within and across industries and countries, using these dimensions as proxies for markets. Columns 1 and 2 of Table 5.2 show the DID estimate of acquisitions that happen within and across 3-digit industries. The reduction in patenting activity experienced by acquired start-ups is more pronounced for acquisitions within the same industry. Columns 3 and 4 extend the analysis to geographic markets, showing that within-country acquisitions lead to a

stronger decline in patenting activity than cross-country deals, albeit differences are smaller than in industry-level comparisons. Finally, Columns 5 and 6 examine acquisitions taking place within the same industry and country and those spanning across different industries and countries. Since firms in the former group are more likely to share a product market, these acquisitions should exhibit stronger effects. Consistent with the killer acquisition hypothesis, the decline in patenting is nearly twice as large for acquisitions within the same industry and country relative to those that occur across both dimensions. Nevertheless, it is worth highlighting that the decline in patenting activity happens across all acquisition types, regardless of industry or geography.

Table 5.2. The impact of acquisitions on the target's patent filings across industries and countries

	Industries		Countries			
	Within	Across	Within	Across	**Within industries and countries**	**Across industries and countries**
Average cumulative effect from t to t+6	-2.1911*** (0.5978)	-0.9989*** (0.2153)	-1.2960*** (0.5002)	-0.8762*** (0.1764)	-2.0306*** (0.7811)	-0.7674*** (0.1653)
Test joint nullity of the effects (p-value)	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
Test joint nullity of the pre-trends (p-value)	0.3958	0.6112	0.9193	0.6075	0.2788	0.7473

Notes: The table shows the evolution of the differences between acquired and not-yet-acquired in the standardised yearly patent count flow using the methodology proposed in de Chaisemartin and D'Haultfoeuille (2024[31]). Rows 2 and 3 show the p-value of the test for the joint nullity of the effects and the pre-trends, respectively. Column 1 restricts the effect to those acquisitions that happen within the same 3-digit industry, while Column 2 restricts to those that happen across 3-digit industries. Columns 3 and 4 present equivalent exercises restricting to acquisitions that happen within the same country or across countries, respectively. Finally, Columns 5 and 6 restrict to both acquisitions that happen within industries and countries and across industries and countries, respectively. In all columns, the year of acquisition is considered the announcement date. The dependent variable is expressed as a percentage of its unconditional average. Coefficients are standardised in the year before the announcement of the acquisition. All specifications include 3-digit NACE Rev.2 industry-country-specific linear trends and firm fixed effects. Standard errors in parentheses. ***: p-value < 1%, **: p-value <5%, *: p-value < 10%.
Source: OECD calculations based on data from PATSTAT, Orbis M&A, and OECD/STI Start-ups Database.

A series of heterogeneity exercises across acquired start-ups is reported in Annex B. Table A B.5 splits the sample of start-ups depending on the technological proximity between the pair of start-ups and acquirors. The results show that the reduction in patenting performance is particularly strong for start-ups that are more technologically different from their acquirors, and especially so when acquisitions happen within countries or industries. The finding aligns with the evidence presented in Bena and Li (2014[17]). Acquirors tend to buy less similar start-ups within their markets than across as suggested by the evidence in Table 4.4. Less similar technologies within their markets might suggest a higher threat to the incumbent (e.g., more differentiated products or more efficient production), triggering the killer acquisition so as to preserve the status quo and avoid the depreciation of its own technology. Conversely, similar technologies from start-ups active in different industries might be driven by different strategies.

Also, Figure A B.6 in Annex B shows the evolution of citation flows, which capture the number of citations received each year by a firm – both for newly issued and existing patents (as explained in detail in Annex B). The figure indicates that citations to acquired start-ups increase following the acquisition. As discussed earlier in this section, most start-ups stop patenting after being acquired. Therefore, the observed increase in citations post-acquisition is likely driven by patents filed prior to the acquisition, suggesting a broader diffusion of these technologies. Further research is warranted to explore the implications of this finding, as evidence of enhanced diffusion of start-up technologies could nuance the overall assessment of start-up acquisitions and their policy implications.

Finally, Figure A B.7 in Annex B explores how these effects vary across regions by focusing on the EU. While the effect on European start-ups is similar to the baseline result, the acquiror side undergoes some

changes. The average effect on the acquiror's innovation is positive and mainly driven by acquisitions that happen across countries and sectors. On the contrary, acquirors who purchase start-ups within their industries and countries in the EU experience a large decline in patenting activity following the acquisition.

Importantly, the alternative channels explored in the paper are not mutually exclusive and do not cover all the possible scenarios, so they must be interpreted with caution. For instance, it cannot be excluded that neither the start-up nor the acquiror is actively looking to decrease the start-up's patenting activity, but this decrease occurs because of inefficiencies associated with the transition from two independent entities into one united corporation. Likewise, the aggregate findings also hide many layers of heterogeneity. Further research would be necessary to establish a causal relationship between the channels driving the observed results.

6 Conclusions

This paper sheds light on start-up acquisitions by established firms, providing a profile of the firms involved and assessing the impact on innovation performance. The paper builds on a unique and comprehensive cross-country dataset that combines information on start-ups, their interactions with established companies, and patenting activity as a measure of innovation. The broad and global coverage of the sample represents a key contribution of the study. By focusing on innovation and growth-oriented young firms, the study offers valuable new perspectives on start-ups and their interactions with established firms, which is particularly important in the context of declining dynamism and rising market power.

First, the analysis on the pre-deal phase offers strong evidence that more innovative start-ups and acquirors engage more frequently in acquisitions, as: i) acquired start-ups typically exhibit stronger innovation performance before the deal; ii) more innovation-oriented firms are more likely to acquire start-ups. Further, technological proximity between acquiror-target pairs increases the likelihood of acquisition.

On the one hand, these results are consistent with the idea that there are innovation motives behind the start-ups' acquisitions, where established companies would seek to access innovative technologies. However, alternative explanations are also possible. For example, the evidence that more innovative firms are more likely to acquire start-ups could suggest that a certain level of absorptive capacity is needed effectively to benefit from these interactions. Alternatively, it may indicate that innovation leaders are active in start-up acquisitions, potentially to suppress disruptive competitors. However, the specific motives behind these acquisitions remain open to interpretation.

Next, the paper finds that acquisitions lead to a decrease in start-ups' innovation performance, which is not offset by increased patenting activity from acquirors. Different measures of the quality of the patents filed after acquisition also corroborate this decline.

This worsened innovative performance can be interpreted in different non-mutually exclusive ways. The analysis includes various exercises to provide *suggestive evidence* of potential channels that might be at play. Among the different channels explored, the analysis finds supportive evidence that the reduction in patenting is stronger in transactions that happen within the same industry and country. These are transactions in which acquirors might feel the threat of the start-up and acquire it to stifle future competition. This evidence is in line with the *killer acquisitions* and with a growing number of evidence (Cunningham, Ederer and Ma, 2021[24]). Importantly, the alternative channels explored in the paper are not mutually exclusive and do not cover all the possible scenario, so they must be interpreted with caution. Further research would be necessary to establish directly which channels are driving the observed results.

Over the past two decades, established firms have increasingly acquired innovative start-ups (Figure 1.1). This trend has unfolded against a backdrop of rising industry concentration (Calligaris et al., 2024b[20]), declining business dynamism (Calvino, Criscuolo and Verlhac, 2020[21]; Calligaris et al., 2024b[20]), and fewer disruptive innovations (Arora, Belenzon and Patacconi, 2017[12]). While some argue that acquisitions can foster synergies and accelerate technological advancements, others contend that they may stifle innovation, particularly for the acquired firms. The findings support the latter view, suggesting a decline in innovation following acquisitions. This outcome carries important policy implications, not lastly for antitrust authorities evaluating such transactions.

Start-ups often do not trigger antitrust scrutiny due to their relatively small market shares (OECD, 2020[1]). However, their acquisition by established companies may have significant long-term consequences, contributing to increased market concentration, declining business dynamism, and reduced innovation and technological progress. These implications extend beyond the (possibly) relatively small, static effects of a merger on prices and consumers, highlighting the need to incorporate innovation impacts into merger assessments. At the same time, the prospect of acquisition can serve as an incentive for start-up entry and innovation. This aspect has been highlighted in the European context, in which start-ups have faced several challenges to scale up during the latter years, and, therefore, being acquired is becoming an increasingly valuable exit strategy for entrepreneurs (Ederer and Pellegrino, 2023[8])). Thus, policymakers should adopt a balanced approach, combining forward-looking antitrust enforcement with measures that lower entry barriers, and promote innovation and the scalability of new firms. This integrated strategy is essential to sustaining the dynamic benefits of innovation while addressing the potential adverse effects of acquisitions on industry dynamism. Lastly, the findings of this paper should also encourage policymakers to ensure alternative exit options for start-ups, reducing dependencies on large established players.

Endnotes

[1] Specifically, as explained in section 3, this paper considers as innovative start-ups those companies that are less than 10 years old when the first relevant event (either the first VC financing round or a patent) takes place. These thresholds are in line with previous literature (Fons-Rosen, Roldán-Blanco and Schmitz, 2022[25]; Ederer and Pellegrino, 2023[8]). Note that, as explained later, the results of the paper are robust to the choice of the thresholds to define the start-up sample.

[2] In the context of this paper, the terms geography, geographical areas, or geographical markets are used interchangeably to refer to national boundaries as further levels of geographical disaggregation are unfeasible.

[3] While these authors use the Crunchbase dataset, this paper highlights the necessity to disentangle which companies in Crunchbase are actually start-ups. Crunchbase is an open-source dataset that combines information from many sources to capture broadly what is known as the "start-up ecosystem". As a result, the dataset does not capture only start-ups, but it also includes other kinds of SMEs and more established companies interacting with start-ups via financial transactions or that are relevant competitors. See section 3 for additional details on the conditions imposed in this paper to select from Crunchbase (and Dealroom) only innovation- and growth-oriented start-ups.

