Company and University Innovation during an Industry Incubation Phase:

Evidence from Quantum Computing

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ABSTRACT

Uncovering factors that shape the trajectories of technologies during the incubation stage is crucial for maximizing value creation potential. Yet, existing studies have predominantly focused on characterizing innovation activities in later industry stages after a technology has already become commercially viable, largely due to difficulties of obtaining incubation stage data. In this study, we document incubation stage innovation efforts in quantum computing guided by insights from the existing literature on industry evolution, on university and company innovation, and on enabling technologies. Our analysis aligns with the hypothesized important roles of company innovation, collaboration between companies and universities, and reduction in demand and technological uncertainty during the incubation stage. It also highlights the critical importance of value capture strategies, which are essential yet challenging to develop during the incubation stage of enabling technologies.

1. Introduction

New industries are often triggered by scientific discoveries (Agarwal, Moeen and Shah, 2017). The discovery marks the beginning of an incubation stage, in which demand and technological uncertainty are reduced. This process of reducing demand and technological uncertainty to a point where commercialization begins to take off can last decades (Moeen, Agarwal and Shah, 2020). Most empirical research on the emergence of new industries starts after the innovation becomes commercially viable (Gort and Klepper, 1982; Utterback and Suarez, 1993; Agarwal and Bayus, 2002). It is rare to empirically examine an innovation from its first appearance in the scientific literature to serious investment by universities, companies, and government. By examining a technology from its initial conception through large-scale investment, it is possible to explore hypotheses on the incentives of companies and universities in reacting to, and guiding, changes in the rate and direction of innovation in a new industry.

In this paper, we describe early innovation in a newly emerging technology, quantum computing. We find that the patterns of early innovation in quantum computing are consistent with ideas from three literatures, specifically work on the incubation stage of industries (e.g. Moeen, Agarwal and Shah, 2020), work on the role of companies and universities in innovation (e.g. Arora et al., 2021a), and work on enabling technologies (e.g. Teece, 2018).

Quantum computing has a clear origin, with the idea initially speculated in a lecture of Nobel Prize winning physicist Richard Feynman (1982). Despite substantial progress in hardware and software, there remains considerable uncertainty as to whether this technology will prove commercially viable. Thus, Feynman's lecture provided a trigger event for the beginning of the incubation stage of a potential new industry, as in Agarwal, Moeen and Shah (2017). Since Feynman's lecture, we identify three eras in terms of major events that affected trends in academic publications and patents in quantum computing. In each era, we observe different patterns of company and university innovation, in hardware and in software. Through these patterns, we document how reductions in demand and technological uncertainty appear to have changed innovation in the incubation stage of the quantum computing industry.

During the first era, from 1982 to 2011, innovation in hardware and software mostly demonstrated the theoretical possibility of useful quantum computing. As an enabling technology,[1]

[1] Quantum computers require innovation in the core hardware and in a variety of complementary software technologies. In this sense, quantum computers require a feedback loop to generate value, like other enabling technologies (Teece, 2018; Rathje and Katila, 2021).

quantum computing requires multiple complementary innovations to be commercially useful. Like other types of computing, the two main categories of innovation are hardware and software. In hardware, innovations during this era included the idea of a gate-based quantum computer that could perform like a standard binary computer, but faster for some calculations, and developments in how to build a quantum gate (Barenco et al., 1995). On the software side, innovation efforts included the development of algorithms by Shor (1994), Grover (1996), and, later, others that proved quantum computers could factor large numbers and sort lists much faster than standard computers. For the first few decades, however, commercial quantum computing seemed far off.

The second era began in May 2011, with the unanticipated commercial lease of D-Wave's quantum machine to Lockheed Martin. This event came at a time when the scientific community believed that hardware scientific research findings were still too embryonic for applied developments (e.g., IARPA, 2004; Knill, 2010). The method to build the D-Wave machine departed from the orthodoxy of scientific research findings at that time and it remains controversial as to whether the D-Wave machine should be classified as a quantum computer (e.g., Jones, 2013; Quantum Zeitgeist, 2024[2]). The machine was acquired by the Skunk Works[3] division of Lockheed Martin as an engineering novelty that had the potential to contribute to quantum computing innovation efforts. Indeed, the D-Wave machine was installed in a University of Southern California (USC) facility where access was split between USC quantum computing researchers and Lockheed Martin's Skunk Works researchers. Therefore, we do not mean to imply that the first lease of a D-Wave machine represented a commercially viable product. Instead, we view this event as having reduced some demand uncertainty with respect to a market for quantum computing (Agarwal, Moeen and Shah, 2017). It signaled that a large technology-savvy company found quantum computing to be of sufficient interest that it was worth a substantial investment. Technological uncertainty remained substantial (Merali, 2011; Hsu, 2013).

The third era began in 2016, when IBM provided access to its early quantum device via the Cloud. Specifically, in May 2016, IBM announced plans to roll out IBM Quantum Experience, a quantum computing service that offered access to IBM's five-qubit quantum processor.[4] This enabled company and university scientists to engage with a prototype. 7,000 users registered within the first week of launch, another 17,000+ registered the following week, and by May 2021, the Cloud service

[2] https://quantumzeitgeist.com/quantum-annealing-vs-gate-based-quantum-computing-round-2
[3] https://www.lockheedmartin.com/en-us/who-we-are/business-areas/aeronautics/skunkworks.html
[4] https://techcrunch.com/2016/05/03/ibm-brings-experimental-quantum-computing-to-the-cloud/

had 325,000+ users.[5] In this way, we argue that the 2016 event reduced some technological uncertainty because it enabled broad engagement with a prototype.

By the end of our period of study in 2020, substantial demand and technological uncertainty remained. Nevertheless, by examining these three eras we document changes in quantum computing innovation, and in the role of universities and companies during the incubation stage.

We document these changes using data on academic publications and US patents in quantum computing since 1982 using the Microsoft Academic Graph (MAG) and PatentsView databases. These datasets provide a method to identify quantum computing academic publications and patents; however, they do not provide a method to separate hardware from software which is important for understanding complementary innovation in quantum computing, especially since software advances often require different resources to develop and deploy than hardware. With tens of thousands of papers and patents in the data, we need some automated way to classify papers and patents by topic. To do so, we execute an n-gram machine learning-based topic modeling technique, Hierarchical Dirichlet Process (HDP) (Teh, Whye, Jordan and Beal, 2006; Teodoridis, Lu and Furman, 2022), and classify the quantum computing publications and patents identified in MAG and in PatentsView into the two trajectories of hardware and software.

We also use n-gram topic modeling to classify patents and papers based on whether the technology is similar to D-Wave's quantum machine or more unambiguously a quantum computer. This distinction is important for assessing whether the changes in innovation in 2011 were likely driven by a reduction in technological uncertainty or demand uncertainty. If the changes were driven by technological uncertainty, we would expect the follow-on innovation to use the same hardware architecture as the D-Wave machine, namely adiabatic instead of the initially theoretically proposed gate model (Barenco et al. 1995). If demand uncertainty, then there is no particular reason for changes in the innovation to build on the adiabatic architecture of the leased machine.

