Digital platform mergers and innovation: Evidence from the cloud computing market

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Abstract: This paper empirically analyses mergers and innovation in the cloud computing market, one of the fastest-growing digital markets. We first examine mergers by big tech firms and venture capital funding for young start-ups in this market. We find that leading firms in the market tend to acquire young startups, whereas non-leading firms tend to purchase more established firms to gain market share. We then conduct an ex-post evaluation of how mergers in this market affect the innovation output – measured by patents. The results show a positive impact of mergers on innovation. In this market, and our measure of innovation, acquisitions do not necessarily harm innovation. The breakdown of this empirical analysis reveals stronger positive effects when the firm holds a leadership position in the market, operates as a multisided platform, or when the target is a publicly traded company. The value of the acquisition does not exert any additional impact.

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Abstract

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Keywords: cloud computing, innovation, mergers, patents.
JEL classifiers: L11, L41, L63.

1 Introduction

The recent wave of mergers and acquisitions by big tech firms has rung the bell for competition authorities about the potential harm to competition and innovation in digital platform markets—the cloud computing market being one of them. The debate has attracted a recent stream of literature on big tech platform mergers and acquisitions. Three influential reports by Crémer et al. (2019), Furman et al. (2019), and Scott-Morton et al. (2019) have argued that one of the shortcomings of current merger control is the difficulty in predicting the effect of the mergers on both competition and future innovation. This difficulty comes from the highly innovative and fast-changing nature of digital platform markets, which challenges the evaluation of future effects. Therefore, more ex-post analysis about the impacts of mergers and acquisitions on competition and innovation in digital platform markets is necessary and will form a good reference for competition authorities in future cases. This research aims to contribute to this gap in the literature. This paper investigates the merger and acquisition (M&A) activities in the cloud computing market and their impacts on innovation. This is a market that, at the time of this writing, has garnered significant attention from regulatory and competition agencies, as evidenced by two market studies conducted by the UK's Communications Regulator and the French Competition Authority .[1]

[1] Refer to `https://tinyurl.com/ym5w3276` (accessed on 15 August 2023) for insights from the French Competition Authority's market study, and to The Office of Communications (2023) for Ofcom's comprehensive market study (referred to the UK Competition and Markets Authority for further examination).

Our empirical analysis relies on US data on the cloud computing market, a highly innovative digital market that has grown exponentially in the last decade. For several reasons, this market is an interesting case to study the relationship between mergers and innovation. Firstly, this is a peculiar market with three out of the five biggest competing tech firms:[2] Amazon, Microsoft, and Google. These firms have direct and indirect spending on research and development (R&D) and are active in mergers and acquisitions to gain market shares and power. In addition to these firms, other players in the market performed acquisition activities, for a total of 430 mergers and acquisitions of US companies during the last decade (source: Crunchbase data). Second, the market has a high concentration, with the leading firms having more than 50% shares.[3] Scott-Morton et al. (2019) argues that the presence of big digital firms in the cloud computing market makes innovation likely to be concentrated, as other firms in the market may not be willing to invest in related innovation since they cannot compete against these giants. Third, cloud computing companies have diverse business models, as they can operate in a vertically integrated or multi-sided platform (MSP) structure. Vertically integrated cloud firms manage the cloud platform in a way that it provides their in-house cloud computing solutions, for example, the SAP cloud platform. By contrast, the firms that operate as MSPs manage the cloud platform to somehow provide both their own and third-party cloud solutions, e.g. Microsoft Azure cloud platform. Therefore, it would be interesting to examine whether mergers and acquisitions impact the innovation outcome of the market and how these impacts differ between leading firms vs. non-leading firms and MSP vs. non-MSP firms. To the best of our knowledge, there has not been any study addressing these issues. In this research, our target is to analyse the impacts of mergers and acquisitions on innovation in the US cloud computing market and provide some insight for competition authorities.

For our empirical analysis, we construct our unique dataset from several sources. We use the merger data from Crunchbase, the company financial data from the Thomson Reuters Worldscope database, and the patent data from the US Patent and Trademark Office website.

While there is a growing branch of research on mergers in digital markets, acquisition strategies of tech firms have not drawn much attention from researchers, except Gautier and Lamesch (2021). This work aims to fill this gap by investigating the merger strategies of firms in the cloud computing market. By studying the data on merging activities, we provide descriptive evidence that shows two different acquisition strategies by two groups of firms in the market. The leading firms in the market like Amazon, Microsoft, and Google follow the strategy of acquiring young start-up firms. This effect is probably due to two reasons. First, these firms already have leading technologies and a large customer base. Thus, they prefer acquiring young firms with innovative ideas or complementary technologies, which can further entrench their market position. Second, this type of acquisition enables these firms to escape the scrutiny of the competition authority. By contrast, non-leading firms in the market like Cisco, Rackspace, or Dell tend to acquire established firms to catch up with the leaders. The purpose of these acquisitions is not only technologies, R&D, or innovation assets but also the large customer base and data. This conclusion would enhance the chance of non-leading firms to gain more market share and profits, narrowing the gap with leading firms. The emphasis on contrasting acquisitions between leading and non-leading firms warrants closer examination. As a result, we also delve into the influence on innovation concerning public target companies and variations in the scale of the acquisition value.

Previous literature has provided empirical evidence of the impacts of mergers on innovation in different markets like pharmaceuticals (Danzon et al. 2007, Ornaghi 2009, Haucap et al. 2019) or hardware (Kapoor

[2]Five largest tech companies in the US are: Google, Amazon, Meta (Facebook), Apple, and Microsoft, which are known as GAMAM (or GAFAM before Facebook re-branded its name to Meta in 2021).

[3]Synergies Research Group https://tinyurl.com/48cwv7vh (accessed on 1 August 2023).

and Lim 2007, Bennato et al. 2021). Nevertheless, there is a lack of studies examining this issue in digital platform markets. This work aims to contribute to this aspect by analysing the effects of mergers in the cloud computing market on the innovation outcome of merged entities. Following such literature, we employ the patent counts as the measurement for innovation outcome and estimate the effect of merger events on the changes in the patenting activity of merging entities before and after mergers. We construct our control group using propensity score matching and then combine this with the DiD estimator. Unlike previous studies from pharmaceutical and hardware markets, our empirical results do not find that mergers harm the patent output in the cloud computing market. On the contrary, our results suggest a rise in the innovation. The dissection of this empirical analysis uncovers significantly heightened positive effects in cases where the firm assumes a market leadership role, functions as a multisided platform, or when the target is publicly traded. The value of the acquisition does not introduce any supplementary impact.

We strengthen the robustness of our analysis through a series of validation measures: by limiting patents to the most widely utilised cooperative patent classification, examining the influence of winsorising extremely skewed covariates, and subsequently utilising citation-weighted patents as the outcome variable.

The rest of the paper is organised as follows. The next section will discuss the related literature. Section 3 provides an overview of the cloud computing industry. Then the data and descriptive evidence are described in Section 4. Section 5 talks about the empirical strategy. Section 6 presents the results and provides robustness checks. Discussions with conclusions are included in Section 7.

2 Literature review

This work is related to the long-standing literature on the relationship between competition and innovation. The earliest discussion on this relationship dates back to the debate between the Schumpeterian perspective that concentrated market structures, such as monopolies, favour innovation, and the opposite view that competition facilitates innovation (Schumpeter 1942, Arrow 1962). This controversy led to the development of extensive literature, which tries to answer the big question of whether competition is good or bad for innovation.

Gilbert and Newbery (1982) relaxes Arrow (1962)'s assumption about the non-competitive threat to the incumbent, and shows that a dominant incumbent may have more incentive to innovate under competitive threat from potential entrants. Whereas, others have shown that this relationship has not always been true and depends on the technology levels of the incumbent and entrants (Vickers 1985, Boone 2001). Aghion et al. (2005) and Aghion et al. (2009) suggest that it is not necessarily the case that either Schumpeter's or Arrow's view is wrong as the relationship is not strictly positive or negative, instead it exhibits an inverted U-shape relationship. They proposed a growth model where the industry can be either neck-to-neck firms or one leader-one laggard firm. When competition is soft, there is a larger fraction of the neck-to-neck industry, in which the innovation incentive is increasing in the degree of competition, as competition would decrease pre-innovation rents relative to post-innovation rents. On the other hand, when the competition is fierce, there is a larger fraction of the laggard industry, in which competition would dampen innovation as it increases pre-innovation rents and reduces post-innovation profits. Shapiro (2012) shares a similar view and argues that there is no essential contradiction between Schumpeter (1942) and Arrow (1962). He claims that intense competition post-innovation discourages firms' innovation, whereas severe competition pre-innovation boosts a firm's incentive to innovate.[4]

[4]For more details this literature, see the comprehensive survey by Jullien and Lefouili (2018).

While there has been extensive literature on the impacts of competition on innovation, the literature answering the question of how mergers affect innovation by firms is relatively small and new. Several papers (Federico et al. 2017, 2018, Motta and Tarantino 2021) have pointed out that the arguments by Schumpeter and Arrow cannot be always applied directly to the analysis of the impacts of mergers on innovation. This is because on the one hand mergers soften competition as the number of firms is reduced. On the other hand, mergers enable the two merging firms to coordinate innovation decisions after the merger and internalise the externalities they exert on each other's demand, which is the so-called *innovation diversion effect*. The coordination effect of mergers on innovation has been discussed thoroughly by Federico et al. (2017), Federico et al. (2018), Denicolò and Polo (2018), and Bourreau et al. (n.d.). Federico et al. (2017) proposes a stylised model of multiple research labs investing in innovation to invent a new product. They show that after a merger between two labs, the merging entity has the incentive to reduce R&D investment. The intuition here is that this decision would enable merging firms to avoid cannibalisation effects on sales when both labs are successful with the R&D investment. However, their results are based on the key assumption that after the merger, the entity would maintain both labs as active, which is criticised by Denicolò and Polo (2018) who claim that this assumption does not always hold. Denicolò and Polo (2018) show that the merging entity's optimal strategy might be to shut one research unit and spend more investment on the other one. This is because closing down one lab would reduce the competition and the innovation diversion effect, which induces a higher incentive to invest more in the remaining one. When this is the case, the merger eventually results in higher total R&D investment and consumer welfare. Federico et al. (2018) extends the Federico et al. (2017) model by studying the interaction between the price coordination effect and the innovation diversion effect after the merger. They find that while the former effect tends to boost the incentive to innovate, the latter effect would discourage the firm's innovation incentive. Bourreau et al. (n.d.) contribute to the literature by decomposing the impacts of mergers on innovation into four different effects: the innovation diversion effect, the margin expansion effect, the demand expansion effect, and the per-unit return to innovation effect. They show that while the first two effects are negative, the third one is positive and the sign of the last effect can be either negative or positive.