[4] Note that Crunchbase does not provide a definition of which kind of transactions are recorded as acquisitions, and it is unclear what constitutes such deals in Crunchbase. Therefore, given the central role that such information play in this paper, acquisitions are identified from Orbis M&A.

[5] Their control group includes acquisition targets, other acquirors, and firms not participating in acquisitions.

[6] Unlike the strategies of Bena and Li (2014[17]) and Seru (2014[33]), Zhao (2009[45]) and Sevilir and Tian (2010[57]) do not dwell on whether the bids were withdrawn for reasons exogenous to innovation.

[7] Namely, acquisitions withdrawn due to adverse macroeconomic conditions, opposition from regulatory bodies, or competing bids.

[8] The narrow focus of this paper on start-ups also alleviates concerns about capturing other mechanisms and motives for M&A engagement, especially the ones concerning gains from changes in market structure (e.g. price increases). This is because it is unlikely that start-ups are acquired for these reasons due to their low market penetration.

[9] The databases also include information on other geographies. For instance, approximately one-fourth of the observations in the OECD/STI Start-ups database are in different regions than North America and

Europe. These datasets also present a better coverage of early-stage deals than other sources used in previous literature, such as VentureXpert (Wang, 2018[43]).

[10] There are instances in which acquirors and start-up targets engage in several minority stake acquisitions which end up in the latter owning more than a 50% stake in the former. These deals are also considered as majority acquisitions, and the date of acquisition is assumed to be the date of the transaction through which the acquiror went from owning a minority stake (<50%stake) to a majority stake (>50%stake).

[11] It is a snapshot of the EPO's bibliographic database, meaning that any patent applied at the EPO or cited by a patent that was applied at the EPO will be in the database. That is, if a patent applied at EPO cites a patent applied in another application authority other than the USPTO or the EPO, it will appear in the dataset as well, even though this one was never applied for in the EPO or USPTO. Note, however, that information on citations received by patents are available only for patents filed at EPO and USPTO.

[12] Here (ln) productivity is defined as the residual of the difference between gross output and the sum of the three input, capital, labour, and material, times the corresponding elasticity of production with respect to each input. To compute TFP, in addition to the balance sheet information, also these elasticities are required. In this specific setting, elasticities are directly obtained from Calligaris et al. (2024[84]). Using the same dataset, and a similar cross-country sample for overlapping years (and to a large extent countries), Calligaris et al. (2024[84]) estimate gross-output production functions in three inputs (capital, labour, and material) using the Ackerberg, Caves, and Garth (2015[87]) methodology. Production functions are 3-digit industry-specific and constant across years.

[13] A pair of companies will be assigned a unique identifier if their Levenshtein distance, Jaro-Winkler distance, cosine similarity, and token frequency measures are above 80%. In a few instances, the algorithm assigns several companies in one dataset to a unique company in another. In these cases, one of the matches is selected at random. Out of approximately 93 thousand start-ups in the final sample, only 2% are affected by this.

[14] Note that all start-ups appearing in the Orbis M&A data must have had some interaction with investors. These investments could be either acquisitions or CVC investments, other VC minority investments, or could also be the result of IPOs or other later-stage investments.

[15] While venture capital rounds could be also potentially identified in Orbis M&A, the OECD/STI Start-ups Database presents more details on the specific kind of financing used, allowing to identify better the ones associated with innovative start-ups. Also, it allows to better track the amount raised in each financing round, which is used as a proxy for technological input.

[16] By established companies, this paper refers to firms who exited the 'start-up' status. In general, this covers companies that went through an IPO or just aged. Sometimes more established companies might appear in the data for several reasons. They might use an instrument traditionally associated with innovative start-ups (like private equity, extensively used, for instance, in company re-structuring), because they were start-ups at some point in time and the data continues providing financing information, or because of the incomplete information on patents published before the analysed period. Therefore, this paper imposes the additional restriction that companies must be less than 10 years old at the time of the first relevant event (i.e. the date of the first VC round or of the first filed patent).

[17] As robustness, the results remain virtually unchanged when replicated by excluding start-ups in both treatment and control groups from the financial sector and those targets acquired by financial acquirors.

[18] For comparison, the number of acquired start-ups analysed in the papers that explicitly address the effect of start-up or small firm acquisitions on innovation at the firm level mentioned in Section 2 ranges between six and sixteen thousand acquired companies. Note that this upper bound comes from Farre-Mensa, Liu, and Nickerson (2022[59]) who track patent acquisitions in the USPTO dataset rather than company acquisitions. Also, these studies are mostly focused on a single country. Most of the papers that use the information on publicly listed companies also fall in this range.

[19] If multiple firms apply for the same DOCDB family, the earliest filing date is assigned to all co-applicants if they applied simultaneously. Otherwise, only the first applicant receives the earliest date, and subsequent applicants are assigned their respective application dates.

[20] See https://www.wipo.int/documents/2948119/3215563/wipo_ipc_technology.pdf for more details on the WIPO technological classification.

[21] Despite citations might be strategically affected by the behaviour of the acquiror post-acquisition, the use of citations to capture the quality of patents is widely established in the literature to assess the question at hand in this paper. Also, note that citations are – to a large extent – under the control of examiners, and so not completely under the strategic control of the acquiror. This is especially the case at EPO, where all citations are provided by the examiners. This might milden the concerns that this measure is directly affected by the acquisition event.

[22] How to allocate patents across WIPO fields can be done in different manners. This paper proceeds as follows. Imagine there are only 2 aggregate technological fields (WIPO families) for simplicity. Each aggregate field is composed of many disaggregated technological classes (IPC families). If a patent contributes to 3 disaggregated families covered by one aggregate technological field and another 2 disaggregated families in the other field, then the aggregate technological family-specific patent stocks will be 3/5 for the first family and 2/5 for the second one.

[23] Note that the number of firms included varies across the upper and lower panels. This is mainly due to firms acquired in the last year of data (2021), for which patents are not observed in the post-acquisition period.

[24] These thresholds rely on previous literature (Barrot, 2016[85]; Fons-Rosen, Roldán-Blanco and Schmitz, 2022[25]). However, the results of the analysis remain qualitatively the same if this choice is not imposed and non-acquired start-ups are used as a control group throughout the timeframe considered. These results, not reported for brevity, are available upon request.

[25] Using the available data, start-ups in the sample exit the market on average when they are 9 years old and have their first IPO when they are 12 years old. Thus, the restriction is consistent with exit dynamics from the start-up status.

[26] The choice of three fictitious counterparts per start-up and acquiror is to some extent arbitrary, even if it is driven by a rationale. The analysis does not allow for replacement in the fictitious deals. In other words, once a non-acquired start-up or a potential acquiror is selected into the deal, they are not allowed to be part of other fictitious deals. In addition, notice that this exercise restricts the sample to patenting firms. These two conditions substantially reduce the sample available to select random pairs, and therefore it

has been chosen the arbitrary number of three to maximise the sample used in the analysis. Nevertheless, different thresholds have been tested and results remain unaltered. Also, as explained later, the reported results are the average of 100 iterations, and each of them draws randomly the fictitious deals.

[27] Note that this probability is different from the underlying probability of being acquired in the full sample, which is approximately 20% (17 thousand get acquired out of 93 thousand total start-ups). In this case, the probability ranges between 2% and 3% because the sample used to compute it is a repeated cross-section, and never acquired firms are repeated multiple times.

[28] It is computed as the ratio between the premium for patent holders, 0.0085, and the unconditional average probability of being acquired, 0.024, multiplied by a hundred.

[29] The specification considers log(1+Patent stock) to include in the sample all start-ups with a patent stock of zero, which otherwise would be removed. Note that this specification restricts the sample to those companies that hold a patent at some point during the sample period, and therefore some observations might have zero patents in some years until they apply for the first patent.

[30]This might also suggest that acquisitions are concentrated on the start-ups that were selected into the sample because they had a patenting event. Table A A.1 in the Appendix shows that while the difference in the premia between extensive and intensive margin decreases when selecting only VC-funded companies, there is still a large difference in magnitudes, suggesting that first-time patenting has a sizable effect, and that sample selection does not affect substantially this result.

[31] While the citations-weighted patent count is one of the most popular measures to proxy for patent quality, it is worth highlighting that it might be subject to endogeneity biases given that it relies on post-acquisition outcomes.

[32] As explained above, to obtain these numbers one needs to add up the premium on having a patent, given by the coefficient on “Has a patent” and its interaction with the age group category, and compare it against the average probability of acquisition in the sample, reported in the table. Therefore, the premium is (0.0040+0.0073)*100/0.025=45.2 and (0.0040+0.0078)*100/0.025=47.2 for companies between 3-5 years old and 6-10 years old, respectively. In Column 1, the row “premium” represents the premium for firms aged 0-2 years old (i.e. the reference category) and can be obtained by dividing the coefficient on “Has a patent” over the row “Mean dep. variable”, i.e. 0.025*100/0.004 = 16.2. The coefficients of the age group (i.e. the baseline probabilities of each age group when not holding any patents) are not reported in the table and are available upon request.

[33] Note that, as already mentioned in the previous section, extensive robustness checks have been performed to assess whether the results depend in any possible way on the choices made while selecting the relevant sample. As written above, all the results of this analysis remain qualitatively unchanged when different choices on the sample selection are made.

[34] As opposed to the binary outcome used in the linear probability model, the Poisson regression allows the use of a discrete dependent variable.

[35] Notice that these large premia are completely driven by the large number of incumbents in the control group, which drives the average of the dependent variable closer to 0. In other words, these premia are inflated by the choice of control group incumbents.