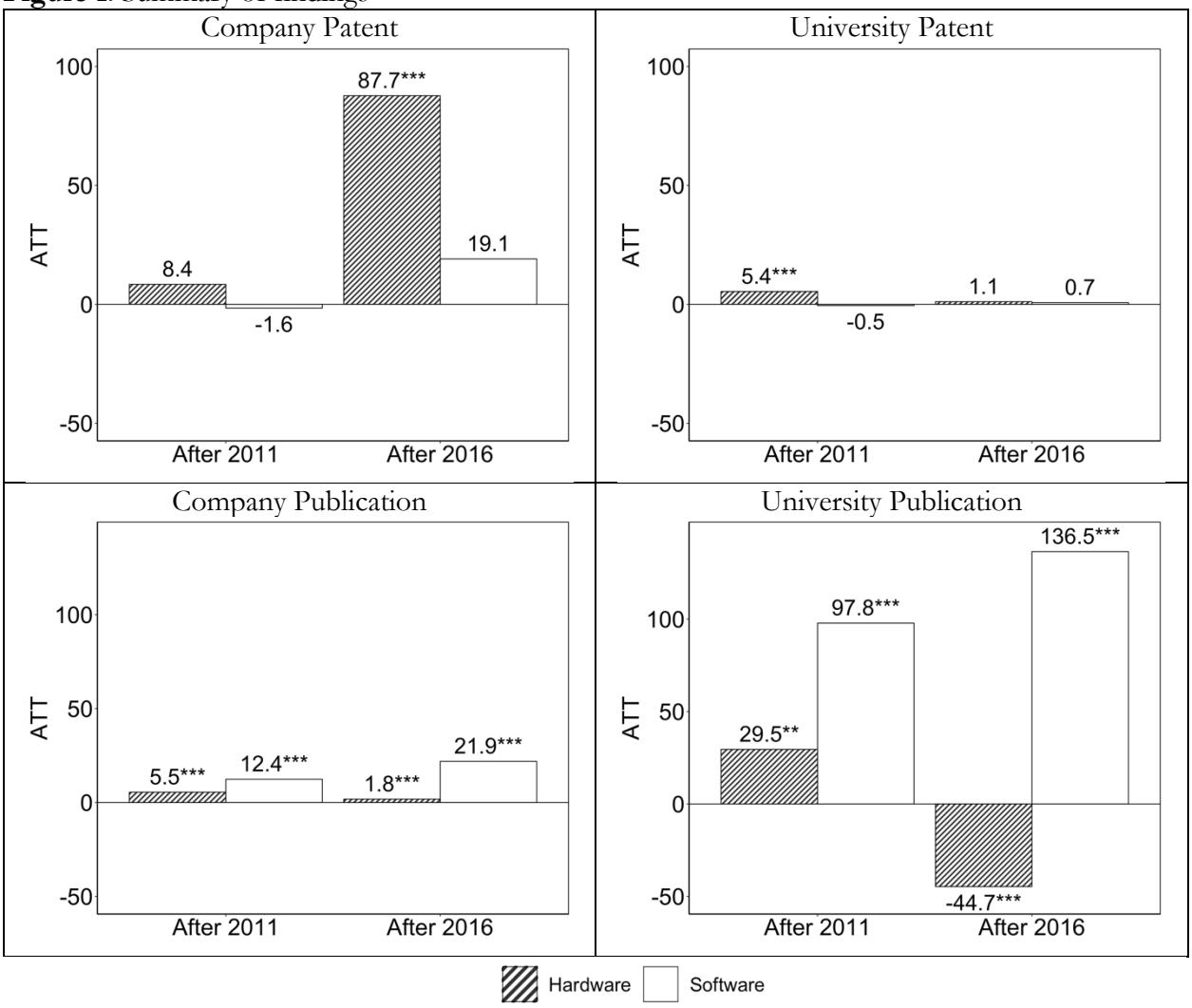
To benchmark changes in quantum computing publications and patents after the 2011 and 2016 events, we compare quantum computing publications and patents to other quantum-related publications and other computing-related patents. While this is not a true natural experiment, as many possible changes could have occurred in quantum computing coinciding with the events in 2011 and 2016, the benchmarks provide a sense of how similar technologies evolved. The trajectory of these benchmark technologies, however, was somewhat different from those of quantum computing.

[5] https://www.ibm.com/quantum/blog/quantum-five-years

Therefore, to enable a better comparison of the trajectory of quantum computing publications and patents relative to similar technologies, we use synthetic difference-in-differences estimation (SDID) (Arkhangelsky, Athey, Hirshberg, Imbens and Wager, 2021). SDID is an extension of the standard difference-in-differences (DID) method that allows for the use of time and unit fixed effects, while allowing more weight on control units that are more similar to the treatment units in the pre-treatment period through a form of synthetic matching.

Figure 1 summarizes our findings. We find that, with the apparent reduction in demand uncertainty in 2011, companies sharply increased their hardware and software publications. Later, we document that the change was primarily driven by collaborative work with university-based researchers. There was also likely a modest increase in company hardware patenting and no increase in software patenting. Universities increased quantum software publications after 2011 but did not increase software patents. For hardware, university publications did not change substantially, and patents increased significantly though by a small absolute number. We do not find a significant increase in patenting or publications related to the D-Wave style adiabatic machine, suggesting that the change in 2011 was not due to a reduction in technological uncertainty. We also find that innovation efforts experienced a burst again in 2016. Company hardware and software publications rose even further, again through collaboration with university researchers. Unlike after 2011, universities did increase hardware patenting.

Figure 1. Summary of findings



We interpret these results to suggest that company innovation, collaboration between companies and universities, and reduction in demand and technological uncertainty were likely essential to move innovation forward in quantum computing during the incubation stage, consistent with arguments in Agarwal et al. (2017) and Arora et al. (2021a,b). However, consistent with arguments in Arora et al. (2021c, 2023), our analysis also suggests that company involvement was conditional on estimating enough value capture potential. Thus, our finding that a reduction in demand uncertainty, and particularly in technological uncertainty, led to an increase in company patenting in hardware, a value capture complementary asset for involvement in open science software innovation, adds to the literature by suggesting a potential strategy to navigate the incubation stage.

This is particularly important for the advancement of enabling technologies where value capture is relatively difficult (Teece, 2018; Gambardella et al., 2021). Value creation from quantum

hardware is limited without advancement in quantum software and a feedback loop between the two. Yet, value capture from at least one of them is essential. For quantum computing, it appears that potential value capture from hardware helped ensure company involvement in software.

These results also add to arguments in Moeen and Agarwal (2017) and Moeen et al. (2020) about the role of intellectual property (IP) protection and ecosystem uncertainty during incubation, by suggesting a strong role for both IP protection and ecosystem uncertainty for enabling technologies. These studies note that, during the incubation period, companies are less focused on IP because technological and demand uncertainty create ambiguity about where to focus IP efforts. Similarly, ecosystem uncertainty is less important in the presence of high demand and technological uncertainty. Without some clarity about a feasible technological design and a minimal customer value proposition, an ecosystem is hard to imagine. Our results suggest that the issues of IP protection and ecosystem uncertainty may take a much more central role during the incubation phase of an enabling technology. The IP can serve as an important complementary asset to incentivize company involvement in enabling technology innovation, while ecosystem uncertainty can hold back the development of an enabling technology. In the case of quantum computing, value creation needs both hardware and software innovation.