Although these above theoretical works analyse different aspects of the merger effect on innovation, they share a similar consensus that the effect can be negative or positive, depending on the industry setting. However, on the empirical side, most works using firm-level data to evaluate the impacts of mergers on innovation, share the common finding that mergers have negative impacts on innovation in general. Our work contributes directly to this branch of literature by examining a novel industry: cloud computing platform, which has not yet been studied in previous literature on mergers and innovation. The main issue in the literature when empirically analysing the effects of mergers on innovation is how to measure innovation. The previous literature suggests two common proxies for measuring innovation: R&D investment and patents. However, both measurements have their own pros and cons and need to be considered carefully when turning to the interpretation of the results. While R&D is a good indicator of the firm's incentive to invest in innovation, it should be considered as innovation input instead of output. Large amounts of R&D investment do not necessarily turn to good innovation outcomes. Moreover, now we see more conglomerate firms operating in many different industries, which means the firm-level data of R&D investment is not always available in some industries as the firm's financial statements only show the total R&D amount. The issue with patents as a proxy for innovation is more trivial as patents can account for both innovation input and output. Nevertheless, not all patents have important impacts and may not lead to commercial value. Constructing a citation-weighted patent instead of a simple patent count can capture the quality of patent activities (Hall et al. 2005b), but it still cannot reflect truly the monetary value of innovation.

One of the very few works that show some evidence of the positive impacts of mergers on innovation is Valentini (2012). Using data on mergers occurring in the US medical devices and photographic equipment industry, he estimates the effects they have on patents measured as patent output, impact, generality, and originality. His results suggest that mergers impact patent output positively but harm the other three measures. Conversely, Kapoor and Lim's (2007) exploration of the US semiconductor industry reveals a diminishing trend in innovation productivity, gauged through annual patent counts, after an acquisition. Other works studying the pharmaceutical industry like Danzon et al. (2007), Ornaghi (2009), or Haucap et al. (2019) also show evidence of negative impacts of mergers on innovation measured by either R&D investment or patent count at the aggregated industry level.

Similar to these works, we also aim to examine the effect at the industry level of mergers in the cloud computing market on innovation measured by patent output. Instead of focusing on a specific industry or geographical limit, Szücs (2014) collects a dataset consisting of 133 mergers by companies located in 25 countries and belonging to various industries to test whether mergers lead to lower R&D investment of acquirer and target firms. The results suggest that mergers impact both R&D investment and the R&D intensity of the target firms negatively. Unlike the above works, Bennato et al. (2021) focuses on the impacts of mergers on innovation at the firm level instead of the aggregated industry level. They analyse three merger cases in the HDD market in 2011/2012: Seagate/Samsung, Western Digital/Toshiba, and Toshiba/Hitachi's 3.5-inch production, which contributes to the literature by employing a more comprehensive set of measurements of innovation: R&D investment and patents as innovation input, number of new models and unit prices as innovation output. They find the mixed effects of mergers on different measurements of innovation. While the mergers significantly increase R&D investments in all cases and the number of new models in two cases, they decrease the patent outputs in all cases and unit prices in two cases.

Equally important, this work contributes to the recent hot debate in the literature about the potential impacts of big tech mergers on competition in digital platform markets. The reason for this debate is a growing number of acquisitions by a dominant digital platform without any scrutiny from competition authorities. This raises the question of how these big tech mergers impact competition and innovation in the platform market. Firstly, there is quite a broad consensus among researchers about the positive impacts of big tech acquisitions on entry and innovation. Bryan and Hovenkamp (2020) and Bourreau and de Streel (2020) both suggest that big tech mergers give young firms and start-ups more incentive to innovate and enter the market, in order to be bought at a high price by the dominant firms. Motta and Peitz (2020) also show that in the case when the innovative start-up is financially constrained, the acquisition can help to improve the innovation level in the market. This view is shared by Crémer et al. (2019) and Scott-Morton et al. (2019), which point out that big tech firms can provide acquired start-ups with financial strength and management experience and this facilitates innovation. Therefore, it would be interesting and crucial to test empirically whether mergers and acquisitions facilitate or reduce innovation, here however, there is still a lack of studies addressing this question. This research aims to tackle this gap by evaluating the impacts of mergers on innovation in the cloud computing platform market.

In contrast with the first school of thought, Kamepalli et al. (2020) proposed a model to examine whether big tech mergers can create a "kill zone", where venture capitalists had little incentive to fund young start-ups. They then employed the Pitchbook data and found empirical evidence that Google and Facebook mergers had decreased both the number and amount of venture capital funding for young start-ups in the same sector as the acquired companies. Whereas, Scott-Morton et al. (2019) suggested that venture capital funding could be a measure of innovation since more funding would encourage young firms to innovate more. They pointed out that in the market where dominant firms kept acquiring to entrench their market-leading positions, venture capitalists might find it not worth funding start-ups that develop new technologies to compete head to head with the giant firm, as the chance of successful entry is very small. This results in a lower level of venture capital investment, which further reduces entry and innovation. Additionally, since the chance of challenging the big tech incumbent is almost zero, innovative entrance may avoid developing new technology to substitute the dominant technology and focus on the innovation that can be complementary to the incumbent products and services. This view is shared by Katz (2020), as he argues that a permissive merger policy would discourage the innovation incentive of the new entrant, whose purpose is so-called *entry for buyout*. The intuition behind this is it may be not profitable to invest more in marginal product improvements when the marginal benefits from a buyout deal do not sufficiently cover the investment cost. In the same vein, Letina et al. (n.d.) studied the effect of the merger policy prohibiting killer acquisitions on the innovation outcome. They developed a four-stage game, in which under two policy regimes of prohibiting or permitting acquisitions, firms decided subsequently whether to invest in a research project, make an acquisition, commercialise the project or compete in the market. They found that prohibiting killer acquisitions would negatively impact the variety of research projects, as that may encourage the incumbent firm to duplicate the entrant innovation to avoid competition, instead of developing other projects. Whereas, the negative impacts of prohibiting mergers would be negligible if firms have sufficient capability to commercialise the research project.

Although there is a significant number of theoretical works on mergers and acquisitions by big tech firms, there are only two papers that have empirically investigated their merger activities: Argentesi et al. (2021) (Google, Amazon, and Facebook) and Gautier and Lamesch (2021) (Google, Amazon, Facebook, Apple, and Microsoft —GAFAM). Both papers employ Crunchbase datasets like us, and they share a similar view that big platforms are more likely to acquire young start-ups in the segment/business that they are already active in rather than in the new market, and these companies usually have complementary products/services/technologies with the acquirer. To the best of our knowledge, Gautier and Lamesch (2021) is the only paper so far explicitly studying the merger strategies by big tech firms. Their main contribution is a novel approach to define market segments based on targeted users instead of products or services. According to their classification, big tech firms are active in six segments: Advertisers, Businesses, Consumers, Content Editors, Merchants, and Platforms. This classification enables the authors to identify the M&A strategies of GAFAM. They conclude that the main motivation of GAFAM acquisitions is to acquire innovative assets, R&D inputs, or talented employees in order to strengthen their market positions in core businesses/segments. They further analyse whether there has been any "killer acquisition" by GAFAM but found no clear evidence. In this paper, we complement the above two works by examining the merging activities and strategies by firms in the cloud computing market.

3 The cloud computing market

Cloud computing is one of the fastest-growing and highly innovative markets, as it is becoming more and more an essential service for business practices around the world, with total spending in 2019 of $96B.[5] This flourishing industry has attracted the participation of three giant GAFAM firms: Amazon, Microsoft, and Google. Amazon had a head start, followed by Microsoft. Of these three, Google is the latecomer but is trying to gain market share.

[5] `https://tinyurl.com/3khn6b2u` (Accessed on 16 May 2022.)

What is cloud computing, and why do we observe more and more businesses and households wanting to use this type of service? According to Amazon,[6] "Cloud computing is the on-demand delivery of IT resources over the Internet with pay-as-you-go pricing. Instead of buying, owning, and maintaining physical data centres and servers, you can access technology services, such as computing power, storage, and databases, on an as-needed basis from a cloud provider". Therefore, we can understand cloud computing as outsourcing services over the Internet, enabling firms to access various technology inputs without directly having to manage them. Cloud computing builds on achieving economies of scale via sharing resources. For instance, a cloud provider can serve 100 or more companies with a cost similar to ten companies. This means a much lower cost for firms to access IT resources via cloud providers relative to building these resources themselves. Firms can avoid upfront IT costs for operating parts of their business, like data storage, customer management systems, etc. In addition, they can run their software/applications on the cloud server with much faster speed and higher computing power, which improves efficiency significantly. The huge advantage of using cloud computing services has led to its widespread adoption and rapid expansion worldwide. In 2019, the total spending worldwide for cloud services increased by 37% compared to the previous year, according to Synergies Research Group (see web link in footnote (5)). This growth, while noteworthy, marked a decrease from the rates observed in preceding years.

The cloud computing market is characterised by three main types of computing services (segments): Infrastructure as a Service (IaaS), Platform as a Service (PaaS), and Software as a Service (SaaS).

1. IaaS is the service that gives businesses access to computing infrastructures on demand, on a pay-as-you-go basis. It provides access to networking, data centres, servers, etc. The service is limited to running applications and software within the cloud providers' infrastructure. Examples are DigitalOcean, Linode, Rackspace, Amazon Web Services (AWS), Cisco Metapod, Microsoft Azure, Google Compute Engine (GCE), etc.

2. PaaS is a service where the platform delivers hardware and software tools needed for application and software development by users. Typically, the platform gives access to an operating system, programming language execution environment, database, web server, etc. It hosts the hardware and software on its infrastructure. Examples are AWS Elastic Beanstalk, Windows Azure, Heroku, Force.com, Google App Engine, and Apache Stratos.

3. Finally, SaaS gives access to cloud-based software. Instead of buying a license and installing software, firms can access the providers' applications via a website or an application programming interface (API). For a user, this had the benefit of not having to install and maintain software, avoiding, in a way, software and hardware management. Examples are BigCommerce, Google Apps, Salesforce, Dropbox, MailChimp, ZenDesk, DocuSign, Slack, and Hubspot.

There are also four cloud computing environment types: private clouds, public clouds, hybrid clouds, and multiclouds.

1. Public cloud is the environment where the provider is responsible for the management, maintenance, security, and upgrades of the software. Clouds are considered public when the environments are partitioned and allocated to multiple renters. The bare-metal IT infrastructure used by public cloud providers can also be abstracted and sold as IaaS, or it can be developed into a cloud platform sold as PaaS. Some of the largest public cloud providers include Alibaba Cloud, Amazon Web Services (AWS),

[6] `https://tinyurl.com/3hf3vy6w` (Accessed on 16 May 2022.)