[36] For instance, Column 5 indicates that a company with a patent has 1.4417 times higher cumulative number of acquired start-ups than a company without patents or, equivalently, about a 44% higher count.

[37] See Wolfers (2006[83]) for a famous application.

[38] The problem with using TWFE estimators to get the unbiased DID estimate is that this methodology runs into what is called *forbidden comparisons*. Simply put, the TWFE estimator fails to get unbiased estimates of the DID estimator because it is the average of two kinds of comparisons (Goodman-Bacon, 2021[88]). First, the estimator compares the outcomes of treated and non-treated or not-yet-treated units, which are generally unproblematic. However, a second term uses differences between early- and late-treated units (when treatment timing differs) or less and more treated units (in the case of a discrete or continuous treatment). This second term is the one that generates a bias when using the typical TWFE estimation.

[39] See de Chaisemartin and D'Haultfoeuille (2023[32]) for an extensive literature review.

[40] Note that reassuringly all the results of this section continue to hold when using any of these alternative methodologies: Callaway and Sant'Anna (2021[67]); Sun and Abraham (2021[68]); Borusyak, Jaravel and Spiess (2024[66]).

[41] Alternatively, the results remain unchanged when simply using the group of start-ups with withdrawn bids as a control group.

[42] The results are robust to omitting any of the categories (competing bids, regulatory bodies, or macroeconomic conditions) and leaving the other two.

[43] From the 457 initially withdrawn bids, 35 were withdrawn due to disagreements in growth strategies or between stakeholders, 44 were withdrawn due to disagreements over the valuation of the transaction, 18 were withdrawn due to negative developments involving one of the parties, and for 238 bids were withdrawn for unclear reasons. This leaves 122 exogenously withdrawn bids (31 due to competing bids, 56 due to adverse macroeconomic conditions, and 35 due to opposition from regulatory bodies or failing to comply with their requirements).

[44] Given that this restricted sample is different from the extended sample used in the baseline exercise in terms of countries covered, sample size, and so on, the analysis should be interpreted with caution and bearing in mind the sample constraints.

[45] Approximately 20% of acquirors active in these industries and countries remain after this restriction is applied.

[46] The baseline specification follows acquired start-ups (acquiring firms) from 4 years previous the acquisition event until 5 years afterwards. Note that, as a robustness, different time intervals for the computation of pre-trends and ex-post effects are considered. Results remain unchanged when changing the time frame considered.

[47] The sample of withdrawn bid is not used directly as a control group because the methodology of de Chaisemartin and D'Haultfoeuille (2024[31]) does not allow the control group to undergo a treatment (i.e. the withdrawn bid). In this paper, the baseline way to perform this exercise is to use the equivalence between two diff-in-diffs and the triple diff-in-diff (Olsen and Moen, 2022[70]). This way, the timing of the treatment, both for acquired start-ups and start-ups receiving a withdrawn bid, is considered. This choice

allows to directly use the *did_multiplegt_dyn* command in STATA to implement the de Chaisemartin and D'Haultfoeuille (2024[31]). In a robustness exercise, as discussed later, the sample of withdrawn bids is simply used as a control group, therefore not considering the timing of the failed acquisition bids.

[48] See the change in the distribution of patents in Table 3.2 to corroborate this.

[49] When restricting to companies that continue patenting after the acquisition, the decline in patenting is still observed. The magnitude of the decline is remarkably similar to the baseline specifications too.

[50] This exercise requires additional information on the patents like their forward and backward citations as well as the IPC fields of the cited patents. These requirements substantially decrease the size of the withdrawn bid sample and, therefore, the analysis abstracts from replicating this exercise.

[51] This exercise, while similar in spirit to the causal analysis presented above, simply uses these firms as a control group. As such, the methodology does not take into account the timing of the withdrawn bid.

[52] These papers combine propensity score matching with simple TWFE, since recent methodologies of DID estimators were not yet available.

[53] The predicted propensity scores are used as weights in the de Chaisemartin and D'Haultfoeuille (2024[31]) estimation procedure, as this technique has been proved to have better finite sample properties than the traditional matching procedures (Busso, DiNardo and McCrary, 2014[86]).

[54] There are several ways in which the treatment can be modelled in the case of the acquiror. Acquirors are more complex to analyse than start-ups because acquisition can take place over several periods or even several times within the same period. In addition to the exercise shown in the main text, in a robustness exercise, the acquisition is modelled also as a binary treatment that switches on when there is at least one acquisition and switches off when no acquisition takes place. The results are qualitatively the same as those reported in the paper and are available upon request.

[55] As explained above, the estimator compares companies that have the same first-period treatment. Allowing for some start-up acquisitions to take place before running the estimation allows the computation of the average treatment effects within groups of acquirors with similar M&A levels. In other words, the so-called serial acquirors will be compared to other serial acquirors and single-time acquirors will be compared to other single-time acquirors. As an example, imagine a sample of four periods and three different acquirors. The number of start-ups acquired in each period by acquiror 1 is given by D_1=(1,0,2,0), acquiror 2 has a treatment path given by D_2=(1,0,0,0), and acquiror 3 has a treatment path given by D_3=(1,0,1,1). The effect on the year of the acquisition can be obtained by comparing the outcomes of acquirors 1 and 3 to that of acquiror 2 in period 3. They all have the same first-period treatment and are not treated before the acquisition event. The effect on the year following the first acquisition, however, will be computed using the differences between acquiror 1 and acquiror 3, as acquiror 2 receives another treatment following the first acquisition and, therefore, is not eligible in the control group. Thus, the estimated effect can be loosely interpreted as the average effect of being exposed to a higher intensity of the treatment.

[56] Notice, however, that Stiebale (2016[58]) restricts acquirors to isolated acquisitions. By employing the methodology developed by de Chaisemartin and D'Haultfoeuille (2024[31]) that allows for discrete treatment, the present paper includes in the analysis the "serial" acquirors, and therefore offers a more complete picture of incumbents' activities.

[57] For this classification, all acquirors across countries and industries are pooled to compute the median value. However, conditioning on the within country and industry median does not change the results.

[58] While a complete characterisation would require also information on trademarks on the acquiror side, this is not feasible due to data limitations.

[59] Similarly to patenting, different sectors and IP offices might have different traditions regarding registered trademarks. For this reason, the paper standardises the trademark count by the number of trademarks granted in a given IP office and year. To ease the interpretation of this variable, the measure is further normalised by its unconditional average value in the sample used in the regression.

[60] The test for the joint nullity of the pre-trends is statistically significant and, thus, one cannot reject that these differences were changing before the acquisition. In particular, the evolution of the differences is flat up to 4 years before the acquisition and starts declining one period before, likely capturing an anticipatory effect.

[61] The baseline results remain robust when restricting the sample to Orbis firms.

[62] In this context, technological classes refer to 4-digit IPC families, which are much more disaggregated than the technological classes used to compute the measures of technological proximity.

[63] These two exercises present the result of a simple regression of the (log) average quality and average radicalness on the (log) number of acquisitions. Controlling for industry and country fixed effects (not interacted) increases both the significance and the magnitude of the coefficients even further.

References

Abadie, A. (2005), "Semiparametric difference-in-differences estimators", *Review of Economic Studies*, Vol. 72/1, pp. 1-19, https://doi.org/10.1093/ectj/utac017. [65]

Abele, C. et al. (2024), "A Taxonomy of Industry Competition", *Protecting Competition in a Changing World, European Comission*, https://competition-policy.ec.europa.eu/system/files/2024-06/A_taxonomy_of_industry_competition_launch.pdf. [81]

Ackerberg, D., K. Caves and F. Garth (2015), "Identification Properties of Recent Production Function Estimators", *Econometrica*, https://doi.org/10.3982/ECTA13408. [87]

Affeldt, P. and R. Kesler (2022), "Competitors' Reactions to Big Tech Acquisitions: Evidence from Mobile Apps", *DIW Berlin Discussion Paper No. 1987*, https://doi.org/10.2139/ssrn.3998875. [55]

Akcgit, U. and W. Kerr (2018), "Growth through Heterogeneous Innovations", *The Journal of Political Economy*, Vol. 126/4, pp. 1374-1443, https://doi.org/10.1086/697901. [7]

Alexandridis, G., N. Antypas and N. Travlos (2017), "Value Creation from M&As: New Evidence", *Journal of Corporate Finance*, Vol. 45, pp. 632-650, https://doi.org/10.1016/j.jcorpfin.2017.05.010. [10]

Alezra, D. and B. Berquier (2024), "Being Acquired and Innovation: An Empirical Study", *Toulouse School of Economics Working Papers*. [44]

Altomonte, C., N. El-Mallakh and T. Sonno (2024), "Business Groups, Strategic Acquisitions and Innovation", *CEP discussion paper CEPDP1996*, https://cep.lse.ac.uk/_NEW/publications/abstract.asp?index=10860. [35]

Arora, A., S. Belenzon and A. Patacconi (2017), "The decline of science in corporate R&D", *Strategic Management Journal*, Vol. 39/1, pp. 3-32, https://doi.org/10.1002/smj.2693. [12]

Arora, A., S. Belenzon and L. Sheer (2021), "Knowledge Spillovers and Corporate Investment in Scientific Research", *American Economic Review*, Vol. 111/3, pp. 871-898, https://doi.org/10.1257/aer.20171742. [13]

Atalay, E., A. Hortacsu and C. Syverson (2014), "Vertical Integration and Input Flows", *American Economic Review*, Vol. 104/4, pp. 1120-1148, https://doi.org/10.1257/aer.104.4.1120. [9]

Bajgar, M. et al. (2023), "Industry Concentration in Europe and North America", *Industrial and* [19]

Corporate Change, pp. 1-18, https://doi.org/10.1093/icc/dtac059.