We proceed by providing background information about quantum computing, followed by drawing insights from the literatures on the incubation stage of technology, on the roles of industry and academic in innovation, and on enabling technologies. We then describe our data and methods, before turning to describing the three eras highlighted above. In doing so, we document how the relative roles of company and university innovation have changed in this emerging industry. We then conclude by further connecting the changes we document back to the literature.

2. Quantum Computers

The term quantum computer refers to a computational device designed to process operations on data based on quantum mechanics phenomena such as superposition and entanglement. The idea of a quantum computational device can be traced back to 1982, to the work of the Nobel Prize–winning physicist Richard Feynman (1982), who showed that a classical Turing machine would experience an exponential deceleration when simulating quantum phenomena whereas his theoretical quantum simulator would not.

Quantum mechanics studies the behavior of invisible particles at atomic and subatomic scales. These particles are subject to laws that differ from those of classical physics. They exist in a

superposition of two states until measured. Quantum computing aims to harness the power of this behavior. Whereas classical computers encode data into binary bits that take values of either 0 *or* 1 at any given time, quantum computers encode data in qubits (quantum bits) that exist in a superposition of 0 *and* 1. This means that a quantum computer with n qubits can be in an arbitrary superposition of up to 2^n different states simultaneously, whereas a classical computer with n bits can only be in one of the 2^n states at any given time. Thus, if large-scale working quantum computers can be developed, they will enable dramatic increases in computational power relative to classical computers.

Hypothesized applications of quantum computers are far-reaching and have significant welfare implications (e.g., Ladd, Jelezko, Laflamme, Nakamura, Monroe and O'Brien, 2010). For example, quantum computers are theorized to be capable of providing significant computational speedups for simulating physical systems, big data analysis, and artificial intelligence (AI). Simulating physical systems is important, as various frontier research trajectories such as nanotechnology rely on understanding the behavior of quantum systems (Nielsen and Chuang, 2000; Ladd et al., 2010). Quantum computers may also accelerate the solving of complex optimization problems such as the pairing up of molecules based on their characteristics. The processing limitations of classic computers are argued to be a hindrance to significant breakthroughs in research fields such as computational biology, nanotechnology, and, more broadly, medicine and pharmaceuticals. Quantum computers may also overcome the processing limitations of classical computers in analyzing very large datasets. An example to consider is the need to analyze the information generated by colliding subatomic particles. It is documented that the Large Hadron Collider at CERN "captures 5 trillion bits of data—more information than all of the world's libraries combined—every second" (Ouellette, 2013). The expected benefits of quantum computing extend even further, with scientists detailing a broader impact in AI research that considers, among other things, the problem of consciousness of machines (Powell, 2013).

These benefits remain elusive. Despite considerable innovation in quantum computing since 1982, it is not clear that a robust quantum computing industry will emerge. As with other emerging technologies, there remains both demand uncertainty as to the characteristics of a quantum computing market and technological uncertainty as to the feasibility of developing large scale useful quantum computers.

3. Theoretical background

We describe the emergence of quantum computing guided by three streams of literature. First, we build on the literature documenting the growth of new industries through several stages from incubation to emergence and growth to maturity and shakeout (e.g. Agarwal, Moeen and Shah, 2017). We focus on the less explored incubation stage where economic actors focus on innovation efforts to bring a new product or service to market. Because our focus is on this early stage of industry evolution, we also draw from studies that evaluate the distinct roles of companies and universities in innovation (e.g., Arora et al., 2021a). Last, we build on the literature on enabling technologies with an emphasis that complementary innovations together create productivity growth in new industries (e.g. Rathje and Katila, 2021; Bresnahan and Trajtenberg, 1995). We do so because technologies vary in their degree of reliance on complementary innovation in order to generate market value.

3.1. Incubation stage

A rich strategy literature explores the evolution of industries (Gort and Klepper, 1982; Utterback and Suarez, 1993; Agarwal and Bayus, 2002). However, until relatively recently, the focus has been on stages of industry evolution after successful commercialization, and less on the earlier incubation stage (Agarwal, Moeen and Shah, 2017). Agarwal et al. (2017) define this stage as "a pre-production period, wherein actors leverage resources and capabilities that are not self-sustained by revenue." (pg. 300). Uncovering factors that facilitate or impede the innovation process during this stage is crucial to understanding how innovation efforts can generate value. This is difficult because data is generally scarce during the incubation stage. It is rare to observe an innovation from its first appearance in the scientific literature to serious investment by universities, companies, and government.

Quantum computing provides an opportunity to contribute to our understanding of the incubation phase. As of the writing of this paper, quantum computing is not self-sustained by revenue. By examining this technology from its initial conception through large-scale investment, it is possible to explore hypotheses on the incentives of companies and universities in reacting to, and guiding, changes in innovation in a new industry.

Quantum computing falls under the category of industries that begin with a scientific discovery as the trigger event -- Feynman's (1982) work -- similar to hybrid corn and nanotechnology (Agarwal, Moeen and Shah, 2017). The discovery marks the beginning of an incubation stage which can last decades (Moeen, Agarwal and Shah, 2020), ending with commercialization that generates sufficient revenue for self-sustainment or abandonment.

Agarwal et al. (2017) provide a comprehensive description of the incubation stage. In this stage, the goal is to reduce technological and demand uncertainty. These uncertainties are qualitatively different than in later stages of industry evolution. During incubation, technological uncertainty refers to uncertainty about achieving a feasible technical design and demand uncertainty refers to uncertainty about what constitutes a minimal value proposition for potential customers, when customers themselves do not know their preferences (Moeen, Agarwal and Shah, 2020; Christensen and Bower 1996; von Hippel, 1986). In contrast, during later stages, technological uncertainty is more about technology's features and cost, and demand uncertainty is more about customers' understanding of a functional technology and its features. In other words, in the incubation stage, it is unclear whether a commercially useful technology is feasible, and it is unclear exactly what it means for the technology to be commercially useful.

Reducing these uncertainties requires the involvement of various economic actors that employ their diverse knowledge bases in open knowledge sharing and development. Knowledge residing in universities plays a key role, but so does knowledge from companies looking to diversify. Thus, knowledge sharing among these economic actors is essential, with the collaborative efforts aimed at experimentation that could shed light on feasible technical designs and customer preferences for a minimal value proposition. This is in line with Rosenberg's seminal research that highlights the importance of open science experimentation through interaction between diverse economic actors (Rosenberg, 1974, 1990, 1992; Rosenberg and Nelson, 1994, 1996; Mowery and Rosenberg, 1993, 1998). It highlights the importance of these dynamics for a successful incubation period that is necessary for technological innovation to create value.

However, it remains unclear if the prospect of value creation is sufficient to compel these diverse economic actors to engage in scientific experimentation and collaboration. Studies that evaluate the distinct roles of companies and universities in scientific research provide further guidance.