Google Cloud, IBM Cloud, and Microsoft Azure. Table 1 documents the global and US revenues of the public cloud in the main service segments. As can be seen in the table, the revenues of the IaaS and PaaS segments are close to one another, even more so for the US. SaaS is the largest segment, with revenues exceeding the other two segments. This gap is not surprising. Due to its easiness to use without managing any platform or infrastructure, SaaS is the most popular category of cloud computing service used by enterprises and individuals.

Table 1: Worldwide public cloud services revenue (billions of US dollars)

segment	2018	2019	2020	2021
		worldwide†		
IaaS	35.4	49.0	67.2	91.3
PaaS	25.8	35.9	47.6	68.2
SaaS	123.9	148.5	197.6	249.0
		US‡		
IaaS	14.1	19.5	26.8	36.4
PaaS	14.2	18.8	24.8	33.8
SaaS	66.8	78.3	90.5	104.8

Notes: †See p.9, Statista, Digital & Trends Cloud Computing (`https://tinyurl.com/4vacazd6` accessed on 11 July 2023). ‡See p.5 , Statista, Digital & Trends Industry Cloud in the Uniteed States (`https://tinyurl.com/2bjv36sr` accessed on 11 July 2023).

2. Private cloud allows firms to host their data centre, in which they have exclusive rights to manage, maintain, and upgrade the software. Thus, private clouds are typically environments allocated to single users with solo access.

3. The hybrid cloud is a mix between public cloud and private cloud, in which firms can flexibly choose to use a partly public and partly private cloud.

4. Multiclouds are environments made up of more than one cloud service, offered by more than one cloud vendor (public or private). All hybrid clouds are multiclouds, but not all multiclouds are hybrid clouds. Multiclouds are hybrid when the clouds are connected by some form of integration. Having multiple clouds is becoming more common across businesses that want to enhance their security and performance in various environments.

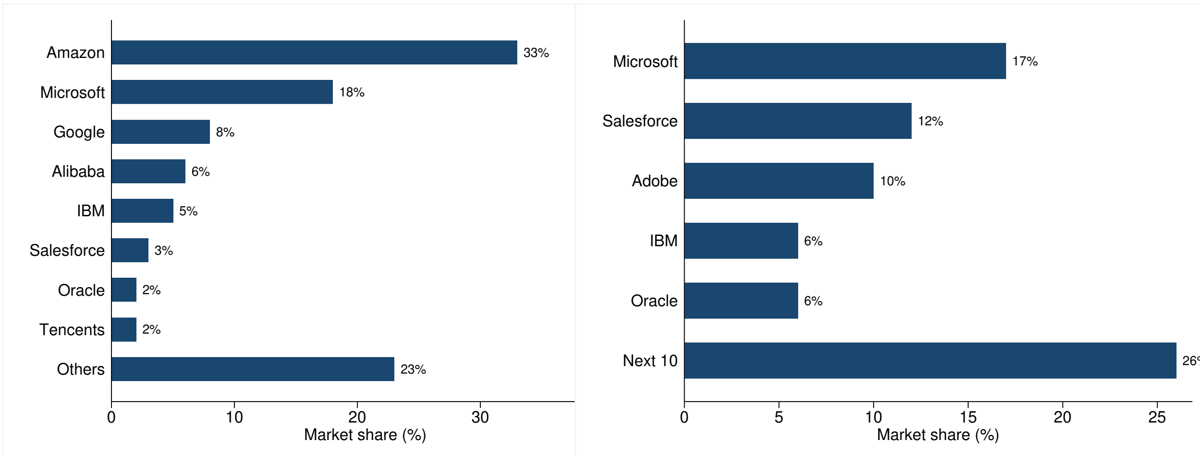
In terms of business models, cloud computing platforms are not a typical multisided market, as firms can also operate in a vertically integrated structure.[7] When they are vertically integrated, they provide both operating systems and their in-house cloud-based applications running on the operating systems, for example, the SAP cloud platform. When they are multisided markets, firms provide a marketplace to connect third-party cloud-based software developers and users, as is the case for the Amazon Web Service marketplace. All leading firms like Amazon, Microsoft, and Google combine both business models, in which they supply operating systems and in-house applications in the cloud marketplace. This position enables these firms to

[7]See Karunakaran (2016) for a discussion of segmentation and business models in the cloud computing market.

enjoy benefits from indirect network effects generated by developers to users and vice versa, which would drive more application variety, besides a more sizeable consumer base for these firms. This strategy entrenches its market dominance and strengthens its leading position.

Figure 1: Global market shares by vendors in cloud computing market in 2019

(a) IaaS and PaaS segments (b) SaaS segments



Source: Synergy Research Group.

As observed by Crémer et al. (2019) and shown in Figure 1, the cloud computing market centralises around several core players, leaving a niche for many fringe (non-leading) firms. Amazon's early entry in the IaaS and PaaS segments has secured about a third of the market shares, but is more recently facing growing competition from Microsoft and Google. Instead, Microsoft is the leading player in the SaaS segment with 17% of the market shares due to its comparative advantage from its long history of developing software for PC operating systems. Microsoft's top position is followed closely by Salesforce and Adobe. Hence, the cloud computing market is controlled by a few big tech firms like Amazon, Microsoft, and Google. These three leading firms count for 59% of the market shares in the IaaS and the PaaS segments, whereas the top five firms have 51% market shares in the SaaS segment. As can be seen from the figure, although the market is concentrated, no firm dominates all the segments, and only a few firms operate in all segments. Amazon, a leading firm in the IaaS and PaaS segments, does not participate in the SaaS segment. This limited coverage is because the cloud computing industry has capacity constraints for the firm. As firms offer more cloud services, fixed and infrastructure costs grow large and exceed the firm's capacity. For example, according to Gartner (2019), there is no single firm offering all 21 categories of services in the PaaS segment, and only 10 out of 360 PaaS vendors cover more than ten service categories. Besides, the SaaS segment is more competitive than the other two segments, with more players obtaining similar shares and the leader acquiring only 17% of the market share. The reason is that SaaS is a much bigger segment than the others and has many service categories to be offered. This advantageous position gives ground to many firms competing in this segment, yielding high profits.

We define two groups of firms based on the global market shares and label those as *leading* firms and *non-leading* firms. A firm is a leader in the market if it is top five in at least one of the segments. The leading firms' group includes Amazon, Microsoft, Google, Salesforce, Adobe, IBM, and Oracle. The non-leading firms are the other firms in the market, such as Rackspace, Cisco, Dell, etc.

4 Data

4.1 Merger data and merger strategies

We collated a dataset on US-based cloud computing companies to investigate the merger strategies (the decisions to merge) of cloud computing firms and how mergers affect innovation in the US cloud computing market. The dataset is cross-sectional and retrieved from the Crunchbase website,[8] covering 2010-2019. It contains information on US cloud computing company characteristics, which include: company name, headquarters location, industry, operating status (whether the company is active or not), founding date, number of employees, funding activities, initial public offering (IPO) activities, number of products alive, number of investors, and importantly for our work, the information on acquisition status (whether the company is acquired or not).

The US cloud computing firms are active in M&A, totalling 430 acquisitions during the ten years of our sample. Cisco and VMware had the most, with nine deals each. Table 2 lists the number of mergers by leading and non-leading firms. Amazon, the leading firm in the market, is not as active as the other firms in acquiring US cloud computing firms. It counts only four acquisitions. The reason is that Amazon enjoyed a first-mover advantage and has developed advanced technologies and infrastructures. To compete with Amazon, the competitors have a higher incentive to buy from other firms, either for their technologies or innovative inventions. Microsoft, Google, and Salesforce acquired six new firms, yet fewer than Cisco, VMware, or Rackspace. IBM acquired eight firms, the highest number among the leading group.

The market leaders own advanced technologies, a great variety of services, and a large customer base. Hence, to strengthen their market position, their strategy is to acquire companies that offer different products or have complementary innovation projects rather than direct cloud computing competitors offering similar services. As a result, these leading companies would acquire more firms in adjacent markets such as AI or big data to empower their cloud computing services. Meanwhile, to catch up with the lead firms in terms of technology, range of products and services, and customer base, the non-leading firms would prefer to acquire proper cloud computing companies.

Table 2: Number of acquisitions by leading vs. non-leading firms 2010-2019

leading firm		non-leading firm	
IBM	8	Cisco	9
Google	6	VMware	9
Microsoft	6	Rackspace	7
Oracle	6	Hewlett Packard	6
Salesforce	5	SAP	6
Amazon	4	Dell	5
Adobe Systems	2	EMC	5

In terms of deal value, the biggest deal is the acquisition of Red Hat by IBM at the price of $34B in 2018 (see Table 3). The same table suggests that of the seven (leading) companies with the highest market shares in the segments (Amazon, Microsoft, Google, Salesforce, IBM, Adobe, and Oracle), only IBM, Microsoft, Oracle, and Salesforce have deals in the top ten most valued acquisitions. This fact suggests that other

[8]Crunchbase is a platform that provides information about startups, companies, investors, and other related entities in the business world. It offers a dataset that contains information such as company profiles, funding details (including funding rounds, investors, and amounts raised), acquisitions and mergers, key personnel (founders, executives, and board members), news articles, and more. It covers a wide range of industries and geographies. It allows users to explore the dynamics of the startup and venture capital landscape.

leading firms like Amazon or Google are more interested in buying small firms and young start-ups. Equally important, none of the non-leading firms has a deal in these top highest-valued acquisitions, which implies that non-leading firms do not have a sufficiently strong financial position to complete such high-value deals. In this case, the alternative option is to acquire more firms. For example, Cisco and Rackspace have the most acquisitions, but none of their deals belong to the top ten highest valued. As a matter of interest, six of the top ten deals belong to firms not competing in the cloud computing market. Two of these (Broadcom Limited and Nvidia) are firms primarily operating in the semiconductor/chip industry that provide data storage hardware for cloud data centres (upstream market). The rest belong to private equity and investment firms, which shows that investors highly value the growth potential of the cloud computing industry.