Barrot, J. (2016), "Investor Horizon and the Life Cycle of Innovative Firms: Evidence from Venture Capital", *Management Science*, Vol. 63/9, pp. 3021-3043, https://doi.org/10.1287/mnsc.2016.2482. [85]

Basberg, B. (1987), "Patents and the Measurement of Technological Change: A Survey of the Literature", *Research Policy*, Vol. 16/2-4, pp. 131-141, https://doi.org/10.1016/0048-7333(87)90027-8. [60]

Bellavitis, C., C. Fisch and S. Vismara (2023), "Monetary Policy and Venture Capital Markets", *Review of Corporate Finance*, Vol. 3/4, pp. 627-662, https://doi.org/10.1561/114.00000053. [11]

Bena, J. and K. Li (2014), "Corporate Innovations and Mergers and Acquisitions", *The Journal of Finance*, Vol. 69/5, pp. 1923-1960, https://doi.org/10.1111/jofi.12059. [17]

Bloom, N. et al. (2020), "Are Ideas Getting Harder to Find?", *American Economic Review*, Vol. 110/4, pp. 1104-1144, https://doi.org/10.1257/aer.20180338. [14]

Bloom, N., M. Schankerman and J. Van Reenen (2013), "Identifying Technology Spillovers and Product Market Rivalry", *Econometrica*, Vol. 81/4, pp. 1347-1393, https://doi.org/10.3982/ECTA9466. [15]

Borusyak, K., X. Jaravel and J. Spiess (2024), "Revisiting Event-Study Designs: Robust and Efficient Estimation", *Review of Economic Studies*, p. rdae007, https://doi.org/10.1093/restud/rdae007. [66]

Breschi, S., J. Lassébie and C. Menon (2018), *A Portrait of Innovative Start-ups across Countries*, https://doi.org/10.1787/f9ff02f4-en. [42]

Busso, M., J. DiNardo and J. McCrary (2014), "New Evidence on the Finite Sample Properties of Propensity Score Reweighting and Matching Estimators", *The Review of Economics and Statistics*, Vol. 96/5, pp. 885-897, https://doi.org/10.1162/REST_a_00431. [86]

Cabral, L. (2021), "Merger Policy in Digital Industries", *Information Economic and Policy*, Vol. 54, https://doi.org/10.1016/j.infoecopol.2020.100866. [37]

Cabral, L. (2018), "Standing on the Shoulders of Dwarfs", *CEPR Discussion Paper No. DP13115*, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3235598. [47]

Callaway, B. and P. Sant'Anna (2021), "Difference-in-Differences with multiple time periods", *Journal of Econometrics*, Vol. 225, pp. 200-230, https://doi.org/10.1016/j.jeconom.2020.12.001. [67]

Calligaris, S. et al. (2024), *Exploring the Evolution and the State of Competition in the EU*. [84]

Calligaris, S. et al. (2024b), "Industry concentration in Europe: trends and methodological insights", *OECD Science, Technology and Industry Working Papers*. [20]

Calligaris, S. et al. (forthcoming), "Some facts on business dynamism among market leaders", *STI working paper*. [22]

Calvino, F. et al. (2018), "A taxonomy of digital intensive sectors", *OECD Science, Technology and Industry Working Papers*, No. 2018/14, OECD Publishing, Paris, https://doi.org/10.1787/f404736a-en. [80]

Calvino, F., C. Criscuolo and R. Verlhac (2020), "Declining business dynamism: Structural and policy determinants", *OECD Science, Technology and Industry Policy Papers*, No. 94, OECD Publishing, Paris, https://doi.org/10.1787/77b92072-en. [21]

Cavenaile, L., M. Celik and X. Tian (2021), "The Dynamic Effects of Antitrust Policy on Growth and Welfare", *Journal of Monetary Economics*, Vol. 121, pp. 42-59, https://doi.org/10.1016/j.jmoneco.2021.04.011. [53]

Chondrakis, G., C. Serrano and R. Ziedonis (2025), "Acquiring Patents in Secret: Disclosure Timing in Markets for Technology", *HEC Paris Research Paper No. ECO/SCD-2025-1559*, https://doi.org/10.2139/ssrn.5212082. [74]

Cunningham, C., F. Ederer and S. Ma (2021), "Killer Acquisitions", *Journal of Political Economy*, Vol. 129/3, pp. 649-702, https://doi.org/10.1086/712506. [24]

Dalle, J., M. den Besten and C. Menon (2017), "Using Crunchbase for economic and managerial research", *OECD Science, Technology and Industry Working Papers*, https://doi.org/10.1787/6c418d60-en. [30]

de Barsy, L. and A. Gautier (2024), "Big Tech Acquisitions and Innovation: An Empirical Assessment", *CESifo Working Paper No. 11025*, https://doi.org/10.2139/ssrn.478305. [56]

de Chaisemartin, C. and X. D'Haultfoeuille (2024), "Difference-in-Differences Estimators of Intertemporal Treatment Effects", *Review of Economics and Statistics*, pp. 1-45, https://doi.org/10.1162/rest_a_01414. [31]

de Chaisemartin, C. and X. D'Haultfoeuille (2023), "Two-way fixed effects and differences-in-differences with heterogeneous treatment effects: a survey", *The Econometrics Journal*, Vol. 26/3, pp. C1-C30, https://doi.org/10.1093/ectj/utac017. [32]

de Chaisemartin, C. and X. d'Haultfoeuille (2021a), "Two-way fixed effects regressions with several treatments", *arXiv preprint arXiv:2012.10077.*. [69]

De Ridder, M. (2024), "MArket Power and Innovation in the Intangible Economy", *American Economic Review*, Vol. 114/1, pp. 199-251, https://doi.org/10.1257/aer.20201079. [79]

Denicolo, V. and M. Polo (2021), *Acquisitions, Innovation and the Entrenchment of Monopoly*, https://doi.org/10.2139/ssrn.3988255. [52]

Dickinson, V. (2011), "Cash Flows Patterns as a Proxy for Firm Life Cycle", *The Accounting Review*, Vol. 86/6, pp. 1969-1994, https://doi.org/10.2308/accr-10130. [64]

Didier, T. et al. (2021), "Capital Market Financing and Firm Growth", *Journal of Inernational Money and Finance*, Vol. 118, pp. 1024-1059, https://doi.org/10.1016/j.jimonfin.2021.102459. [18]

Dijk, E., J. Moraga-González and E. Motchenkova (2024), "How Do Start-up Acquisitions Affect the Direction of Innovation?", *Journal of Industrial Economics*, Vol. 72/1, pp. 118-156, https://doi.org/10.1111/joie.12349. [39]

Ederer, F. and B. Pellegrino (2023), "The Great Start-up Sellout and the Rise of Oligopoly", *AEA Papers and Proceedings*, Vol. 113, pp. 274-278, https://doi.org/10.1257/pandp.20231024. [8]

Eisfeld, L. (2024), "Entry and Acquisitions in Software Marekts", *Unpublished Manuscript*. [38]

European Commission (2024), *The Future of European Competitiveness*. [29]

Farre-Mensa, J., Z. Liu and J. Nickerson (2022), *Do Start-up Patent Acquisitions Affect Inventor Productivity?*, https://doi.org/10.2139/ssrn.4071917. [59]

Federico, G., G. Langus and T. Valletti (2017), "A Simple Model of Mergers and Innovation", *Economic Letters*, Vol. 157/C, pp. 136-140, https://doi.org/10.1016/j.econlet.2017.06.014. [51]

Fons-Rosen, C. et al. (2021), "Quantifying Productivity Gains from Foreign Investment", *Journal of International Economics*. [72]

Fons-Rosen, C., P. Roldán-Blanco and T. Schmitz (2022), *The Effects of Startup Acquisitions on Innovation and Economic Growth*, https://doi.org/10.2139/ssrn.3785485. [25]

Fumagalli, C., M. Motta and E. Tarantino (2020), *Shelving or Developing? The Acquisition of Potential Competitors Under Financial Constraints*. [49]

Gans, J., H. H. and S. Stern (2002), "When Does Start-up Innovation Spur the Gale of Creative Destruction?", *RAND Journal of Economics*, Vol. 33/4, pp. 571-586, https://doi.org/10.2307/3087475. [6]

García-Santana, M. et al. (2024), *Firms' Participation in Capital Markets and Real Economic Outcomes*. [50]

Gautier, A. and J. Lamesch (2021), "Mergers in the Digital Economy", *Information Economics and Policy*, Vol. 54, https://doi.org/10.1016/j.infoecopol.2020.100890. [54]

Goodman-Bacon, A. (2021), "Difference-in-differences with variation in treatment timing", *The Journal of Econometrics*, Vol. 225/2, pp. 254-277, https://doi.org/10.1016/j.jeconom.2021.03.014. [88]

Gregori, W., M. Martinez-Cirello and M. Nardo (2023), "The Effects of Cross-Border Acquisitions on Firms' Productivity in the EU", *The World Economy*, Vol. 47/1, pp. 9-36, https://doi.org/10.1111/twec.13521. [82]

Guadalupe, M., O. Kuzmina and C. Thomas (2012), "Innovation and Foreign Ownership", *American Economic Review*, Vol. 102/7, pp. 3594-3627, https://doi.org/10.1257/aer.102.7.3594. [71]

Hall, B. (2011), "Innovation and Productivity", *National Bureau of Economic Research*. [75]

Haltiwanger, J., R. Jarmin and J. Miranda (2013), "Who Creates Jobs? Small Versus Large Versus Young", *The Review of Economics and Statistics*, Vol. 95/2, pp. 347-361, https://doi.org/10.1162/REST_a_00288. [2]