3.2. Innovation in companies and universities

Open science often originates with university scientists who publish academic publications. Corporate scientists nevertheless play an important role in innovation. Not only are companies that employ scientific researchers and invest in instrumentation and experimental equipment better able to absorb new knowledge (e.g., Cohen and Levinthal, 1990), but corporate scientific research can be complementary to university science (e.g., Rosenberg, 1994). For example, Arora, Belenzon, Patacconi and Suh (2021, p. 74-78) emphasize that corporate labs have access to richer and more diverse resources and focus more towards solving practical problems. In a comprehensive review of the

academia-industry collaboration literature, Perkmann et al. (2013) detail these and other complementary differences between university and corporate researchers. It is this complementarity that Agarwal et al. (2017) denote as a necessary ingredient of a successful incubation phase.

However, the incentives for corporations to engage in scientific research appear to be declining over time, with an increasing division of scientific research labor where corporations focus on patenting that relies more and more on scientific research produced in universities rather than inhouse (Arora, Belenzon and Patacconi, 2017; Arora, Belenzon, Patacconi and Suh, 2021). Moreover, Arora, Belenzon and Sheer (2021) show that even for companies that maintain some involvement in scientific research, the level of investment is conditional on ownership of complementary assets that ensure sufficient returns to countervail spillovers to rivals. In other words, companies are less likely to engage in open and collaborative scientific experimentation during an incubation stage if they estimate a low value capture potential relative to the total potential value creation. Complementary asset ownership mitigates this issue. For example, Arora, Belenzon, Patacconi and Suh (2021) note that corporations endowed with rich datasets invest heavily in AI scientific research because, at this stage of AI developments, it is clear that the value creating technology is machine learning, a prediction technology (Agrawal, Gans and Goldfarb, 2022) that requires data to generate value.

In quantum computing, the decline in corporate science may hinder the development of useful quantum computers because the complementary role of rich corporate resources is necessary to push quantum computing hardware innovation forward. It is expensive to engage in experimentation to build quantum hardware. However, it is unclear what might constitute complementary assets to quantum hardware to incentivize companies to engage in scientific research on quantum hardware.

This bottleneck also affects quantum computing software innovation which depends on advancements in hardware. Quantum software is necessary to create value from quantum computers, as hardware without software applications is not useful. Moreover, quantum hardware would constitute a complementary asset to quantum computing software, thus likely incentivizing company software innovation. However, without incentives to invest in hardware, it is unclear how to advance software, creating a conundrum.

These observations imply that the decline in corporate science and reliance on complementary asset ownership for involvement in scientific research are particularly damaging for technologies where the magnitude of value creation increases with complementary invention (Teece, 2018). These technologies are called enabling technologies. We turn to the emerging strategy literature focused on

these technologies (e.g., Teece, 2018; Gambardella, Heaton, Novelli and Teece, 2021; Rathje and Katila, 2021) for further guidance.

3.3. Enabling technologies

Enabling technologies share many of the features of general purpose technologies (GPTs), particularly a feedback loop between complementary technologies, but may not have the macroeconomic impact of GPTs. True GPTs are rare, with recent examples including the internet and AI (Lipsey et al., 2005; Goldfarb, Taska and Teodoridis, 2023). Steam engines and electricity are earlier GPTs. Examples of enabling technologies include light detection & ranging (LIDAR) and 5G broadband cellular networks (Rathje and Katila, 2021). The enabling technologies literature shows that technologies can be represented on a continuum of their propensity to enable other innovations (Rathje and Katila, 2021), with GPTs representing technologies with the highest enabling potential.

Enabling technologies generate increasing value through an innovation feedback loop. The viability of an enabling technology is initially shown in scientific research followed by applied developments. Once adopted in application sectors of the economy, the applied developments spur additional innovations in these sectors, which, in turn, feed ideas back into further advancing innovation in the producing sector, and so on. The value created increases with each feedback loop. For example, electricity's early uses focused on street lighting and street railways (Lipsey et al., 2005). Innovation in these application sectors led to further improvements in upstream advances in power generation which, over time, translated into other downstream innovations such as those in reorganization of manufacturing plants and household appliances and technologies, all the while the producing sector innovation continued to advance (e.g., from coal burning, to hydropower and nuclear, to wind and solar power).

Quantum computers require innovation in hardware and software. Same as classical computers, it is expected that the value created will increase as advances in hardware make possible advances in software, which in turn inform further hardware innovation, and so on. In this sense, quantum computers require a feedback loop to generate value, like other enabling technologies (Teece, 2018; Rathje and Katila, 2021).

Teece (2018) points out that complementary asset ownership is a weak value capture strategy in the case of enabling technologies. For these technologies, relevant complementary assets cannot be completely envisioned during early stages, are developed over time, and require application sector knowledge. Furthermore, Arora et al. (2021c) demonstrate that companies have little incentive to engage in scientific research without a clear value capture strategy. The diversity and creativity of

software applications for classical computers over time demonstrate this challenge. The breadth of these applications would likely have been difficult to imagine during the early days of classical computing hardware development. That means "the innovator of an enabling technology has a special business model challenge because the applicability to many downstream verticals forecloses, as a practical matter, ownership of all the relevant complements" (Teece, 2018, pg.1). Combined with the insights of Arora et al (2021c), the consequence is a significant reduction in company incentives to invest in enabling technology innovation in the first place.

As a solution, Teece (2018) suggests a strong focus on intellectual property (IP) protection. Gambardella et al. (2021) demonstrate that strong IP protection is not always sufficient for enough value capture to justify engaging in enabling technology innovation. IP helps most when uncertainty about a dominant design is sufficiently reduced and when the innovator has a significant amount of complementary knowledge about potential applications.

3.4 Implications

To recap, the above discussion suggests that for a technology to advance to create a new productive industry, it must successfully complete an incubation stage. To do so, university and company innovators need to engage in open scientific experimentation and collaboration. This is necessary to reduce demand and technological uncertainty to create economic value. However, while open science is a foundational principle of universities, it is not one of companies. Companies need to anticipate enough value capture potential from their efforts to justify involvement in value creating open science innovation. For enabling technologies, the traditional value capture strategy of complementary asset ownership is insufficient. A combination of intellectual property, complementary asset ownership, and complementary application knowledge ownership, especially once there is reduced uncertainty about the market for a particular dominant design, constitute a superior value capture strategy.

This implies that reductions in levels of demand and/or technological uncertainty should lead to an increase in innovation efforts since companies will be more incentivized to engage in open science. That is because a reduction in either demand or technological uncertainty reduces uncertainty about the market for a dominant design. A reduction in demand uncertainty is a step forward in clarifying what constitutes a commercially viable technological design. A reduction in technological uncertainty is a step forward in clarifying what constitutes a feasible technological design.

If indeed there are complementarities between university and company scientific innovation, then the increase in open scientific research should include collaborative innovation efforts.

Collaboration also benefits the transfer of knowledge from these scientific research efforts to follow-on applied innovation in companies (e.g., Arora et al., 2021a).