Table 3: Top (by value) acquisitions in the US cloud computing market

	target company	acquired by	announced date	price
1	Red Hat	IBM	Oct 28, 2018	\$34.0B
2	CA Technologies	Broadcom Limited	Jul 11, 2018	\$18.9B
3	NetSuite	Oracle	Jul 28, 2016	\$9.3B
4	GitHub	Microsoft	Jun 3, 2018	\$7.5B
5	Mellanox Technologies	NVIDIA	Mar 12, 2019	\$6.9B
6	Mulesoft	Salesforce	Mar 20, 2018	\$6.5B
7	Informatica	Permira	Aug 7, 2015	\$5.3B
8	Rackspace	Apollo	Aug 26, 2016	\$4.3B
9	Publicis Sapient	Publicis Groupe	Nov 3, 2014	\$3.7B
10	Riverbed Technology	Thoma Bravo	Dec 15, 2014	\$3.5B

Remark 1: *Non-leading firms are more active in acquiring US cloud computing companies than the leading firms but do not complete such high-value deals as the leaders.*

Table 4 compares the characteristics of targets bought by leading firms (Amazon, Microsoft, Google, Salesforce, Oracle, IBM, and Adobe) and the other major non-leading firms (Cisco, Rackspace, Dell, etc.). The comparison shows that relative to the non-leading firms, the firms acquired by leading firms are younger, have fewer employees, investors, and funding, and have not launched an IPO yet. This difference confirms that leading and non-leading firms have different purposes for acquiring new firms. Leading firms only need additional complementary technology/innovation/products to entrench their market position, which can be found in young start-ups. By contrast, the other companies must buy established firms with a large customer base and innovative technology to gain market share and compete against the leading firms. Another reason for leading firms buying only young start-ups is that they escape the scrutiny of competition authorities since young start-ups, typically, have not generated a sufficient amount of revenue. The mere existence of merger control mechanisms can act as a deterrent, dissuading companies from pursuing mergers that may lead to anti-competitive outcomes. The primary objective of merger control in the United States is to ensure that mergers do not harm competition and consumers. In this respect, the Hart-Scott-Rodino Act (1976) requires large mergers to notify the two relevant agencies, the Federal Trade Commission -FTC- and the Department of Justice -DOJ-, to obtain clearance before completing the acquisition.[9] If a merger is subject to review, the FTC and DOJ examine a variety of factors to assess possible anti-competitive effects. These factors include market concentration, barriers to entry, and potential effects on pricing and innovation. Therefore, merger

[9] See FTC `https://tinyurl.com/2vv2vze2` accessed on 12 July 2023.

control also considers the factor of competition between the merging firms in terms of product development and innovation. If the merger would lead to a reduction in innovative efforts, it might be a cause for concern and therefore investigated further. Due to the fear a large merger is blocked or remedied, acquisitions by large firms in this market tend to target smaller firms. The result that innovation is higher than for smaller companies may give room to speculate that these companies may target companies that offer complementary innovation.

Finally, it is also possible that the dominant firms, with their superior advantage of data, would have a better algorithm to detect young potential firms and optimise their acquisition decision.

Table 4: Comparison of acquired target characteristics between leading firms (Amazon, Microsoft, Google, IBM, Oracle, Salesforce, and Adobe) and non-leading firms (Cisco, Dell, Rackspace, etc.)

	targets by leading firms					targets by non-leading firms				
variable	obs	mean	se	min	max	obs	mean	se	min	max
age*	40	7.200	0.813	1	18	110	9.336	0.857	1	58
number of employees*	40	3.175	0.299	1	9	108	4.185	0.234	1	9
number of investors*	34	4.265	0.526	1	16	83	5.470	0.360	1	16
funding amount ($M)	31	48.261	14.072	1	350	84	71.993	21.992	1.2	1704
number of funding rounds	34	3.088	0.320	1	6	84	3.643	0.259	1	12
IPO status	40	0.050	0.035	0	1	95	0.116	0.033	0	1

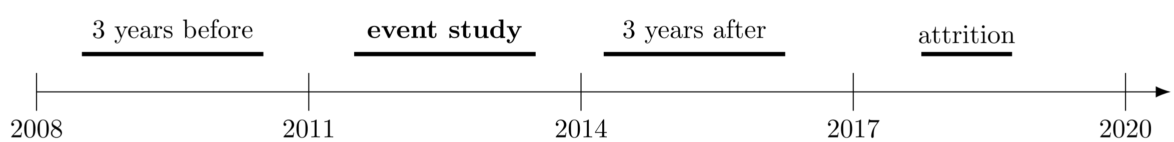
Note:* The mean values of the two groups are statistically different at a 5% significance level. The number of employees is a categorical variable, which takes the value one if the company has 1-10 employees, two if 11-50 employees, three if 51-100 employees, four if 101-250 employees, five if 251-500 employees, six if 501-1000 employees, seven if 1001-5000 employees, eight if 5001-10,000 employees, and nine if the company has more than 10,000 employees. IPO status has the value of 1 if the company has a successful IPO, zero otherwise.

Remark 2: *While leading firms tend to acquire young start-ups, non-leading firms are more likely to buy well-established firms.*

4.2 Data for estimating the impacts of mergers on innovation

4.2.1 Merger data sample

To estimate the impacts of mergers on innovation measured by patents in the cloud computing market, we only select mergers from 1/1/2011 to 31/12/2014. We restricted it to these four years because we are interested in analysing the data three years before the merger and three years after. See timeline below,



Cloud computing is a new market, and therefore almost no patents are available before 2008. As for the right-hand side of the interval, patents often need time to be recorded and granted. We choose to be conservative and allow three years for the patenting registration and concession. We hope, in this way, to count all patents that occurred in 2017 (three years after a merger that took place in 2014). This sample restriction enables us to evaluate the effect on post-merger innovation. The period 2011-2014 includes 145 firms acquiring 177 targets. This is the sample that we used to construct Table 4. We downloaded the data for acquirers and targets on net sales/revenue, R&D investment, net income, total assets, total debt, and gross profit margins from Thomson Reuters Datastream. The matching of target and acquiring companies with this dataset reduces the sample to 36 acquirers and 62arget firms. When an acquirer acquires more than one merger in one year, the observations are pooled. This contracts the merger sample from 62o 51 We will use this number of acquisitions in the main empirical analysis and explain when the observations differ. Finally, as in Haucap et al. (2019), we combine the value of acquirers and targets to avoid double counting. When the acquirer acquires more than one target firm during 2011-2014, we will pool all patenting activities throughout the period 2008-2017.

4.2.2 Measuring innovation by patent data

Among popular measures of innovation, R&D investment is not applicable in our research as most leading firms in the cloud computing market are operating in many other industries. For instance, Amazon's business is also in the online marketplace or tablet PC manufacturing. Microsoft also produces personal computers, smartphones, and software. Therefore, it is problematic to identify which amount of R&D investment these firms invest in cloud computing technology. For this reason, we will focus on measuring innovation by the firm's patent activity.[10]

We downloaded information on 10,836 patents related to cloud technology from the US Patent Office (USPTO) Patentsview API. Based on this data, we then constructed the measure for innovation using a simple count of the number of new patents each year. We count the number of patents granted to a firm in a year. Patenting is a lengthy process. It takes months or years to grant patents after filing them. The lengthy, uncertain, and costly patenting process discourages small firms from patenting their inventions when the costs outweigh their commercial values. In addition, there are alternative options to protect inventions, like trade secrets or copyrights. Hence, patents do not capture all innovation activities and may undermine the innovation output, particularly for small firms. Finally, not all patents will lead to inventions/commercial values, as firms may use patents to protect their existing patents rather than innovate. Despite all these limitations, patent activity is still a reliable measurement of innovation, as it is closely related to innovation output, the bias against small firms exhibits milder effects in our dataset since a considerable number of these firms are excluded from our analysis upon the matching of merger entities and control firms.

The simple patent count is the most straightforward measure of a firm's patent output. The innovation literature criticises this measure for its wide variation and lack of accountability for quality (Hall et al. 2001, 2005b,a), preferring patent citations to patent count due to its ability to capture quality. Therefore, citation-weighted patent counts are often seen as a good indicator, as they incorporate information about both the number of patents and the quality of patents.

However, the variable patent count has its own merits. It is informative to capture the patenting trend and is thus often used in the empirical literature. It has the advantage of being easy to calculate. It involves simply counting the number of patents filed, while measuring patent citations requires an analysis of the references made to a patent by other patents. In this respect, patent counts provide a more objective measure of innovation since they are based solely on the number of patents filed, which is a concrete and measurable quantity. Patent citations, on the other hand, can be influenced by various factors, including the

[10] In principle, besides examining the impact of M&A on innovation, we could have also explored its effect on share prices since most acquirers are publicly listed companies. However, many of these acquirers are multinational and operate across multiple markets. Consequently, the acquisition of a target firm might only have a relatively minor influence on the overall share price of the acquiring company. Hence, we exclusively focus our analysis on patents.

citing practices of patent examiners and the strategic behaviour of patent applicants, which may introduce some subjectivity into the analysis. Moreover, patent citations may take several years to emerge, as it often requires time for other inventors to develop technologies or innovations based on the original patent. This lag can make patent citation-based measures less timely and less suitable for assessing recent innovation, as is the case in a new industry like cloud computing. In this respect, the citation-weighted patent measure may not fully reflect the actual patent quality. Therefore, we will not use this indicator as an outcome in our main results, as it may not truly capture the innovation trend. Nevertheless, we will incorporate this measure into our analysis for the purpose of robustness checks and (in its lagged form) as a control in the propensity score matching process.Besides patent count , we construct one more indicator to capture the pre-merger patent information of firms: patent stock. Following Haucap et al. (2019), we will use its value in 2007 (the year before our analysis period), to estimate the propensity score. We compute firm i's patent stock (PS)in year t by the formula $PS_{it} = (1 - \delta)PS_{i,t-1} + P_{it}$ as in Bloom and Reenen (2002). We set the discount factor δ to be 0.15—a typical value in the innovation literature (Bloom and Reenen 2002, Bloom et al. 2016). P_{it} denotes the number of new patents granted to the firm in that year. The patent stock in 1998 is set to zero since this is the first year we observe cloud-related patents. We treat the values of all patent measures for both the acquirer and target as one entity.

Table 5 presents descriptive statistics of merging entities in the period before the merger. As can be seen, in the pre-merger period, there is not much activity by merged entities as the average number of new patents in one year is 11.549, and the average patent stock is 28.57. By contrast, the R&D statistics (with the limitations presented earlier) show that cloud computing is a highly innovative industry; the average R&D to sale ratio is 12.074%, either implying that cloud computing firms have a high incentive to invest in innovation or that R&D includes expenditures in markets beyond cloud computing. The sales, net income, and asset statistics suggest that the firms active in M&A are all big tech firms in terms of revenues and assets. Hence, these firms are likely to make high-value acquisitions, as shown previously in Table 3.