Haucap, J., A. Rasch and J. Stiebale (2019), "How Mergers Affect Innovation: Theory and Evidence", *International Journal of Industrial Organization*, Vol. 63, pp. 283-325, https://doi.org/10.1016/j.ijindorg.2018.10.003. [28]

Hoberg, G. and G. Phillips (2010), "Product Market Synergies and Competition in Mergers and Acquisitions: A Text-Based Analysis", *Review of Financial Studies*, Vol. 23, pp. 3773-3811, https://doi.org/10.1093/rfs/hhq053. [41]

Hsu, P. et al. (2021), "2021", *Journal of International Money and Finance*, Vol. 112, https://doi.org/10.1016/j.jimonfin.2020.102320. [46]

Jaffe, A. (1986), "Technological Opportunity and Spillovers of R & D: Evidence from Firms' Patents, Profits, and Market Value", *American Economic Review*, Vol. 76/5, pp. 984-1001. [63]

John Haltiwanger, E. (ed.) (2017), *High-Growth Young Firms: Contribution to Job, Output, and Productivity Growth*, University of Chicago Press. [3]

Kortum, S. and J. Lerner (2000), "Assessing the Contribution of Venture Capital to Innovation", *RAND Journal of Economics*, Vol. 31/4, pp. 674-692, https://doi.org/10.2307/2696354. [4]

Letina, I., A. Schmutzler and R. Seibel (2021), *Killer Acquisitions and Beyond: Policy Effects on Innovation Strategies*, https://doi.org/10.2139/ssrn.367150. [48]

Mendonca, S., T. Santos and M. Mira (2004), "Trademarks as an Indicator of Innovation and Industrial Change", *Research Policy*, Vol. 33/9, pp. 1355-1404, https://doi.org/10.1016/j.respol.2004.09.005. [76]

Millot, V. (2009), "Trademarks and an Indicator of Product and Marketing Innovations", *OECD Science, Technology and Industry Working Papers*, https://doi.org/10.1787/224428874418. [77]

OECD (2020), *Start-ups, Killer Acquisitions and Merger Control*, https://doi.org/10.1787/dac52a99-en. [1]

Olsen, A. and J. Moen (2022), "The triple difference estimator", *The Econometrics Journal*, Vol. 25/3, pp. 531-553, https://doi.org/10.1093/ectj/utac010. [70]

Park, M., E. Leahey and R. Funk (2023), "Papers and Patents Are Becoming Less Disruptive Over Time", *Nature*, Vol. 613, pp. 138-144, https://doi.org/10.1038/s41586-022-05543-x. [23]

Phillips, G. and A. Zhdanov (2013), "R&D and the Inventives from Merger and Acquisition Activity", *The Review of Financial Studies*, Vol. 26/1, pp. 34-78, https://doi.org/10.1093/rfs/hhs109. [36]

Rhodes-Kropf, M. and D. Robinson (2008), "The Market for Mergers and the Boundaries of the Firm", *The Journal of Finance*, Vol. 63/3, pp. 1169-1211, https://doi.org/10.1111/j.1540-6261.2008.01355.x. [16]

Schnitzer, M. and M. Watzinger (2022), "Measuring the Spillovers of Venture Capital", *The Review of Economics and Statistics*, Vol. 104/2, pp. 276-292, https://doi.org/10.1162/rest_a_00937. [5]

Serrano, C. (2019), "Estimating the Gains from Trade in the Market for Patent Rights", *International Economic Review*, Vol. 59/4, pp. 1877–1904, https://doi.org/10.1111/iere.12338. [34]

Seru, A. (2014), "Firm Boundaries Matter: Evidencefrom Conglomerates and R&D Activity", *Journal of Financial Economics*, Vol. 111/2, pp. 381-405, https://doi.org/10.1016/j.jfineco.2013.11.001. [33]

Sevilir, M. and X. Tian (2010), *Acquiring Innovation*, https://doi.org/10.2139/ssrn.1731722. [57]

Shane, S. (2001), "Technological Opportunities and New Firm Creation", *Management Science*, Vol. 47/2, pp. 205-220, https://doi.org/10.1287/mnsc.47.2.205.9837. [62]

Squicciarini, M., H. Dernis and C. Criuscolo (2013), "Measuring Patent Quality: Indicators of Technological and Economic Value", *OECD Science, Technology, and Industry Working Papers 2013/03*, https://doi.org/10.1087/5k4522wkw1r8-en. [61]

Stiebale, J. (2016), "Cross-Border M&As and Innovative Activity of Acquiring and Target Firms", *Journal of International Economics*, Vol. 99, pp. 1-15, https://doi.org/10.1016/j.jinteco.2015.12.005. [58]

Stiebale, J. and F. Reize (2011), "The Impact of FDI through Mergers and Acquisitions on Innovation in Target Firms", *International Journal of Industrial Organization*, Vol. 29, pp. 155-167, https://doi.org/10.1016/j.ijindorg.2010.06.003. [27]

Sun, L. and S. Abraham (2021), "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects", *Journal of Econometrics*, Vol. 225, pp. 175-199, https://doi.org/10.1016/j.jeconom.2020.09.006. [68]

van Ark, B., M. O'Mahoney and M. Timmer (2008), "The Productivity Gap between Europe and the United States: Trends and Causes", *Journal of Economic Perspectives*, Vol. 1, pp. 25-44, https://doi.org/10.1257/jep.22.1.25. [78]

Veugelers, R. and C. Schneider (2018), "Which IP Strategies Do Young Highly Innovative Firms Choose?", *Small Business Economics*, Vol. 50, pp. 113-129, https://doi.org/10.1007/s11187-017-9898-y. [73]

Wang, X. (2018), *Catering Innovation: Entrepreneurship and the Acquisition Market*, https://doi.org/10.2139/ssrn.3247274. [43]

Warg, K. (2022), *The Acquisition Option and Start-up Innovations*. [26]

Weiss, J. (2023), *Market Concentration, Growth and Acquisitions*. [40]

Wolfers, J. (2006), "Did Unilateral Divorce Laws Raise Divorce Rates? A Reconciliation and New Results", *American Economic Review*, Vol. 96/5, pp. 1802-1820, https://doi.org/10.1257/aer.96.5.1802. [83]

Zhao, X. (2009), "Technological Innovation and Acquisitions", *Management Science*, Vol. 55/7, pp. 1170-1783, https://doi.org/10.1287/mnsc.1090.1018. [45]

Annex A. Supplementary material

Table A A.1. Descriptive statistics of the acquisition sample

		Start-ups	Incumbents
Firms		91 914	156 681
	Treatment	17 854	11 120
	Control	74 060	145 561
3-digit sectors		204	217
Top 5 sectors			
		Information services (28%)	Financial services (31%)
		Scientific R&D (9%)	Auxiliary services to financials (15%)
		Publishing (9%)	Information services (6%)
		Computer services, consultancy, and programming (8%)	Computer services, consultancy, and programming (5%)
		Manufacture of computer, electronic and optical products (5%)	Activities of head offices (3%)
Countries		60	74
Top 5 countries			
		US (44%)	US (28%)
		EU (17%)	EU (22%)
		UK (8%)	China (11%)
		China (8%)	UK (9%)
		India (4%)	Japan (5%)

Note: Number of firms and their composition across industries and countries in the acquisition sample.
Source: OECD calculations using Orbis M&A and the OECD/STI Start-ups Database.

Annex B. Robustness and Extensions

A description of VC-funded acquired start-ups

As described in the section 3, the sample is cleaned and selected following some steps, including criterion 2 – according to which only start-ups receiving a VC or filing a patent when are young are considered as innovation- and growth-oriented start-ups. Because of the sample selection, start-ups that have a patent might be driving the results of the ex-ante analysis if VC firms are not usually holders of patents. While this per se does not go against the idea that acquisitions are concentrated in innovative companies, it complicates the interpretation of the intensive and extensive margins of innovation. For this reason, Table A B.1 shows the description of the acquired start-ups restricting to those that have VC, i.e. excluding the start-ups that have only received a patent. As can be observed, the magnitudes remain substantially different across the extensive and intensive margins, suggesting that the first-time patenting event is indeed more influential than the subsequent ones even when excluding from the sample firms selected on patents.

Table A B.1. The effect of patenting activity and VC stocks on the likelihood of acquisition

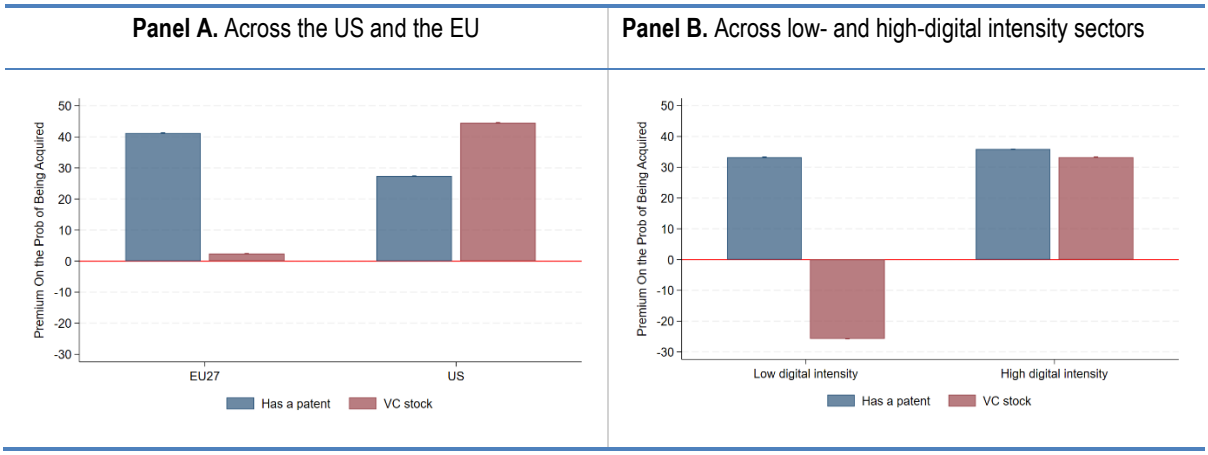
VARIABLES	(1)	(2)	(3)
Has a patent	0.00103*		
	(0.000606)		
Patent stock		0.0266**	
		(0.0108)	
Citations-weighted patent stock			0.0165***
			(0.00405)
VC stock	0.000482***	0.00121***	0.00119***
	(3.43e-05)	(6.06e-05)	(6.08e-05)
Only patenting start-ups	No	Yes	Yes
Firm FE	No	No	No
Industry-Country-Year FE	Yes	Yes	Yes
Observations	515 471	157 370	157 370
R-squared	0.054	0.064	0.064
Mean dep. variable	2.2	2.0	2.0
Premium	4.6	0.8	2.2