Because quantum computing is an enabling technology that evolves through a feedback loop, the initial burst in open scientific innovation should be in hardware. Demand and/or technological uncertainty keeps company involvement low because of low value capture potential. Then, a reduction in uncertainty should increase company open science hardware innovation more than university open science hardware innovation. In contrast to companies, universities are less incentivized to change behavior in open science hardware innovation after a reduction in uncertainty because universities are not incentivized by value capture in the same ways as companies.

Software open science innovation should not be far behind the increase in open science hardware innovation because insights from one should lead to insights into the other and so on, as per the feedback loop evolution of enabling technologies. The increase should come from both companies and universities because the university-complementary company open science hardware innovation feeds ideas for advancing software. Moreover, for companies, building knowledge in software through open scientific research is part of the value capture strategy of enabling technology innovation as identified in Gambardella et al. (2021). Involvement in software open science research allows companies to build knowledge about potential applications.

IP should also play an important role. Not only it is part of the value capture strategy of enabling technology innovation, but IP in hardware constitutes a complementary asset to software innovation.

Companies should be more likely to seek IP protection in hardware following a reduction in technological uncertainty, when compared to a reduction in demand uncertainty. Moeen and Agarwal (2017) and Moeen, Agarwal and Shah (2017) note that, during the incubation period, companies are less focused on IP protection of their innovation efforts. It is not clear where IP efforts should be directed given uncertainty about what constitutes a feasible technological design or a commercially viable technology. However, given the importance of IP protection for the value capture strategy of enabling technology innovation, we expect companies to invest in IP during incubation more than they would invest during incubation of a non-enabling technology. A reduction in technological uncertainty is more helpful to identify potentially useful IP than a reduction in demand uncertainty, although both should benefit IP efforts. If the technological design is not feasible, there is nothing to attempt to commercialize.

In summary, the theoretical background in the literature on the incubation stage of an industry, innovation in companies and universities, and enabling technologies, suggests that following themes for quantum computing.

1) Reductions in demand uncertainty and/or technology uncertainty will lead to an increase in company open science innovation efforts in both hardware and software.
2) Reductions in demand and/or technological uncertainty will lead to an increased rate of open science collaboration between universities and companies in both hardware and software.
3) Increased company involvement in open science hardware innovation following reductions in demand and/or technological uncertainty will lead to an increased rate of university open science software innovation.
4) Reductions in demand and/or technological uncertainty will lead to an increase in company IP protection efforts, mostly in quantum computing hardware. The increase will be higher for a reduction in technological uncertainty when compared to a reduction in demand uncertainty.

We use these emerging themes to guide our data analysis. Quantum computing provides a rich setting that allows us to track a technology's evaluation through the incubation stage, and to separate the effects of a reduction in demand uncertainty from those of a reduction in technological uncertainty. While it may not be feasible to uncover causal insights from the data, we hope that our correlational analysis, guided by the above theoretical themes, provides useful documentation of hard-to-observe incubation stage patterns.

4. Data and Empirical Strategy

We analyze data on the evolution of quantum computing innovation from its inception in 1982 until 2020. We collect data on academic publications and patents in quantum computing and divide our analysis into three different eras. In each era, we observe different patterns of company and university innovation. The first era starts in 1982, with the seminal work of Richard Feynman that constitutes the trigger event for quantum computing innovation. It ends in May 2011 with the commercial lease of D-Wave's quantum machine to Lockheed Martin. The second era starts after the D-Wave lease, and ends in May 2016 when IBM provided access to their quantum computer via Cloud, enabling broad engagement with a prototype. The third era starts after the IBM Cloud event and our analysis of it ends in 2020, the last available year in our data. Section 5 provides details.

4.1. Datasets

Our main data come from PatentsView, a database commissioned by the Office of the Chief Economist at the United States Patent and Trademark Office (USPTO), and from the Microsoft Academic Graph (MAG), one of the largest databases for academic publications (e.g., Yin et al., 2022; Wang et al., 2020; Arora et al., 2021b).

We analyze USPTO patent data collected from PatentsView. The USPTO assigns patents to different technology classes based on the Cooperative Patent Classification (CPC) schema. We identify quantum computing patents using the class "G06N10/00" ("Quantum computing, i.e., information processing based on quantum-mechanical phenomena"). We identified 1,575 granted quantum computing patents with application years between 1993-2020, with the first ever granted quantum computing patent being applied in 1993.

To identify patents assigned to universities separately from patents assigned to companies, we restrict our data to the "company or corporation" assignee type in PatentsView. This category clusters all university and company patents. To further separate the two types of assignees, we search for keywords. We define a company affiliation as those assignees with names that contain "*corporat*" or "company," or names that end with "inc", "ltd", "llc", "corp", or "limited."[6] We define a university affiliation as those assignees with names that contain "universi*", "college," or "institute of techno*". We perform a series of manual checks to ensure classification accuracy.

We analyze academic publications and conference proceedings data collected from the Microsoft Academic Graph (MAG), one of the largest databases for academic publications (e.g., Yin et al., 2022; Wang et al., 2020; Arora et al., 2021b). A unique advantage of MAG is that it applies machine learning techniques to construct a non-mutually exclusive hierarchy of research fields.[7] For example, under the MAG research field "Quantum", there are 778 quantum-related research subfields, such as "Quantum Computer", "Quantum Entanglement", "Quantum Measuring", etc. We identify academic publications related to quantum computing using the MAG research field "Quantum Computer" for a total of 23,518 academic publications and conference proceedings in quantum computing research spanning the period 1982 to 2020.

To identify academic publications authored by university scientists separately from publications authored by company scientists, we rely on the MAG classification of author affiliation. MAG

[6] "*" is used for wildcard search and it represents any number of characters.
[7] This feature is similar to the MeSH keywords in the PubMed database, which covers biomedical academic publications.

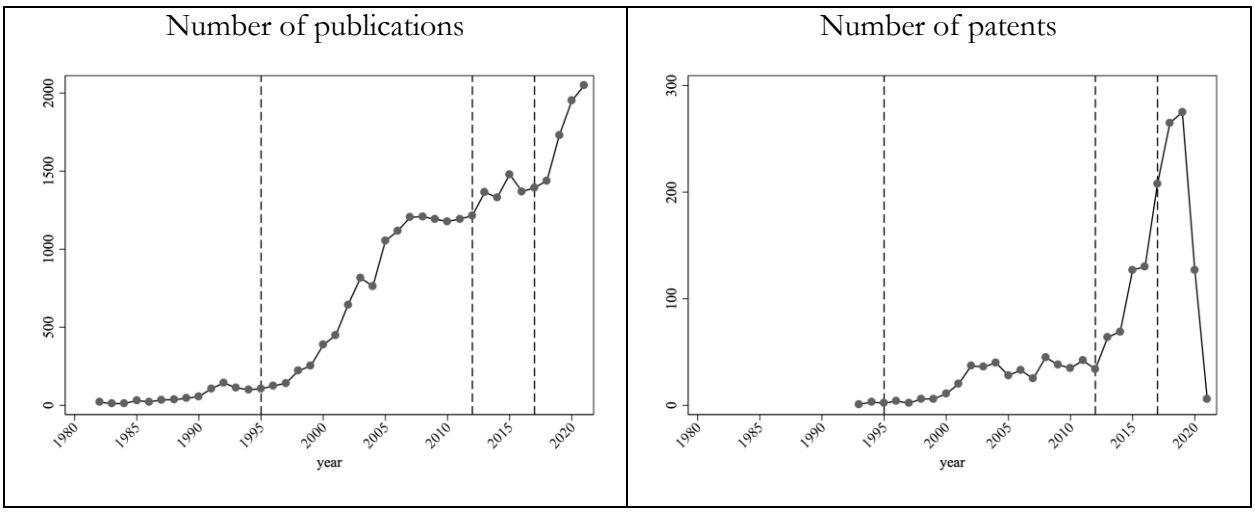
provides information on the types of most affiliations,[8] which include university, company, government, nonprofit, etc. We define a company affiliation as MAG affiliation "company" and we define a university affiliation as MAG affiliation "university."[9] In cases where affiliation types are not available, we use the same keywords as in our patent data to distinguish between authors with a company affiliation and authors with a university affiliation.