Table 5: Summary statistics of merged entities based on pre-merger observations

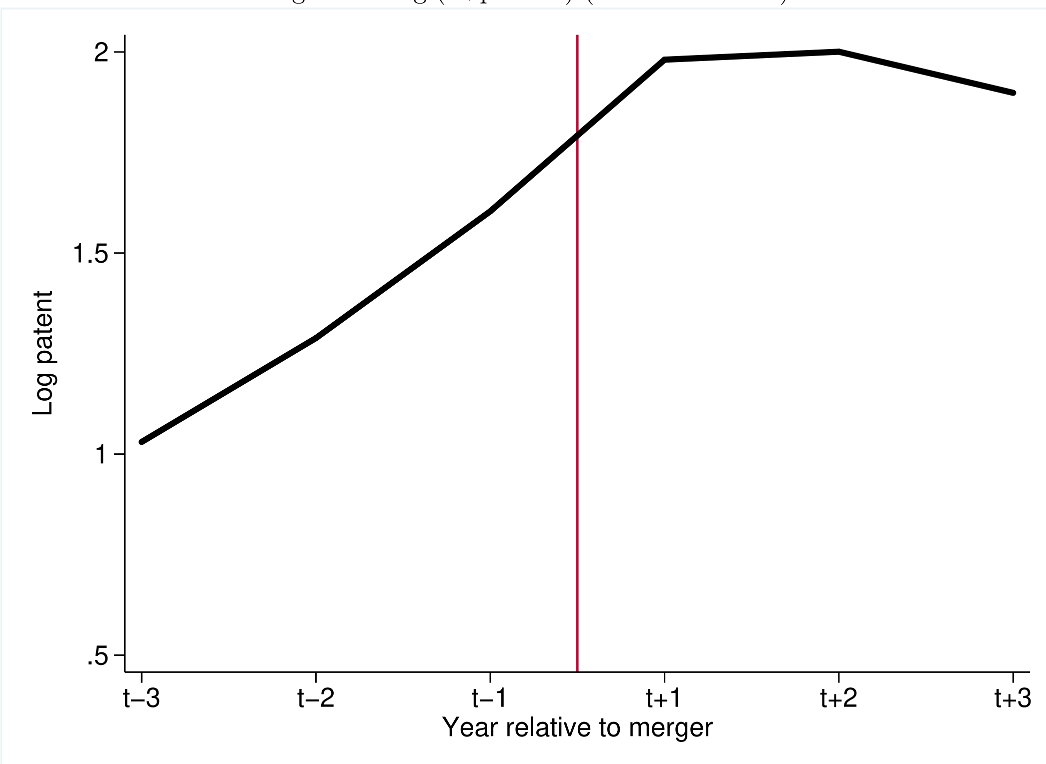
variable	mean	std	min	max
patents per year	11.549	23.610	0	134
citations per patent	12.216	38.782	0	276
citations weighted patent	83.686	115.869	0	474
patents stock	28.570	63.952	0	379.369
net sale (million US$)	23252.056	31493.637	63.563	112069.158
R&D/sale (%)	12.074	6.368	0	25.550
net income (million US$)	2782.319	5167.197	-3122.808	23150
total asset (million US$)	34325.764	49620.303	47.338	220005
total debt/total asset(%)	13.212	11.261	0	41.180
gross profit margin(%)	63.147	20.219	10.200	90.960
leader dummy	0.196	0.401	0	1
multi-sided platform dummy	0.497	18.851	0	1
public target dummy	0.039	0.196	0	1
high-value acquisition ($> 1B$\$) dummy	0.098	0.300	0	1

4.2.3 Descriptive evidence-innovation activity before and after

Figure 2 illustrates how the patent count (in logs) of the merging entities (recalling the combined value of acquirers and targets) changes after the merger. This descriptive evidence does not account for the causality and time trend and only visually shows the innovation trend of merging entities before and after the merger. As one can see in the figure, the number of new patents builds up gradually before the merger, spikes in the year after the merger, and then reaches a plateau.

The figure represents the average logarithm of one plus the number of patents held by both the 62 target companies and their respective acquirers, either before or after the merger. For example, one of the 62 observations pertains to the logarithm (plus one) of patents held by Riverbed Technology and Thoma Bravo (see item 10 in Table 3) for the years 2011 (t-3), 2012 (t-2), 2013 (t-1), 2015 (t+1), 2016 (t+2), and 2017 (t+3), within the specified time period.

Figure 2: Log (1+patents) (before and after)



Notes: The red line is the year of the merger.

5 Empirical strategy

We employ propensity score matching. We perform a counterfactual analysis and combine this with the DiD estimator to estimate the causal effect of mergers on the innovation of merging entities, which is the difference between the actual outcome in the post-merger period and the corresponding outcome had the merger not taken place in the same period.

A counterfactual analysis involves comparing the observed outcome of a treatment, with what would have happened in a hypothetical scenario where that treatment did not occur. In our context, it allows researchers to assess the impact of a merger (the treatment) on the outcome measured by patents while controlling for other confounding factors. When studying causal inference, researchers tend to encounter challenges in establishing causal relationships due to confounding variables that can distort the effect of an intervention. Propensity score matching helps address these challenges by creating a balanced comparison group that closely resembles the treatment group in terms of observed characteristics. By matching individuals based on their likelihood (propensity) of receiving the treatment, researchers can control for confounding factors, leading to more accurate and reliable estimates of the treatment's impact (refer to Cunningham 2021 for further reading on this topic).

We aim to quantify the average treatment effect on the treated (ATT) k periods after the merger. We label with t the merger period and with i the firm. We denote with $P^1_{i,t+k}$ and $P^0_{i,t+k}$ the patent output k periods after the merger, in its occurrence (1), and in the counterfactual situation of its absence (0). The outcome depends on a set of pre-merger control variables $X_{i,t-1}$. We include only pre-merger values to mitigate the reverse causality problem. $\mathrm{MA}_{i,t}$ is a dummy, which takes the value one if there is a merger and zero otherwise. The ATT can be expressed as follows:

$$\begin{aligned} ATT_k &= E\left(P^1_{i,t+k} - P^0_{i,t+k} | X_{i,t-1}, \mathrm{MA}_{i,t} = 1\right) \\ &= E\left(P^1_{i,t+k} | X_{i,t-1}, \mathrm{MA}_{i,t} = 1\right) - E\left(P^0_{i,t+k} | X_{i,t-1}, \mathrm{MA}_{i,t} = 1\right). \end{aligned} \tag{1}$$

A widely used approach to estimate the ATT in the literature is to construct a panel of treated firms (merging entities) and a control group of firms with similar characteristics but independent of the merger. The core step of this procedure is to identify the control group, as this would allow us to estimate the causal effect of the merger on innovation by using the DiD estimator. Unfortunately, this is problematic as it can be a challenge to find a perfect comparator in terms of geographical space for the cloud computing market, which is a worldwide market. In terms of product space, it is also challenging to find hi-tech products that have a similar innovation trend to cloud computing technology. One of the most obvious choices, other cloud computing firms not involved in mergers, is questionable as their innovation activities can be indirectly affected by the merger decisions. As shown in the data section, most cloud computing firms are young and have not submitted an initial public offering , meaning that it is not possible to gather R&D and financial data on these firms and, as explained earlier, this is the reason why the number of merger observations more than halves. Fortunately, in our sample, various firms operate in businesses outside the cloud computing market and own cloud technology-related patents. We employ this group of firms as the control group. These firms by not having a direct presence in the cloud computing market are potentially a valid control group since they are not competing directly with merged entities in the cloud computing market.[11] However, this does not mean that these firms' innovation is independent of the treatment, which is one condition for unbiased ATT estimates. For example, Samsung is a firm that owns cloud-related patents and does not compete in the cloud computing market. However, it still needs to use many cloud services offered by Amazon. Merging activities strengthen Amazon's market power, enabling it to raise its price. This process would encourage Samsung to invest more in cloud innovation to be less dependent on Amazon services. When firms in the control group are not independent of the effect of mergers, the estimates are biased. The sign of the bias depends on whether there is substitutability or complementary between the treated group and the control group. Nevertheless, it would be complex to test such a relationship formally.

The second condition that needs to be satisfied is the control group needs to be similar to the treatment group in terms of both characteristics and innovation patterns before the treatment (parallel trend). To

[11] Companies are categorised as participants in the cloud computing market if they generate revenues from cloud computing products within our analysis time frame, spanning from 2008 to 2017. This period encompasses three years before the first merger in our selected sample and three years after the final merger. Consequently, even companies that did not offer cloud computing products during this specified period but subsequently acquired a cloud computing entity – such as the 2019 acquisition of Mellanox Technologies by Nvidia – could still be considered eligible as control firms. We also investigate the scenario wherein these companies are excluded from our control group and find that our results remain highly consistent.

deal with this condition, we first estimate the propensity score (the predicted probability of conducting a merger) from the Probit model $\Pr(MA_{i,t} = 1|X_{i,t-1})$. In order to estimate the propensity score, we employ various control variables, including the number of new patents (in logs) lagged one year relative to the merger. Following Haucap et al. (2019), we also control for the log of pre-sample (1999-2007) patent stock prior to the time period of our propensity score estimation. Additional variables that lagged one year relative to the merger are , log of citations per patent, log of net sales, %R&D to sales ratio, net income, log of total assets, %total debt to assets ratio, and %gross profit margin. For the case of firms conducting multiple mergers, if these mergers are within a year, we consider this as one merger with multiple targets and consolidate the values of all firms involved. When these mergers are in different years, we treat these as separate observations.[12] Then, we construct our control group with similar characteristics and innovation patterns to the treatment group by using nearest neighbour matching methods. The similarity and parallel innovation patterns are shown and discussed in the results section.

Upon constructing the treatment and control matching groups, we estimate the ATT by using the DiD estimator as in the following specification:

$$\Delta \ln P_{i,t+k} = \beta_k + \gamma_k \mathrm{MA}_{i,t} + \varepsilon_{i,t+k}. \tag{2}$$

Where γ_k is the ATT effects with $k = 1, 2, 3$. To avoid the problem of taking the log of zeros, we define $\Delta \ln P_{i,t+k}$ as the change in the natural log of (1+number of new patents) between the period $t+k$ and $t-1$ of the difference between the treatment and the control units had these merged. One aspect worth noting of the DiD estimator is that it controls for time-invariant but not time-varying unobservables. The challenge when estimating equation (2) is the endogeneity of $\mathrm{MA}_{i,t}$. The merger decision can be correlated with unobserved time-varying characteristics not eliminated by the DiD estimator. Haucap et al. (2019) suggest using an IV estimator to deal with this concern. Unfortunately, our data is not rich enough to construct valid instruments.