Note: This table restricts observations to those that have a VC-funding event before the age of 10. The table shows the results of the linear probability model (Equation 1) using cross-sectional variation for different specifications. The first column allows the effect of having a patent to vary across age categories. The second and third columns only include acquisitions that happen across and within 3-digit NACE Rev. 2 industries, respectively. The fourth and fifth columns only include acquisitions that happen across or within countries, respectively. The control group never changes. The mean dependent variable reports the unconditional probability of being acquired in the relevant sample as a percentage. The premium represents the ratio between the coefficient of having a patent and the mean dependent variable as a percentage. All regressions control for the firm's age and industry-country-year fixed effects. *: p-value < 10%, **: p-value < 5%, *: p-value < 1%.
Source: OECD calculations based on OECD/STI Start-ups Database, Orbis M&A, and PATSTAT data.

Ex-ante heterogeneity in acquired start-ups across regions and sectors

The EU-US productivity wedge during the last decades has sparked a lively policy debate aimed at understanding its causes and consequences (van Ark, O'Mahoney and Timmer, 2008[78]; European Commission, 2024[29]). Many have linked it to the increasing importance of the intangible and digital economy (De Ridder, 2024[79]). For this reason, this box provides an additional portrayal of acquired innovative start-ups, exploring the differences between the US and the EU, as well as between low and high digitally intensive sectors. Starting from their industry of activity, start-ups are associated with different levels of digital intensity using the taxonomy developed by Calvino et al. (2018[80]). Figure A B.1 plots the increase in the likelihood of acquisition from having a patent or raising an additional million dollars in VC as a percentage of the average probability of being acquired in the sample.

Figure A B.1. The innovation premium across regions and sectors.



Note: The figure shows the results of Equation 1 for different specifications exploring heterogeneity across start-up targets in the EU27 and the US and low and high digital intensity sectors. In particular, it runs Equation 1 for four different subsamples: (i) EU start-ups, (ii) US start-ups, (iii) start-ups in log-digital intensity sectors, and (iv) start-ups in high-digital intensity sectors. For each subsample, the average probability of being acquired is computed. The premium on having a patent is computed as the coefficient of having a patent over the corresponding average probability of acquisition. The premium on raising USD one million (2011) in VC is computed by multiplying the coefficient of VC times the log of one plus one million and scaling this number by the average probability of acquisition in each subsample.
Source: OECD calculations based on OECD/STI Start-ups Database, OBIRS M&A, and PATSTAT data.

Panel A of Figure A B.1 shows the heterogeneity of acquired start-ups in the EU and the US, highlighting some important differences. First, having a patent seems to be more relevant in the EU. As shown in the main text, acquirors select targets with patents more frequently when acquisitions happen across markets. As cross-country acquisitions are more frequent in the EU (approximately 40% of EU acquisitions happen across countries, mostly involving two EU players), this is reflected in the increased probability of acquisition for firms that have a patent. Second, it shows that the stock of VC is positively associated with acquisition in the US but not in the EU. On the one hand, this may suggest the larger role that VC markets play in the US vis-à-vis the EU: VC levels in the EU are considerably lower than in the US, with around 45% of start-ups in the EU without VC funding in the sample, compared to 30% in the US. Given the relative scarcity of VC funding in the EU, patents might serve as a stronger signalling mechanism for investors, helping them to obtain better investment opportunities. On the other hand, it might also reflect different financing needs or options across regions.

Panel B instead compares the premium of having a patent and raising USD one million in VC between low- and high-digital intensity sectors. As can be seen, having a patent yields a similar premium for acquisition probability in both macro-sectors, with the premium being slightly higher in low-digitally intensive sectors. Note, however, that these sectors are primarily manufacturing-based and traditionally associated with more patenting activity. By contrast, firms in highly digital-intensive sectors tend to raise significantly more VC funds. This suggests that VC plays a more prominent role in driving innovation in high-digital-intensity sectors, and the latter are more attractive for private investors.

Combining the two graphs allows for further insights. For example, the patterns observed in Panel B help explain the difference in VC funding between the EU and the US. VC funding in the EU is relatively more concentrated in medium- and low-digital-intensity sectors than in the US: in the EU, 70% of VC-funded start-ups are in low- or medium-digital-intensity sectors, whereas in the US, 80% of VC-funded start-ups are in high-digital-intensity sectors.

Heterogeneity across acquirors in ex-ante characteristics

Table A B.2. Heterogeneity across acquirors.

	Industries		Countries	
	Across	Within	Across	Within
	(1)	(2)	(3)	(4)
$\text{Has a patent}_{t-1}$	0.0103***	0.0055***	0.0050***	0.0107***
	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Industry-Country-Year FE	Yes	Yes	Yes	Yes
Observations	2 987 542	2 983 380	2 982 498	2 988 424
R-squared	0.038	0.046	0.048	0.040
Mean dep. variable	0.3	0.2	0.1	0.3
Premium	334.6	320.3	354.2	317.8

Note: The table shows the results of the linear probability model using cross-sectional variation for different specifications exploring heterogeneity across acquirors. The first and second columns only include acquisitions that happen across and within 3-digit NACE Rev. 2 industries, respectively. The third and fourth columns only include acquisitions that happen across or within countries, respectively. The average dependent variable reports the unconditional probability of being acquired in the relevant sample. The premium shows the coefficient of interest as a percentage of the mean dependent variable. *: p-value < 10%, **: p-value < 5%, *: p-value < 1%.
Source: OECD calculations based on OECD/STI Start-ups Database, Orbis M&A, and PATSTAT.

Estimating the effect of acquisitions on innovation using propensity score matching

In this section, an alternative to using not-yet-treated as a control group is presented. The methodology used in this section combines the de Chaisemartin and D'Haultfoeuille (2024[31]) estimation strategy with the traditional propensity score matching as in Guadalupe, Kuzmina, and Thomas (2012[71]). In particular, this methodology computes the propensity score to be treated of each firm by running a logit specification where the dependent variable is a dummy that takes the value 1 if an acquisition takes place and 0 otherwise. The independent variables are again the age of the start-up and its VC stock level. The results of the propensity score estimation and the balance check across acquired start-ups and start-ups in the control group are reported in Table A B.3.[64] As observed, the matching procedure produces comparable groups for the estimation with similar levels of patenting activity, age, and VC stocks. These propensities scores are used as weights in the de Chaisemartin and D'Haultfoeuille (2024[31]) estimation. Treated

companies are weighted according to *1/PS* and never-treated companies are weighted by *PS/(1-PS),* where *PS* is each firm's propensity score.

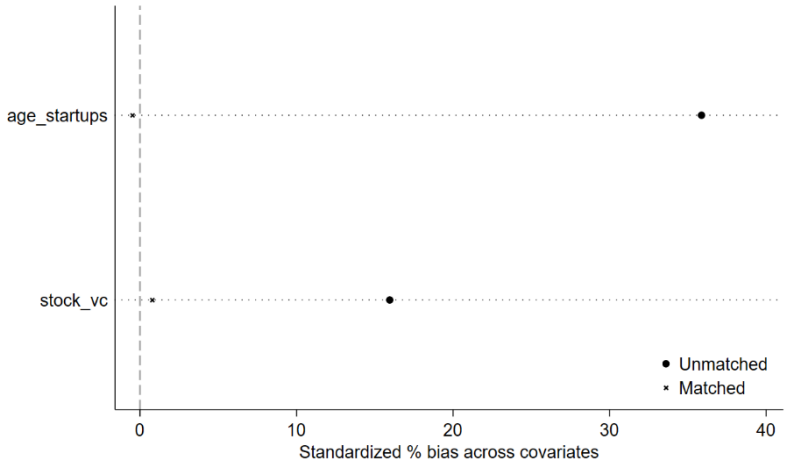
Table A B.3. Propensity score estimation and balance test

Panel A. Propensity score estimation		
Age	0.0266***	
	(0.0005)	
VC stock	0.0137***	
	(0.0005)	
Observations	954 023	
Pseudo R-squared	0.02	
Panel B. Balance test: Patent flows		
Treated	Control	Difference (t-statistic)
0.0004	0.0005	-0.0001 (-1.6)

Note: Panel A in this table shows the results of the logit estimation of the probability of acquisition on age and VC stock level. Panel B shows the average standardised patent flows across treated and untreated observations as well as their difference. t-statistic in parenthesis.
Source: OECD calculations based on OECD/Start-ups Database, Orbis M&A, and PATSTAT.