Figure 2 shows a steady increase in the number of quantum computing publications and patents in these databases over time. The decrease in the number of patents in 2019 and 2020 is a function of right truncation of the data combined with a delay between patent application and patent approval. We date patents by application date, but only observe them once approved.

Among the quantum computing patents, 1,333 patents are assigned to firms, 213 patents are assigned to universities, and 41 patents are assigned to firms and universities (coassignees). There are 262 distinct assignees that ever patent in quantum computing between 1993 and 2020. 168 of them are industry assignees, and 83 are university assignees. Among the 168 industry assignees, 127 of them had at least one patent (in any patent class) before 2011 and 145 had at least one patent (in any patent class) before 2016; 60 of them had at least one quantum computing patent before 2011 and 104 had at least one quantum computing patent before 2016. Among the 83 university assignees, 82 of them had at least one patent (in any patent class) before 2011 and all of them had at least one patent (in any patent class) before 2016; 42 of them had at least one quantum computing patent before 2011 and 62 had at least one quantum computing patent before 2016.

[8] MAG identifies the affiliation type via the Global Research Identifier Database.
[9] Our results remain robust to including public research labs as university.

Figure 2. Quantum computing innovation over time



4.2. Identifying quantum computing hardware and software trajectories using topic modeling

We identified four main categories of quantum computing patents and publications, two comprising hardware and two software.[10] The two hardware categories are (1) methods of building qubits (e.g., superconducting, quantum dot, trapped ions, etc.) and (2) models of manipulating qubits for computation (gate-, adiabatic-, topological-based, etc.). The two software categories are (1) techniques that address obstacles to quantum computation (e.g., qubit manipulation, error correction) and (2) quantum computing applications (e.g., quantum algorithm, quantum machine learning, quantum optimization, etc.). In our analysis, we focus on the hardware/software distinction as most important for understanding the changes in innovation in quantum computing, in line with the equivalent distinction in classical computing. However, future research might benefit from exploring the four categories separately.

The main challenge is that these categories are not sharply identified in either the patent data or the academic publication data. For example, until recently, the CPC patent classification has only provided a main CPC patent class for quantum computing technologies (G06N10/00). In 2022, the CPC announced a more granular classification of quantum computing patents that breaks down the G06N10/00 class into various subclasses such as G06N10/20 for methods of manipulating qubits and G06N10/40 for methods for building qubits. The patent reclassification process using the new CPC schema is under development at the time of this paper's writing. Nevertheless, the fact that the

[10] We worked with a research assistant studying quantum computing, Vivek Dhande, to help us understand the content of the patents and papers.

newly announced CPC schema maps onto the categories we identified through our conversations with quantum computing experts lends validity to the categories of interest we identified.

To address this challenge, we adopt a well-established machine learning topic modeling technique called Hierarchical Dirichlet Process (HDP) to classify our quantum computing publications and patents into the different categories (Teh et al., 2006; Teodoridis et al., 2022).[11] HDP is an unsupervised topic model that performs a hierarchical Bayesian analysis of text (Buntine and Jakulin, 2004; Teh et al., 2006; Hofmann, 1999). The intuition is that of a generative process, where the data are assumed to be characterized by a set of observed variables (words in the document) that developed from a set of hidden variables (the topic structure). The algorithm generates collections of words (topics) that are found to appear together in the input text with a certain probability. In other words, the input text is "assigned" to topics with a certain probability. Teodoridis et al. (2022) describe the algorithm in detail, including an application to USPTO patent data. Furman and Teodoridis (2020) employ the same process to analyze changes in academic publication innovation trajectories.

We apply the HDP topic modeling algorithm on quantum computing academic publications and patents between 2001 and 2020, the end of our observation period at the time of data collection. We focus on years after 2000 because the count of publications and patents is low before that; the very early years can be described without any sophisticated methods. We follow the convention in topic modeling analysis to conduct data cleaning and preprocessing steps (Furman and Teodoridis, 2020; Teodoridis et al., 2022; Kaplan and Vakili, 2015). We perform detailed and rigorous vocabulary cleaning with the help of a research assistant with a background in quantum computing research. Specifically, we convert the acronyms in the text into fully spelled words (e.g., QC into "quantum computing")[12] and identify bigrams, trigrams, four-grams and five-grams, namely groups of two, three, four, and five words that have a meaning distinct from that of each of the words separately (Krieger et al., 2022; Arts et al., 2021). In addition, we conduct additional standard preprocessing steps such as lowercasing, tokenizing, lemmatizing, and removing stop words and words with only one character (Teodoridis et al., 2022; Arts et al., 2021).

Upon executing the HDP algorithm, we obtain 74 HDP-generated topics and the words that describe the topics.[13] After confirming that these topics provide an accurate representation of the

[11] The HDP is a more advanced version of the more well-known latent Dirichlet allocation (LDA). A main advantage is that it can automatically determine the optimal number of topics (Teh et al., 2016). In this way, HDP can capture a more nuanced topic structure in the data, including topics that might not be ex ante on researchers' mind.

[12] We tested the accuracy of such acronym conversion using random samples. We achieved an accuracy of over 98%.