Besides the main effect of mergers on the innovation of the merged entities, it is also interesting to examine whether this effect would be different for leading firms versus non-leading firms or multi-sided firms versus one-sided firms. Leading firms are expected to generate more efficiencies from their acquisitions, which would enhance their innovation outcome.[13] In the cloud computing market, efficiency is the ability of cloud service providers to deliver computing resources, such as storage, processing power, and applications, in a cost-effective and optimised manner. It involves achieving the best possible outcomes in terms of performance, reliability, and resource utilisation while minimising operational costs and environmental impact (see Rashid and Chaturvedi (2019)). Likewise, firms operating as multi-sided platforms would leverage the effect of mergers through indirect network externalities. A subsequent step in the analysis, comparing leaders and non-leaders, involves examining the size-related implications by investigating the effects of public versus private acquisitions and highly valuable mergers. We will test these heterogeneous effects by estimating the following equations:

$$\Delta \ln P_{Z,i,t+k} = \beta_{Z,k} + \gamma_{Z1,k} \mathrm{MA}_{i,t} + \gamma_{Z2,k} \mathrm{MA}_{i,t} \times \mathrm{Z}_i + \varepsilon_{Z,i,t+k}, \tag{3}$$

where $Z \in \{\text{leader, MSP, public, } > 1B\$\}$. Leader$_i$ takes the value one if the firm is in the leading group,

[12] Szücs (2014) suggests removing firms with multiple mergers to avoid confounding effects. However, we could not do this as our sample is too small to apply this rule.

[13] Efficiency and innovation are closely interconnected, forming a dynamic relationship that drives economic growth. Efficiency refers to the ability to achieve optimal outcomes with the least amount of resources, to enhance productivity. On the other hand, innovation involves the creation of new products or processes that bring about changes and competitive advantages.

zero otherwise. MSP_i is a dummy indicating whether or not firms have a multisided platform business model. Public is a binary variable indicating whether the target is a publicly traded company. Lastly, $> 1B\$$ is a binary variable denoting mergers of substantial value.

6 Results

We first discuss the propensity score (the probability of conducting a merger), whose estimates are reported in Table 6. The propensity score is estimated for three periods before the merger. Most of the estimated coefficients are not statistically significant (though some are mildly significant), except for the coefficient for gross profit margin. This latter suggests firms with higher profitability are more likely to be involved in merger activities.[14] The number of observations, 662, is the sum of 51 (treated firms) x 3 (periods) = 153 treatment observations and 509 control observations.[15] As this is an event study analysis, we are also able to control for the time effects of the year of the merger.

Table 6: Propensity score estimation

variable	coefficient	se
ln(1+patents)$_{t-1}$	0.307	0.223
† $\ln(1 + \text{patent stock})_{2007}$	-0.157	0.396
ln(1+citations per patent)$_{t-1}$	0.314*	0.182
ln(net sales, M$)$_{t-1}$	0.968	0.551
%(R&D/net sales)$_{t-1}$	-0.062*	0.032
‡(net income, M$)$_{t-1}$	-0.062	0.049
ln(total assets, M$)$_{t-1}$	-0.775	0.495
%(total debt/total asset)$_{t-1}$	-0.008	0.016
%(gross profit margin)$_{t-1}$	0.067***	0.015
N	662	
R-squared	0.324	

Notes: $p < .01$(***), $p < .05$(**), $p < 0.10$(*). The dependent variable is one in the case of a merger. Time-varying regressors lagged one year relative to the merger. The regression includes time-fixed effects. †Just like in Haucap et al. (2019), we have computed the patent stock exclusively for the year 2007. This aligns with the fact that our initial propensity score estimation begins in the subsequent year. ‡Net income is presented in levels, reflecting the presence of negative values.

Table 7 shows the result of differences between the matched groups of treatment and control firms after applying the nearest neighbour matching. Some characteristics show significant differences between the two

[14] One could question a reverse causality, where the merger firms could also have higher profitability. However, this is more a concern for R&D investment than patents. The impact of financial considerations on R&D investment differs from that of patents. R&D investment is typically a crucial component of a business plan, with decisions being made on an annual basis, though the frequency may vary among firms. Aligning strategies with the fiscal year is a common practice for many businesses. A company's strong financial performance in year $t-1$ can often lead to increased allocations for R&D in year t (though business plans are often more affected by the anticipation that the realisation of higher profits, in which case it would be $t+1$). On the other hand, patents operate under a different set of uncertainties. The success of an investment in patent development is uncertain, and the process of obtaining patent registrations can be time-consuming, often spanning two to three years, with patent citations taking even longer to materialise.

[15] The number of control observations is not a multiple of three, as certain control firms lack observed covariates across all periods.

groups. However, the mean value of features like a log of sales, log of assets, debt/assets, and gross profit margins are not statistically different across treatment and control groups. Importantly, we do not reject the equality of means of the propensity score between the two groups. These results let us infer that firms in the treatment and control group after matching have a similar probability of merging and characteristics in the pre-merger period, validating the control group. The matching reduces the sample to 51 treatment units and 51 control units, for a total of 102 observations.

Next, in Figure 3 we plot the average trajectories of log patents for merged entities relative to the respective control firms after the matching. As can be seen, before the merger, the innovation patterns of merged entities and control firms display a parallel trend. Hence, the condition that treatment firms and control firms behave similarly is met. Furthermore, we conduct a regression-based test to assess the validity of the parallel trend assumption. The outcomes of this test are presented in Table A.1 in the appendix, affirming that we do not have grounds to reject the parallel trend hypothesis between the treatment and control groups. After the merger, the merged entities augment their patent activity in year $t+1$. Then while the number of patents by merged entities becomes flat in year $t+2$ before a fall in $t+3$, the control group experiences a gradual decrease in $t+2$ and $t+3$. Though we observe a fall in patents in the third year after the merger, the level of patents by merged entities is still higher than the pre-merger level. Whereas, in the case of control firms, the level of patents in year $t+3$ is lower than its pre-merger value in a year. This aftermath visually shows that mergers have the potential to impact positively the patent activity of merged entities.

Table 7: Balancing property after matching

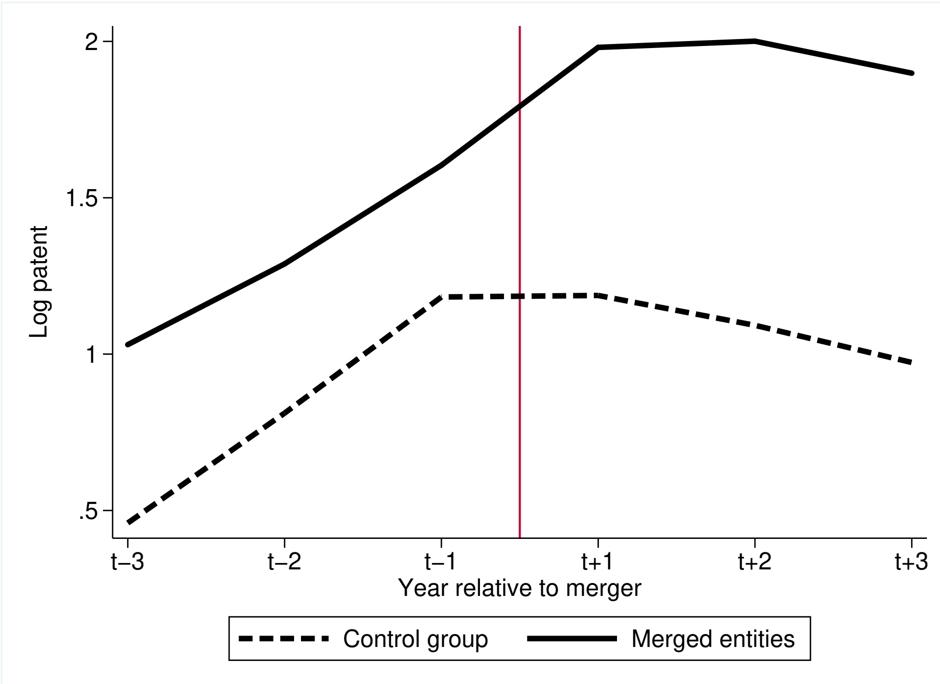
variable	treated	control	t-stat	p-value
ln(1+patents)$_{t-1}$	1.604	1.183	1.809	0.074
† $\ln(1+\text{patent stock})_{2007}$	0.199	0.300	2.090	0.041
ln(1+citation per patent)$_{t-1}$	1.533	1.133	1.683	0.095
ln(net sales, M$)$_{t-1}$	15.456	14.773	1.549	0.125
%(R&D/net sales)$_{t-1}$	12.074	13.137	-0.684	0.496
(net income, M$)$_{t-1}$	2.782	1.415	1.663	0.101
ln(total assets, M$)$_{t-1}$	15.846	15.114	1.674	0.097
%(total debt/total asset)$_{t-1}$	13.212	10.410	1.360	0.177
%(gross profit margin)$_{t-1}$	63.147	66.524	-0.765	0.446
propensity score	0.302	0.290	0.292	0.771

Notes: The table shows mean differences between treated (merging entities) and control observations for the matched sample, based on the propensity score. †See note in Table 6.

The main results of the estimated ATT effects of mergers on patents of merged entities are documented in Table 8. The merged entities augment their patents by 45%, 63%, and 66% in the first year, second year, and third year after the merger. Consistently with the visual evidence provided in Figure 3 the magnitude of the effect grows. These effects are statistically significant. Therefore, we have evidence that mergers impact positively the innovation activities of merging firms. This effect is probably because mergers generate enough synergies/efficiencies to boost the innovation outcome. These results suggest that mergers do not cause harm to innovation.

Table 9 documents the results of heterogeneous effects of mergers on innovation by different groups of firms. The comparison of leading firms versus non-leading firms is displayed in the first three columns of the top panel. The estimated coefficient on the interaction term between two dummies of merger event

Figure 3: Trajectories of log patent count for merged entities and control group



Notes: t denotes the time period in which the merger takes place.

Table 8: Average treatment effects on the treated (ATT) estimation results

	Δ ln(1+patents)		
	(1) t+1	(2) t+2	(3) t+3
MA	0.372**	0.487***	0.504***
	(0.143)	(0.148)	(0.173)
N	102	102	102

Notes: $p < .01$(***), $p < .05$(**), $p < 0.10$(*). The table shows regressions based on the matched sample after using propensity score matching. Dependent variable is ln(1+patents)$_{t+k}$ - ln(1+patents)$_{t-1}$, where t refers to the year of the merger. Robust standard errors are in parentheses. MA is an indicator variable that takes on a value of one if a firm is involved in a merger.

and leading firms is positive and statistically significant, with the highest effect achieved in year three after the merger. Mergers would be estimated to increase the innovation measured by patents of leading firms by 212% relative to other firms in the third year after the merger. This effect confirms that beyond the general significant impact of mergers on the merged entities, leading firms derive notable benefits from their acquisitions, resulting in a substantial enhancement of their innovation outcomes. The intuition is that leading firms can generate more synergies from mergers, and fully capitalise on these effects to boost their innovation compared to non-leading firms. Moreover, as analysed above, leading firms are more likely to acquire young start-ups with talented people and innovative projects. Hence, mergers would enable these projects to be successful, and drive innovation outcomes.