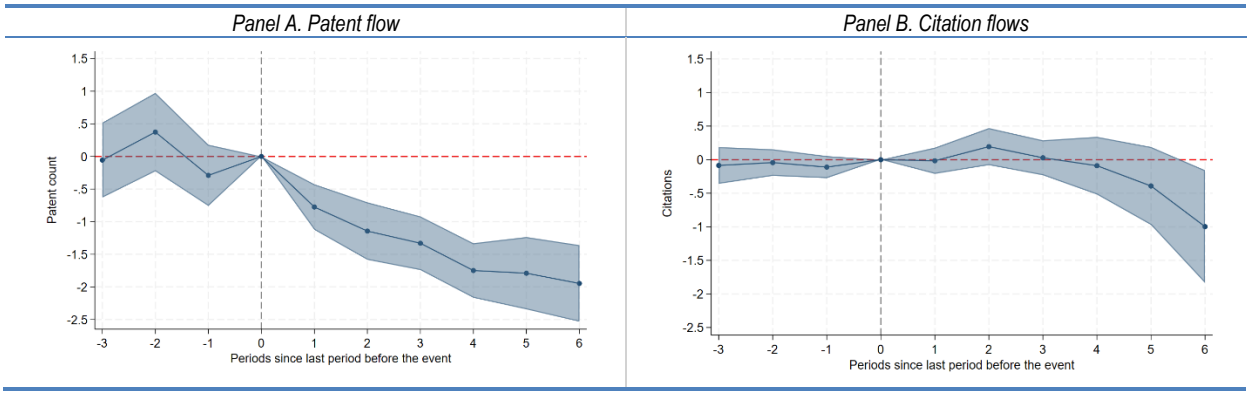
The results of DID estimation using the propensity score matching technique is shown in Figure A B.3. As can be observed, the results remain qualitatively similar when using this technique to analyse the post-acquisition performance of start-ups. While the patent flow decreases substantially after the acquisition, the citations remain constant until declining due to the absence of new patents and the obsolescence of old ones. The magnitude of the coefficient, nevertheless, increases substantially. While the DID in Figure A B.3 showed that the patent flow decreases by one time its average value before the acquisition, here the reduction is almost twice as large. As for citations, the results mimic those of the baseline specification in Section 5.

Figure A B.2. Bias reduction in observable characteristics across treatment and control start-ups



Note: This figure shows the reduction in the differences across the age of start-ups and their VC levels when weighting observations by their propensity scores. The round point indicates the difference in averages in percentages in the start-ups age and VC stock across treatment and control groups when firms are not weighted by their propensity scores. The crosses indicate the difference in averages in percentages in the start-ups age and VC stock across treatment and control groups when firms are weighted by their propensity scores.
Source: OECD calculations using data from the OECD/Start-ups Database, ORBIS M&A, and PATSTAT.

Figure A B.3. The effect of acquisitions on patenting activity using propensity score matching



Notes: Figure A B.3 shows the difference in the number of applied inventions in Panel A of acquired companies vis-à-vis not-yet-treated start-ups using the methodology proposed in de Chaisemartin and D'Haultfoeuille (2024[31]). All panels use announcement dates. The dependent variable is expressed as a percentage of its unconditional average. Coefficients are standardised in the year before the announcement of the acquisition. All specifications include 3-digit NACE Rev.2 industry-country-specific linear trends and firm fixed effects.
Source: OECD calculations based on data from PATSTAT, OECD/STI Start-ups Database, and Orbis M&A

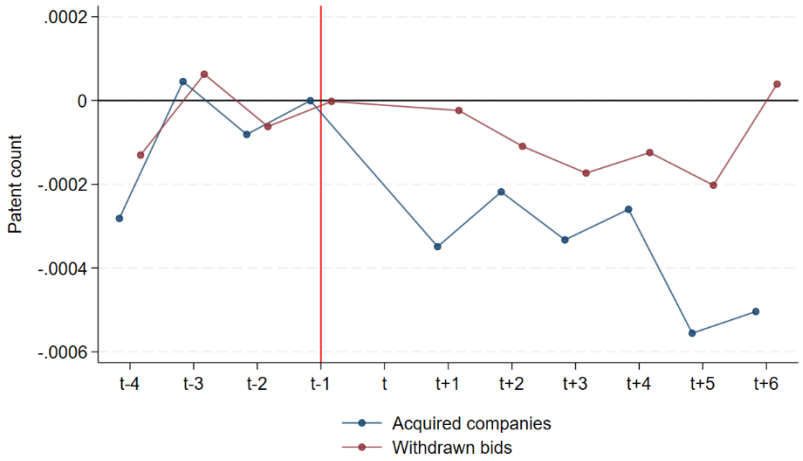
Estimating the effect of acquisitions on innovation using an exogenous shock

Table A B.4. Balance checks across exogenously withdrawn and successful bids

VARIABLES	(1)
log(1+Patent flow)	0.0126
	(0.1706)
log(1+Citations)	0.7737
	(9.5656)
Industry-Country-Year FE	Yes
Observations	7 016
R-squared	0.197

Note: The table shows the results of Equation 1 using cross-firm variation. The specification shows the effect of the patent flow and the patent citations on the probability of acquisition as in the ex-ante exercises. The treatment group is restricted only to the year of acquisition and the control group only to those start-ups that received exogenously withdrawn bids on the year of the withdrawal. All regressions control for the firm's age, VC stock levels, and industry-country-year fixed effects. *: p-value < 10%, **: p-value < 5%, *: p-value < 1%.
Source: OECD calculations based on data from PATSTAT, OECD/STI Start-ups Database, and Orbis M&A.

Figure A B.4. Event study of the patent flow across acquired start-ups and start-ups with exogenously withdrawn bids

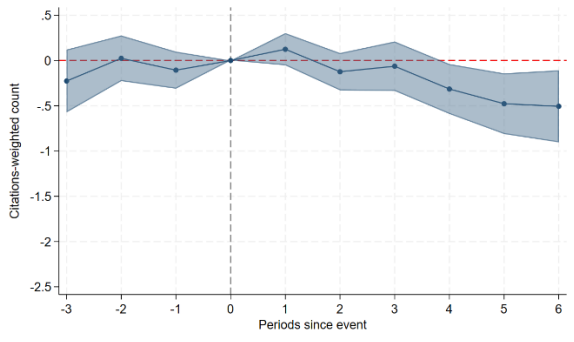


Note: This figure shows the average standardised patent flows across acquired start-ups and those start-ups with exogenously withdrawn bids after the acquisition event or the acquisition withdrawal.
Source: OECD calculations based on OECD/Start-ups Database, Orbis M&A, and PATSTAT.

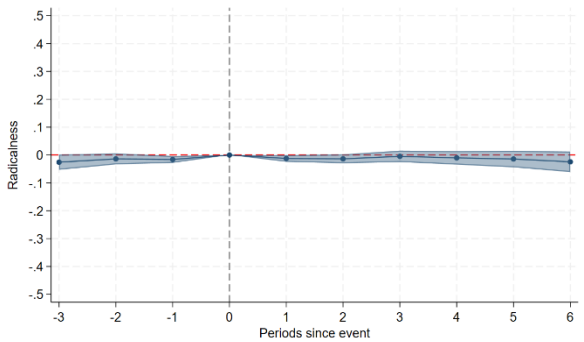
Causal analysis using withdrawn bids for acquirors

Figure A B.5. The effect of acquisitions on the patent quality of acquirors

Panel A. Citations-weighted patent counts



Panel B. Radicalness



Notes: The figure shows the difference in the number of applied inventions across single-time acquiring incumbents and never-acquiring incumbents in Panels A and and the difference between incumbents who withdrew a bid and never-acquiring incumbents in Panel B, using the methodology proposed in de Chaisemartin and D'Haultfoeuille (2024[31]). All panels use announcement dates. The dependent variable is expressed as a percentage of its unconditional average. Coefficients are standardised in the year before the announcement of the acquisition. All specifications include 3-digit NACE Rev.2 industry-country-specific linear trends and firm fixed effects.

Source: OECD calculations based on data from PATSTAT, Orbis M&A, and OECD/STI Start-ups Database.

Heterogeneous ex-post responses by technological proximity

This subsection performs a series of heterogeneity exercises across acquired start-ups, similar to the analysis reported in Table 5.2. The first panel (rows 1 and 2) in Table A B.5 shows the results including all the acquisitions in the sample, while the second and third panels (rows 3 and 4, and rows 5 and 6, respectively) restrict to acquisitions that happen either within the same industry and country or across different industries and countries

Table A B.5. Ex-post effects on the number of filed patents by start-up targets by technological proximity with the acquiror.

		Technological proximity (N = 3 584)	
		Low and Medium	High
All acquisitions	Average cumulative effect from t to t+6	-1.8899*** (0.4484)	-0.3367 (0.3167)
	Test joint nullity of the effects (p-value)	0.0012***	0.6399
	Test joint nullity of the pre-trends (p-value)	0.0010***	0.0040***
Within industries and countries	Average cumulative effect from t to t+6	-6.0340* (3.2828)	-0.6587 (0.4198)
	Test joint nullity of the effects (p-value)	0.0500**	0.0071***
	Test joint nullity of the pre-trends (p-value)	0.6035	0.0714*
Across industries and countries	Average cumulative effect from t to t+6	-1.1331*** (0.2563)	0.8730*** (0.1229)
	Test joint nullity of the effects (p-value)	0.0000***	0.0000***
	Test joint nullity of the pre-trends (p-value)	0.2521	0.0000***

Notes: The table shows the evolution of the standardised yearly patent count flow using the methodology proposed in de Chaisemartin and D'Haultfoeuille (2024[31]). The first two columns use the classification of industries in Abele et al. (2024[81]) to classify the start-ups' acquirors into operating in low or high competition levels. The next two columns show the results for start-ups distinguishing between those in the last three quartiles of the technological proximity distribution and those at the top. The first panel does not restrict analysed acquisitions. The next two restrict to those acquisitions that happen within industries and countries or across industries and countries, respectively. All columns use announcement dates. The dependent variable is expressed as a percentage of its unconditional average. Coefficients are standardised in the year before the announcement of the acquisition. All specifications include 3-digit NACE Rev.2 industry-country-specific linear trends and firm fixed effects. Standard errors in parentheses. ***: p-value < 1%, **: p-value <5%, *: p-value < 10%.
Source: OECD calculations based on data from PATSTAT, Orbis M&A, and OECD/STI Start-ups Database.