[13] We follow best HDP practices by adopting a 2,000-iteration stopping rule (Boyd-Graber et al., 2017). To ensure the stopping rule is optimal, we plot the likelihood metric and the number of algorithm-identified topics per number of

technological landscape in quantum computing, with the help of our quantum computing research assistant, we manually label these topics to identify the ones that comprise the four different categories discussed above, plus a set of other, smaller topics that are generic. Appendix A, Figure A1 shows three example topics for each of the four categories in a word cloud format.[14] The word clouds present the top words describing each topic. Words that are closer to the center and larger in size are of higher relevance to the topic. As suggested in the figure, the word clouds are consistent with our interpretation of the topics and of the labels assigned. For example, topic 1 is comprised of top words such as "trapped ion", "optic", "laser", "atomic", which are frequent keywords describing a trapped ion approach for building qubits for quantum computing, and it is highly consistent with the definition of a trapped ion quantum computer – "Trapped ion computers are quantum computers in which the qubits (quantum units of information) are ions trapped by electric fields and manipulated with lasers."[15] Topic 14 is comprised of top words such as "adiabatic", "hamiltonian", "ground state", "adiabatic quantum computing", "time dependent", "evolution", which is consistent with the description of an adiabatic quantum computation model – "First, a (potentially complicated) Hamiltonian is found whose ground state describes the solution to the problem of interest. Next, a system with a simple Hamiltonian is prepared and initialized to the ground state. Finally, the simple Hamiltonian is adiabatically evolved to the desired complicated Hamiltonian. By the adiabatic theorem, the system remains in the ground state, so at the end the state of the system describes the solution to the problem."[16]

Figure 3 compares company and university patents and papers, for hardware and software. Because there are many more company patents than university patents, and many more university publications than company publications, we use different scales. Company values are shown on the left side and university values on the right side. This enables an easier comparison of trends over time.

The main takeaways from this raw data are a sharp increase in hardware patents after 2011 and an increase in software publications after 2016. From image alone, differences between the companies

iterations (Appendix A, Figures A1a and A1b). The plots show how the likelihood metric and the algorithm-identified number of topics change with each iteration. A good point to stop iterating is when the plots show a relatively flat line, namely when the likelihood metric and the algorithm-identified number of topics are stable. As shown in the figures, the shape of the plotted curves suggests convergence at 2,000 iterations, which indicates that the algorithm performance is optimized, and the optimal number of topics is identified (Boyd-Graber et al., 2017). Our empirical results remain robust to an alternative number of iterations that also fall under the flat line area of the likelihood metric.

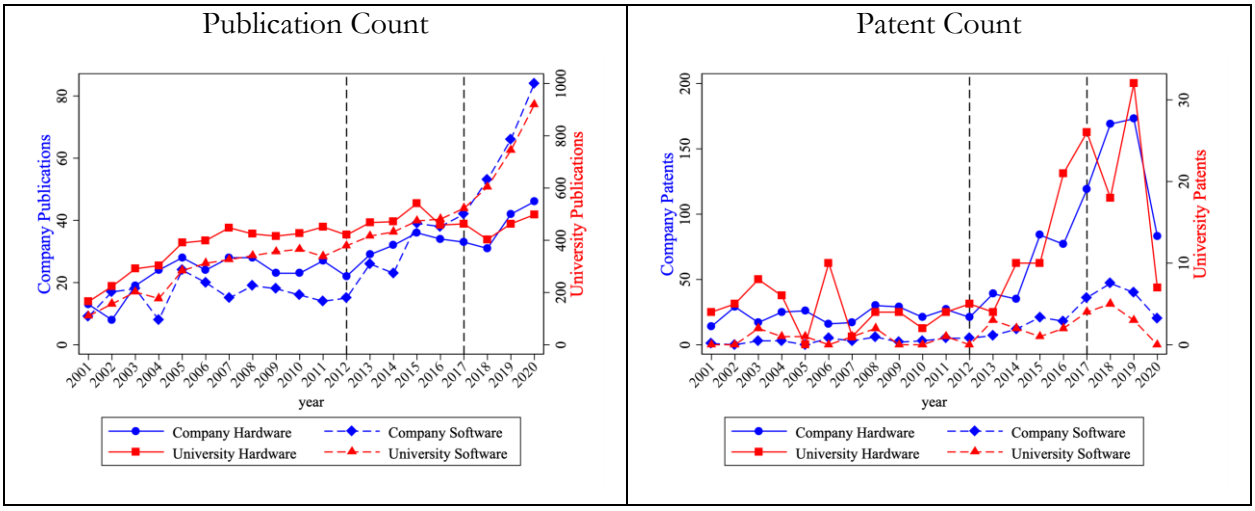
[14] We present the full list of topics and words generated by the HDP topic modeling algorithm in our Appendix A, Table A1. We categorize 13 topics as Hardware: Building Qubits, 5 topics as Hardware: Manipulating Qubits, 7 topics as Software: Obstacles to Quantum Computation, 14 topics as Software: Applications, and the remainder as Other.

[15] https://phys.org/news/2022-08-coherently-qubit-ion-species.html

[16] https://en.wikipedia.org/wiki/Adiabatic_quantum_computation. Accessed April 9th, 2023.

and universities are not readily apparent. Nor is it clear whether patents and publications in related areas followed a similar trajectory. Therefore, we next turn to more systematic empirical analysis to see if trajectories differ across companies and universities, and relative to hardware and software. We present descriptive statistics for all variables in Appendix B, Tables B.1 and B.2, demonstrating a substantial right skew in publications and patenting.

Figure 3. Overall changes in the rate of innovation following the two events



4.3 Measuring change in patents and papers, by topic, after the 2011 and 2016 events.

We conduct an analysis at the topic level to estimate changes in the counts of publications and patents in the two trajectories after D-Wave's entry event and after the IBM Cloud launch event. We compare changes in counts of quantum computing hardware and software publications and patents with changes in counts of publications and patents in control groups. Thus, our dataset is a panel of counts of academic publications and patents per year per MAG research field (for academic publications) or per CPC classes (for patents), by universities and companies.

We conduct a synthetic difference-in-differences estimation (SDID) (Arkhangelsky, Athey, Hirshberg, Imbens and Wager, 2021). SDID is an extension of the standard difference-in-differences (DID) method. It combines two-way fixed effects with attractive features of the synthetic control (SC) method of constructing a counterfactual. As suggested and proved in Arkhangelsky et al. (2021), the SDID method has a few advantages relative to DID and SC. In SC, a synthetic control unit is created as the weighted average of all untreated units that best match the pre-treatment trend of the treated unit. The SC method is not amenable to large panel analyses because it does not include time weights and unit fixed effects. The lack of time weights is problematic because the difference between the

treated and control groups varies over time in the pre-treatment period, and, in cases where this difference over time is predictive of the differences in the post-treatment period, the estimation results would be biased. Omitting unit fixed effects is problematic because they could explain much of the variation in the outcome variable. Therefore, by including unit fixed effect and time weights, SDID has improved precision and robustness over SC.

The SDID method also has benefits over the standard DID. By including both unit and time weights, SDID allows more emphasis on control units that are more similar to the treated units in the pre-treatment period, and on time periods that are more similar to the treatment periods. This improves the robustness and precision of the estimator by implicitly removing systematic (predictable) parts of the outcome. In essence, the idea of weighting is closely aligned with matching empirical practices, where the treated and control units in raw data rarely exhibit parallel trends and researchers often need to employ various techniques, such as Coarsened Exact Matching (CEM), to address this issue. The SDID estimator makes this process automatic with statistical guarantees.