The last three columns of the top panel show how mergers affect MSP firms versus non-MSP firms. As expected, the coefficients for the interaction between MA and MSP are highly positive and significant in both periods $t+2$ and $t+3$. For instance, three years after the merger MSP firms are expected to increase their innovation by 68% relative to non-MSP firms. This result is possible because of the role of indirect network effects. By acquiring other firms with different/complementary products, MSP firms could expand their range of products/services, attract more users, and drive more developers to join their cloud marketplace. This effect would lead to more sales revenue, enabling firms to spend more on R&D investment and eventually generate a healthier innovation.

When facing the trade-off between building and buying, firms may prefer to use acquisitions to access competitors' patents and technologies instead of developing themselves. Hence, one can wonder whether the results above are actually driven by the firm's acquisitions in years that are subsequent to the mergers identified in our data sample. While it is true that the leading firms and MSP firms in our analysis continue to acquire other cloud companies after our data sample period, this does not affect the above results/findings for two reasons. First, most of the targets acquired by leading firms and MSP firms are young companies/start-ups, which do not have any patents or very few patents. Second, even when these targets have a number of patents, these patents have not been reassigned to acquirers, which means that our measurement of patents for leading/MSP firms is not affected by these acquisitions.

The findings from the bottom panel of Table 9 reveal other noteworthy trends in patenting behaviour following M&A activity. Specifically, patents tend to increase significantly for public acquisitions compared to private acquisitions. This observation suggests that when acquirers target public companies, there may be greater synergies at play, resulting in heightened innovation and patenting activity. Public targets, being larger and subject to regulatory scrutiny, often necessitate a more thorough and strategic merger policy. This, in turn, can lead to enhanced efforts to integrate and leverage the technological capabilities of both firms, contributing to an upsurge in patenting activity, and hinting towards an effective merger policy.

Interestingly, the data do not demonstrate a significant difference in patenting behaviour between very large acquisitions (exceeding 1 billion) and smaller acquisitions. This unexpected finding suggests that the deal value alone might not be the primary driver of increased patenting activity. While large acquisitions involve substantial financial investment, they may not consistently lead to a significant boost in innovation or patenting. Instead, other crucial factors, such as the strategic fit between acquiring and target firms' technologies, culture, and capabilities, likely exert a more influential role in determining the impact on patenting behaviour.

This exercise highlights the importance of considering the nature of the target firm and the deal size when examining the patenting behaviour resulting from M&A activity.

Our results are consistent with theoretical evidence by Bourreau et al. (n.d.), and Jullien and Lefouili

Table 9: Effects on leading vs non-leading firms, MSP vs non-MSP, public vs private targets, and acquisition value $> 1B\$$ vs $< 1B\$$

	Δ ln(1+patents)					
	(1) t+1	(2) t+2	(3) t+3	(4) t+1	(5) t+2	(6) t+3
MA	0.282**	0.413***	0.370**	0.272*	0.319*	0.320
	(0.146)	(0.151)	(0.174)	(0.155)	(0.166)	(0.197)
MA × leader	0.762**	0.635*	1.139***			
	(0.325)	(0.356)	(0.281)			
MA × MSP				0.284	0.478**	0.521**
				(0.249)	(0.229)	(0.251)
N	102	102	102	102	102	102

	(1) t+1	(2) t+2	(3) t+3	(4) t+1	(5) t+2	(6) t+3
MA	0.346**	0.451***	0.488***	0.387***	0.463***	0.505***
	(0.143)	(0.146)	(0.175)	(0.143)	(0.149)	(0.179)
MA × public target	1.354***	1.836***	0.820***			
	(0.113)	(0.110)	(0.130)			
MA × acquisition value$> 1B$				-0.251	0.411	-0.013
				(0.693)	(0.598)	(0.388)
N	102	102	102	102	102	102

Notes: $p < .01$(***), $p < .05$(**), $p < 0.10$ (*). The table shows regressions based on the matched sample after using propensity score matching. Dependent variable is ln(1+patents)$_{t+k}$ - ln(1+patents)$_{t-1}$, where t refers to the year of the merger. Robust standard errors are in parentheses. MA is an indicator variable that takes the value of 1 if a firm is involved in a merger. Leader is a dummy variable taking the value one if the firm is in the group of leading firms. MSP is an indicator that takes the value one if firms have a multi-sided platform business model. Public target is a dummy variable taking the value one if the target firm is public at the time of the acquisition. Acquisition value$> 1B\$$ is an indicator that takes the value one if the acquisition value is greater than 1 billion USD.

(2018) that mergers can have overall positive or negative impacts on innovation. The key policy implication from our result is that mergers do not necessarily lead to less innovation. Our intuition here is in the cloud computing market, most of the merger cases are young start-up firms acquired by big tech firms, and this type of merger is more likely to promote innovation in this specific market. As mentioned in the descriptive evidence, the leading firms in the cloud computing market prefer to acquire young firms that develop complementary instead of substitute products. Thus, the merger would not generate any cannibalisation effect, which could discourage the innovation incentive. Since leading firms in cloud computing acquire young start-ups because of their talented employees, innovative assets, or R&D projects, the merger would generate synergies, for instance, by allowing start-ups to have enough funding to develop their projects. These synergies would enhance significantly the innovation outcome, which would result in new or higher quality products/services and increased consumer welfare. Mergers in the cloud computing market do not necessarily soften market competition, as the key players remain the same. They compete intensely to acquire more market shares and profit in this expansive market. Therefore, there is no evidence to believe that innovation is harmful because of M&A weakening competition in the market. To recap, prohibiting start-up acquisitions by big tech firms may do more harm than good. However, this does not mean that competition authorities should not scrutinise merger cases between big tech firms and young start-up firms. Specifically, when young start-up firms have great potential to be successful and challenge the dominant firms through a large customer base or superior technologies.

6.1 Robustness checks

In this section, we will outline a series of checks aimed at confirming the robustness of our findings.

6.1.1 Most popular patent category

Recognising the potential contention that post-merger patent outcomes might be influenced by patents of lesser significance, we conduct an additional DiD regression using patent counts from the category G06F - Electric digital data processing within the Cooperative Patent Classification (CPC) system. Notably, this category holds paramount importance in our patent dataset, encompassing 74% of the cloud computing patents in our sample. As a result of only counting the patents in this category, our sample has been reduced to 66 observations: 33 treated firms and 33 control firms. In addition, merged entities with public target has also been dropped out due to the fact that they do not have any patent in the category G06F. Therefore, we could not estimate the moderating effects of public targets in this case. The outcomes of the average treatment effects on the treated (ATT) and moderating effects are documented in Tables 10 and 11. As evident from Table 10, the calculated ATT effects continue to exhibit positive sign in all periods and remains statistically significant in years two and three post-merger. Table 11 corroborates the trends observed in our benchmark outcomes. Notably, the moderating effects attributed to leading/MSP firms companies remain positive and considerably more pronounced than the primary ATT in the case of MSP firms. However, the role of acquisition value in influencing the patent outcomes within the G06F category appears mixed: firms acquiring high-value targets exhibit a lower patent count in this category one-year post-merger. Conversely, this relationship is reversed in the subsequent two periods, although these effects lack statistical significance.

Table 10: Average treatment effects on the treated (ATT) estimation results with cloud patent count in the CPC category G06F as the outcome

	(1)	(2)	(3)
	Δ log(patents)		
	t+1	t+2	t+3
MA	0.266	0.511**	0.487**
	(0.205)	(0.215)	(0.224)
N	66	66	66

Notes: Refer to the notes in Table 8 for further details.

Table 11: Effects on leading vs. non-leading firms and MSP vs. non-MSP with cloud patent count in the CPC category G06F as the outcome

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ log(patent)					
	t+1	t+2	t+3	t+1	t+2	t+3
MA	0.213	0.483**	0.433*	0.020	0.157	0.242
	(0.218)	(0.229)	(0.236)	(0.223)	(0.223)	(0.257)
MA $\times$ leader	0.582***	0.309	0.587***			
	(0.217)	(0.328)	(0.183)			
MA $\times$ MSP				0.737**	1.063***	0.732**
				(0.347)	(0.319)	(0.304)
N	66	66	66	66	66	66
MA	0.266	0.511**	0.487**	0.304	0.506**	0.481**
	(0.205)	(0.215)	(0.224)	(0.207)	(0.221)	(0.230)
MA $\times$ public target	NA	NA	NA			
	NA	NA	NA			
MA $\times$ acquisition value$> 1B$				-1.253***	0.159	0.183
				(0.172)	(0.179)	(0.174)
N	66	66	66	66	66	66

Notes: Refer to the notes in Table 9 for further details.

6.1.2 Winsorising skewed covariates in the propensity score estimation

In order to mitigate the potential influence of outliers, we re-conduct the propensity score matching and DiD regression analyses following the application of 90% winsorisation to the two most skewed covariates: %R&D/net sales and net income (both exhibiting a skewness exceeding 2).[16] The calculated ATT and moderating effects subsequent to winsorisation are displayed in Tables 12 and 13, respectively. These outcomes resemble our benchmark results, providing robust evidence that our findings remain unaffected by the presence of outliers.

Table 12: Average treatment effects on the treated (ATT) estimation results after 90% winsorisation

	Δ ln(1+patents)		
	(1) t+1	(2) t+2	(3) t+3
MA	0.372**	0.487***	0.504***
	(0.143)	(0.148)	(0.173)
N	102	102	102

Notes: Refer to the notes in Table 8 for further details.

Table 13: Effects on leading vs non-leading firms, MSP vs non-MSP, public vs private targets, and acquisition value > $1B$§ vs < $1B$\$, after 90% winsorisation

	Δ ln(1+patents)					
	(1) t+1	(2) t+2	(3) t+3	(4) t+1	(5) t+2	(6) t+3
MA	0.282**	0.413***	0.370**	0.272*	0.319*	0.320
	(0.146)	(0.151)	(0.174)	(0.155)	(0.166)	(0.197)
MA × leader	0.762**	0.635*	1.139***			
	(0.325)	(0.356)	(0.281)			
MA × MSP				0.284	0.478**	0.521**
				(0.249)	(0.229)	(0.251)
N	102	102	102	102	102	102
MA	0.346**	0.451***	0.488***	0.387***	0.463***	0.505***
	(0.143)	(0.146)	(0.175)	(0.143)	(0.149)	(0.179)
MA × public target	1.354***	1.836***	0.820***			
	(0.113)	(0.110)	(0.130)			
MA x acquisition value¿$1B$				-0.251	0.411	-0.013
				(0.693)	(0.598)	(0.388)
N	102	102	102	102	102	102

Notes: Refer to the notes in Table 9 for further details.

6.1.3 Using citations weighted patent as outcome variable

As discussed earlier, the utilisation of patent count as an outcome variable may not fully encompass innovation quality. To address this limitation, alternative metrics incorporating patent citations are employed. Here, we

[16] This involves replacing the top 5% of the variable with its value at the 95^{th} percentile, and similarly, substituting the bottom 5% of the variable with its value at the 5^{th} percentile.

present estimation outcomes using citation-weighted patents as the outcome variable to capture the impact of mergers on patent quality.