Columns 1 and 2 in Table A B.5 classify start-up targets according to their technological proximity with acquirors. This exercise is restricted to those acquisitions for which there is information on both the acquiror and target patenting. The start-ups in this subset are classified into quartiles according to their level of technological proximity with their acquirors. The first column restricts to start-ups in the lowest three quartiles of the technological proximity distribution, and the second column restricts to start-ups in the highest quartile. As can be seen, the negative impact on patenting activity is concentrated in those start-ups that are less similar to the acquiror. The magnitude of the effect is also particularly strong when acquisitions happen within the same market, since this column reports the highest coefficient across all heterogeneity exercises. This finding goes in line with the evidence presented in Bena and Li (2014[17]) but contrasts with that of Altomonte, El-Mallakh, and Sonno (2024[35]).

The evidence reported in Section 4 suggests that pairs are more likely to be formed within industries, but in these cases, the pairs are usually between less technologically similar firms than when formed across

industries. If the rationale behind this is that less technologically similar firms present some competitive edge over incumbents within their markets (for instance, a more differentiated product or a more efficient technology), it makes sense that acquirors suppress more actively the technology of these start-ups to maintain their status quo (Weiss, 2023[40]). Meanwhile, firms active in similar technologies but different markets might offer incumbents a complementary patent portfolio that can be somehow used and leveraged by the incumbent to improve its own technology.

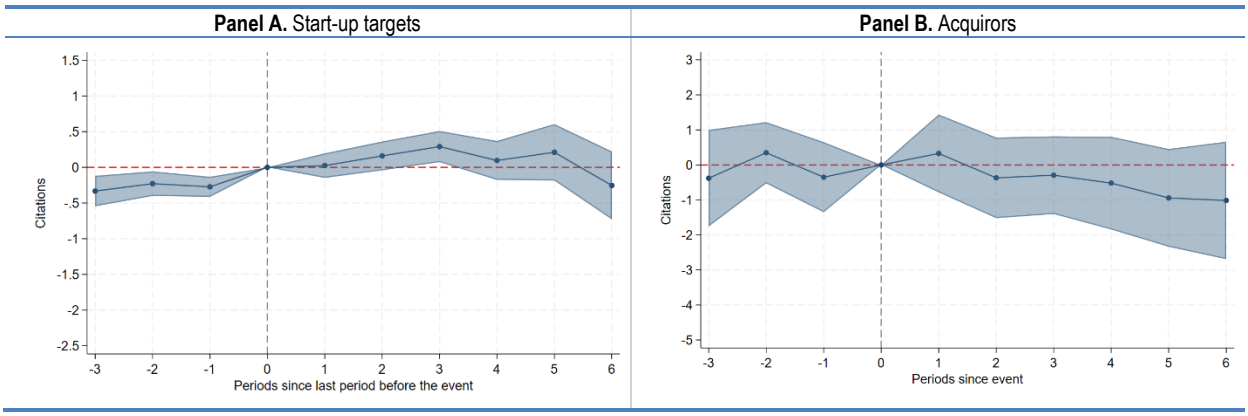
The impact on citation flows

This subsection analyses the evolution of citation flows, as commented in Section 5. While the citations-weighted and unweighted patent flows will only increase if the firm publishes a new patent, this measure also captures citations to older inventions. Therefore, this measure enables to distinguish between the rate at which firms create new ideas, reflected in the count measures, and the use of the new and old ideas of the firm, reflected in its citations.

The yearly number of citations to the documents published by each firm is computed. Similarly, they are standardised by all citations given to documents in a specific publication authority, WIPO technological class, and year. Similarly to citation-weighted patent counts, note that information on citations is only available for patents applied at the EPO or USPTO.

Figure A B.6 shows the evolution of the differences in citation flows between acquired and no-yet-acquired start-ups in Panel A and acquirors with different treatment intensities in Panel B. Panel A shows an overall positive impact on the target's citations albeit following an increasing pre-trend. Since most targets stop patenting, this maintenance of citation flows reflects a potential increase in the citations per patent to those patents filed before the acquisition. In other words, while citation flows before the acquisition reflect citations to old and contemporaneous inventions, those after the acquisition reflect mostly citations to old inventions. This might indicate that acquirors indeed take advantage of the inventions patented before the acquisition, as suggested in de Barsy and Gautier (2024[56]). Further research would be needed to understand the underlying patterns behind this increase in citations. Panel B, however, shows that patent citations to acquiror patents stay unaltered, albeit a decline is observed by the end of the period, likely reflecting the decline in the quality of filed patents shown in Figure A B.5.

Figure A B.6. The impact of acquisitions on target and acquiror citations



Notes: The figure shows the evolution of the difference in the citation flows between acquired and not-yet-acquired start-ups in Panel A and between acquirors with different treatment intensities in Panel B, using the methodology proposed in de Chaisemartin and D'Haultfoeuille (2024[31]). All panels use announcement dates. The dependent variable is expressed as a percentage of its unconditional average. Coefficients

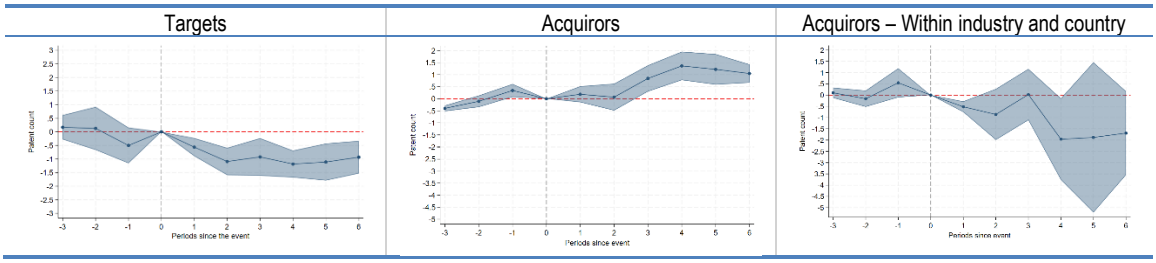
are standardised in the year before the announcement of the acquisition. All specifications include 3-digit NACE Rev.2 industry-country-specific linear trends and firm fixed effects.

Source: OECD calculations based on data from PATSTAT, Orbis M&A, and OECD/STI Start-ups Database.

Ex-post heterogeneity

This box analyses the evolution of patenting activity for EU start-ups and acquirors worldwide. The number of papers looking into acquisitions in the EU is scarce, and the overall results suggest that there is a negative effect on the target's patenting activity (Stiebale and Reize, 2011[27]; Stiebale, 2016[58]) and their TFP (Gregori, Martinez-Cirello and Nardo, 2023[82]). In the context of cross-border acquisitions, Stiebale (2016[58]) shows that the decline in the patenting activity of the target is more than compensated by an increase in the patenting activity of the acquiror, while the rest of the papers do not provide evidence on both sides of the transaction.

Figure A B.7. The effect of acquisitions on the patenting activity of targets and acquirors in the EU



Note: The figure shows the evolution of the standardised yearly patent count flow using the methodology proposed in de Chaisemartin and D'Haultfoeuille (2024[31]). The first panel shows the evolution of the differences between acquired and not-yet-acquired start-ups in the EU. The second panel shows the evolution of the differences between acquirors with different treatment intensities. The third panel restricts to the evolution of differences between acquirors that acquire within their industry and country with respect to acquirors with lower treatment intensities. All panels use the announcement date. The dependent variable is expressed as a percentage of its unconditional average. Coefficients are standardised in the year before the announcement of the acquisition. All specifications include 3-digit NACE Rev.2 industry-country-specific linear trends and firm fixed effects.
Source: OECD calculations based on PATSTAT, Orbis M&A, and OECD/STI Start-ups database.

Figure A B.7 shows the baseline specification but focusing on start-ups and acquirors in the EU in the first two panels (irrespectively of the origin of their acquirors and target start-up, respectively) and the evolution of the patenting activity of acquirors that engage in within-industry and within-country acquisitions in the last panel (so, by definition, transactions within EU countries). Along the lines of the papers mentioned above, this paper finds that in the EU there is a negative impact of acquisitions on the target's patenting performance (first panel). In particular, the difference between not-yet-acquired and acquired start-ups increases by one time the average flow of patents in the sample. This finding is consistent and similar in magnitude when restricting the sample of acquired start-ups to those happening across and within industries and countries. However, acquirors observe an increase in their patenting activity, also equivalent to one time the average patent flow of acquirors in the sample. Comparing the magnitudes of the effects on start-ups and acquirors, the increase in patenting performance of acquirors more than compensates for the reduction experienced by start-ups (as incumbents patent more on average as shown in Table 3.3).

The increase in patenting of acquirors reported in the second panel hides strong and important heterogeneities. Consistent with Stiebale (2016[58]), the effect on the acquiror side is mainly driven by acquisitions that happen across industries and countries, that is, when firms are less likely to share a market. In fact, when restricting to acquisitions within industries and countries, there is a decrease in patenting activity on the side of the acquiror as well, as shown in the last panel. Further research would be

needed to investigate additional heterogeneities in the aggregate patterns and to understand better the drivers of the observed different results.

Endnotes

[64] The command **psmatch2** in STATA is implemented to compute the propensity score matching.