The estimated ATT of mergers on citation-weighted patents in Table 14 exhibit similar positive signs as in our benchmark results but become statistically insignificant. Similarly, the moderating effects of leading and MSP firms, as reported in Table 15, lack statistical significance, except for the effect of leading firms at the $t+3$ period. In contrast, the effects of public targets and acquisition value show statistical significance at both the $t+1$ and $t+3$ periods post-merger, albeit with negative implications. This suggests that merged entities acquiring public targets and having higher acquisition values are more prone to experiencing diminished patent quality.

It is worth noting that while the results derived from using citation-weighted patents as the outcome variable appear notably divergent from our benchmark findings, they should be interpreted cautiously. This divergence can be attributed to the fact that patents often continue to receive citations long after their issuance. Consequently, employing citation-weighted patents as a measurement may underestimate actual patent quality, ultimately leading to these effects being deemed insignificant.

Table 14: Average treatment effects on the treated (ATT) estimation results with citation weighted patents as the outcome

	Δ ln(1+patents)		
	(1)	(2)	(3)
	t+1	t+2	t+3
MA	0.166	0.255	0.035
	(0.281)	(0.256)	(0.289)
N	102	102	102

Notes: Refer to the notes in Table 8 for further details.

Table 15: Effects on leading vs. non-leading firms, MSP vs. non-MSP, public vs. private targets, and acquisition value $> 1B\$$ vs $< 1B\$$ with citation weighted patents as the outcome

	Δ ln(1+citation weighted patents)					
	(1)	(2)	(3)	(4)	(5)	(6)
	t+1	t+2	t+3	t+1	t+2	t+3
MA	0.086	0.228	-0.099	0.203	0.215	-0.058
	(0.293)	(0.270)	(0.299)	(0.312)	(0.297)	(0.321)
MA $\times$ leader	0.682	0.231	1.138**			
	(0.691)	(0.536)	(0.513)			
MA $\times$ MSP				-0.104	0.114	0.262
				(0.504)	(0.405)	(0.440)
N	102	102	102	102	102	102
MA	0.205	0.248	0.068	0.287	0.271	0.114
	(0.283)	(0.260)	(0.292)	(0.285)	(0.266)	(0.296)
MA $\times$ public target	-1.993***	0.352*	-1.684***			
	(0.230)	(0.199)	(0.207)			
MA $\times$ acquisition value$> 1B$				-2.059***	-0.280	-1.339***
				(0.294)	(0.332)	(0.278)
N	102	102	102	102	102	102

Notes: Refer to the notes in Table 9 for further details.

7 Conclusions and discussion

While there are increasing discussions and debates among researchers and practitioners on whether M&A by big tech firms harm innovation, there has not been any ex-post analysis providing empirical evidence to address this. This work aims to fill this gap by studying merger activities and their impacts on innovation in the cloud computing market.

Our first descriptive evidence suggests two different M&A strategies by leading and non-leading firms, defined by their market shares. The leading firms are more likely to target young start-ups; the non-leading firms prefer to acquire more established firms. This result complements previous studies on merger activities and strategies (Argentesi et al. 2021, Gautier and Lamesch 2021)—they only focus on big tech mergers' strategies, in general, and not on a specific market. Most importantly, in addition to descriptive evidence, we provide an ex-post-merger analysis to evaluate the impact on the innovation activity of merged entities. Our results suggest that mergers undertaken by leading, MSP firms or targeting a public company affect innovation in the cloud computing market positively. This result is in line with previous theoretical findings, confirming that the effect of mergers on innovation is not always negative and can be positive. The intuition is that in the cloud computing market, synergies are likely to occur between big tech firms with funding resources and project management experience and young start-ups with talented employees and innovative ideas. These synergies are more pronounced for leading, MSP firms, and when the targets are publicly traded companies, thanks to their ability to capitalise efforts and leverage synergies via indirect network effects. This amplification will eventually generate positive feedback on the innovation outcome of these firms. The value of the merger appears to have minimal significance. Our results help ease some of the rising concerns about the potential harms of mergers and acquisitions in the digital platform market.

We enhance the robustness of our analysis through a range of validation measures. This includes focusing patents on the extensively utilised cooperative patent classification, investigating the impact of winsorising highly skewed covariates, and employing citation-weighted patents as the outcome variable. The outcomes with the widely adopted cooperative patent classification affirm the baseline findings, highlighting even more pronounced innovation values. Notably, outliers do not play a significant role in our data. However, results stemming from citation usage exhibit variations, but their limitations require warranting cautious interpretation.

Patents display significant influence over market dynamics by boosting efficiency, introducing novel product varieties, and enhancing existing ones. Consequently, they have the capacity to shape demand through the expansion of quality offerings or the reduction of prices via increased cost efficiency. It is worth noting that an unforeseen demand upheaval, e.g., the one caused by the Covid-19 pandemic, which falls beyond the scope of the empirical analysis conducted within this study's time frame, could potentially serve as a valuable indicator, linked to the decision to acquire a new business. Its influence on the decision to register patents in the short and medium term might be less pronounced. This effect could become even more pronounced when employing patent citations as a gauge of innovation. The research conducted by Lim and Morris (2023) represents an initial endeavour to examine how the Covid-19 shock influences the interplay between innovation and business outcomes. Their study reveals distinct pandemic resilience across industries, indicating that services (including IT) exhibit greater stability compared to manufacturing within European Union member countries.

Our study has some limitations and can be extended in several ways. First, we only have a small sample of merging firms over a short period relative to other studies. The potential solution is to expand the number of merger cases by looking at extra merger cases in the rest of the world. Since firms in the cloud computing market are genuinely competing globally, it is sensible not to limit merger cases in terms of geographical borders. To deal with the short time frame, we can employ quarterly data instead of yearly data to enrich the variation over time. Yet, the issue here is the firms' financial data like revenue, R&D, and income may not be available quarterly. Secondly, firms with multiple mergers can likely cause some co-founding effects, which bias the results. However, we cannot exclude these firms as suggested in the literature due to our small sample. This problem can be solved when we extend our data sample. Finally, we have not dealt with the endogeneity of merger decisions by using IV regression as in previous studies. It is possible to extend our work by evaluating the impacts of mergers on the innovation activity of non-merging competitors in addition to merged entities as in Haucap et al. (2019). Furthermore, it would be interesting to analyse the effects of mergers on the entry and exit of the cloud computing market by using survival analysis. Finally, there is room to study the effect of patent originality, which reflects the novelty and uniqueness of an innovation. This metric would allow us to assess the breadth of search and the extent to which M&A activity may influence the generation of genuinely new and groundbreaking ideas. By incorporating originality as a measure, we could better assess whether anti-competitive M&A deals have any bearing on the quality of innovation produced by the firms involved. Regrettably, we lack information on patent originality, but it may be scope for future research.

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Appendix

A.1 Parallel trend assumption test

Following a common practice in the literature, we evaluate the parallel trend assumption through an event-study regression performed after the matching process. This regression incorporates both leads (post-treatment periods) and lags (pre-treatment periods) of the treatment dummy variable:

$$Y_{it} = \theta_t + \eta_i + \sum_{l=-K}^{K-1} D_{it}^{l} \mu_l + v_{it}. \tag{4}$$

In the presented model, Y_{it} denotes the outcome variable for firm i, specifically $\ln(1 + \text{patents})$. θ_t and η_i represent the fixed effects associated with time and firm, respectively. The variable D_{it}^{l} takes the value one if firm i has undergone a merger for a duration of l periods at time t. For instance, if firm i merges at $t = 3$, then D_{it}^{0} equals one for $t = 3$ and zero for other periods, D_{it}^{3} equals one for $t = 6$ and zero for other periods, and D_{it}^{-2} equals one for $t = 1$ and zero for other periods. The parameter μ_l captures the impact of treatment for various exposure lengths to the treatment.

Following the established practice in the literature, we normalise μ_{-1} to 0. As a result, the interpreted effects of μ_l reflect changes in outcomes relative to the control group during the period l preceding the treatment period. Consequently, when the estimated μ_l values for $l < -1$ lack statistical significance compared to 0, the validity of the parallel assumption cannot be disregarded.

We execute the regression based on equation 4 using a sample comprising 51 treatment firms and 51 appropriately matched control firms throughout the period spanning from 2008 to 2017. Following Callaway and Sant'Anna (2021), to address the issue of selective treatment timing in the event study regression,[17]we construct the aggregated group-year treatment effects by using the R package *did*[18]. The outcomes of the collective group-year treatment effects during the lag periods extending up to six years before the merger are documented in table A.1. Notably, the estimated effects lack statistical significance for all the periods ranging from $t - 6$ to $t - 2$, indicating that there is no basis to reject the parallel trend assumption.

Table A.1: Parallel trend assumption test

variable	coefficient	se
lag_{t-6}	-0.612	0.338
lag_{t-5}	-0.219	0.253
lag_{t-4}	-0.086	0.171
lag_{t-3}	-0.112	0.110
lag_{t-2}	-0.184	0.112
lag_{t-1}	0	NA
N	1020	

Notes: $p < .01$(***), $p < .05$(**), $p < 0.10$(*). The regression includes time and firm-fixed effects. Only pre-treatment periods are reported.

[17]For example, there would be selective treatment timing if a firm chooses to be merged in earlier periods in order to experience larger benefits from the merger.

[18]See more details about this package at `https://cran.r-project.org/web/packages/did/vignettes/pre-testing.html`

A.2 Fixed-effects estimation results

We also run a simple before and after fixed effects regression, which ignores the selection bias and endogeneity of merger decisions. Based on the sample of 62 target firms, we regress several patent measurements on the dummy $\text{postMA}_{i,t}$, which takes the value one, up to three years after the merger and zero up to three years before the merger. The year of the merger is excluded from the analysis. Thus, the total number of observations is $62 \times 6 = 372$. We also control for the time and firm fixed effects. The results are presented in Table A.2. As can be seen in the table, there is evidence that merger events would increase the number of new patents of merged entities, but reduce patent quality. However, these results can be misleading as they ignore selection and endogeneity biases.

Table A.2: Before and after fixed-effects regressions

	(1)	(2)	(3)
	ln(1+patents)	ln(1+citations weighted patent)	ln(1+citations per patent)
postMA	0.619***	-0.212	-0.832***
	(0.113)	(0.169)	(0.114)
N	372	372	372

Notes: $p < .01$(***), $p < .05$(**), $p < 0.10$(*). postMA is an indicator that takes a value of one in all post-merger periods for the merged entity. Variables are based on consolidated companies before and after M&As. Clustered standard errors in parentheses.