For our estimation of changes in patenting activity, we use all other patent classes under the parent "Quantum Computing" CPC class of our treated class G06 ("Computing; Calculating; Counting") as candidate controls. These classes capture all other technologies related to computing. From this set, we exclude all artificial intelligence (AI) patents because AI has experienced unrelated events that led to an increasing patenting trend during our observation period. We identify AI patents based on the Artificial Intelligence Patent Dataset created by the USPTO (Giczy, Pairolero and Toole, 2021).[17] Our candidate control group includes 4,233 CPC classes, which on average contain 357 patents with application years between 2007-2020.[18]

We follow a similar process to identifying candidate control research fields for our academic publication analysis. Specifically, we use all other 777 research fields under the "Quantum" MAG research field as the candidate controls. The average number of academic publications and conference proceedings in the candidate control research fields is 629. Our results remain robust to various alternative ways of defining the treatment and control groups for academic publications.[19]

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[17] https://www.uspto.gov/ip-policy/economic-research/research-datasets/artificial-intelligence-patent-dataset

[18] An alternative control group for our patent analysis would have been the group of quantum-based technology patents. Unfortunately, CPC does not have a class that identifies these patents. We do find some other quantum-based technology patents scattered across different patent classes, such as B82Y10/00 ("Nanotechnology for information processing, storage or transmission, e.g., quantum computing or single electron logic"), B82Y20/00 ("Nanooptics, e.g., quantum optics or photonic crystals"), and Y10S438/962 ("Quantum dots and lines"). Our results remain robust to using these classes as candidate controls.

[19] First, we tried alternative definitions of control topics. Instead of using other subtopics under "Quantum" as control groups, we used all other subtopics under "Quantum Mechanics" – a MAG research field that is one level higher than

We separately estimate SDID for academic publications and for patents. Matching covariates are not required in SDID, as the estimator is focused on the pre-treatment trends of the dependent variable, as explained above (Arkhangelsky et al., 2021). As such, we conduct all our main analyses without including any covariates in our estimations in addition to the treated and after period covariates.

Our main outcomes of interest are the number of patents and the number of academic publications in hardware and software respectively, before relative to after 2011, and before relative to after 2016. We focus on two 10-year observation windows, namely 2007 to 2016 and 2011 to 2020. Because both events occurred close to the middle of their respective years, we use the first year after each event as the cut-of between the before and after periods. We also separately consider publications and patents authored by companies, universities, and in collaboration.[20]

5. Uncertainty reduction during the incubation phase of an industry

In this section, we first briefly describe patenting and publishing in quantum computing prior to 2011. We then detail how patenting and publishing changed, in hardware and software, after 2011 and again after 2016. While the analysis is quantitative, the interpretation should be as a narrative understanding of the evolution of innovation in quantum computing over time, guided by the four themes identified in Section 3. While we identify particularly likely trigger events for the changes in 2011 and 2016, empirically all we document is how the nature of innovation changed after 2011 and after 2016.

5.1 Quantum computing prior to 2011

The starting point for research in quantum computing was the 1982 academic publication "Simulating Physics with Computers" of Feynman's speech at the 1981 MIT Physics of Computation conference. Related to work by Paul Benioff, this publication hypothesized that a computer based on quantum principles would be better at simulating quantum physics than a

"Quantum" – as control groups. We also tried using all subtopics under "Computer Science", the combination of "Computer Science" and "Quantum," and the combination of "Computer Science" and "Quantum mechanics." The results remained robust. Furthermore, instead of relying on the MAG research fields, we also used a keyword-based approach to identify the treatment group. We defined quantum computing as academic publications and conference proceedings that included keywords such as "quantum computer", "quantum computing", and "quantum computation." Our main results remain robust.

[20] We used authors' affiliation to identify university, company, and collaborative publications. We identify university, company, and collaborative patents based on the assignee names. Patents assigned to companies could include patents invented by academic researchers who also hold a position in a company. Unfortunately, USPTO does not provide the affiliation information of patent inventors but rather only the institutional assignee for the patent. In this way, we underestimate the number of collaborative patents.

standard binary computer. In 1985, David Deutsch showed the possibility of a universal quantum computer, such that there was a quantum generalization of the universal Turing machine.

By the early 1990s, as shown in Figure 2, academic publications in quantum computing started to grow. This included a combination of research related to hardware, such as work on laser-cooled ions at Max Planck and NIST, and quantum algorithms. Shor's (1994) paper on exponential speedup in the factoring of large numbers demonstrated the use of quantum computers for decryption. The algorithm showed the potential of quantum computers to decrypt data that had been encrypted with what had been seen as unbreakable tools using classical computers. Two years later, Grover's (1996) theoretical algorithm showed another practical application, namely quadratic speedups for database search. Along with other software developments, these algorithms showed that a fully functioning large scale quantum computer would be of value in national security and other impactful applications.

During this time, we also observe the first patent related to quantum computing in 1993 by Hitachi, Ltd, titled "Quantum Memory Device." In 1994, three more quantum computing patents were filed and granted, two by Sony Corporation, and one by IBM. Before 2001, a total of 34 quantum computing patents were granted. Among these was the first D-Wave patent in 1999, the year the company was founded.

The innovation activity picked up in early 2000, particularly in academic publishing. By then, scientists made some progress in building on the early theoretical quantum computing knowledge to reduce some technology uncertainty (1,602 publications before 2000). For example, in 2000 and 2001, scientists from IBM's Almaden Research Center and Stanford University managed to complete an implementation of the Shor's algorithm (Vandersypen et al., 2001).[21] These and similar efforts continued to contribute to reducing technological uncertainty through open-science innovation as observed in the growing rate of academic publications (Figure 2). Figure 3 indicates that these efforts were driven by university scientists. Among the institutions that produced the most publications during this period of time were Los Alamos National Laboratory, California Institute of Technology, MIT, and the IBM Thomas J. Watson Research Center. Figure 3 also shows that the hardware publication volume was somewhat higher than the software publication volume.

[21] Max and Scharfmann (2024) show an increase in academic publications associated with a patent application that builds on open science following the 2001 American Inventor's Protection Act (AIPA). It is possible that some of the post 2001 increase to be a result of AIPA, and not only advance in quantum computing innovation.

Unlike publication, patenting continued at about similar levels until 2011 (Figure 2). Companies patented more than universities at a relatively steady rate of about 30 hardware patents per year through 2011 (Figure 3). Figure 3 also shows that software company patenting and university patenting in both hardware and software remained very low until 2011. 82.5% of the patents between 2001 and 2010 were hardware and 17.5% were software. The top company patent assignees in the first decade of the 2000s were D-Wave, HP, Microsoft, Toshiba, IBM, and Northrop Grumman. The top university patent assignees, albeit with a very low number of patents, were Johns Hopkins, Stanford, University of California, KU Leuven, Northwestern, Texas A&M, University of Michigan, New Mexico Highlands University and University of Toronto. Overall, the number of institutions involved in patenting remained small through 2010, with a total of 55 companies and 36 universities filing approved patents by the end of 2010.

D-Wave, the top patenter during this time period, pursued an alternative approach to a quantum machine. Founded in 1999, D-Wave focused on quantum annealing, a technology that departed significantly from the orthodoxy of the scientific community which believed useful quantum computers required a gate model. Thus, the scientific community did not take D-Wave seriously (e.g., Jones, 2013). Even the 2007 first public demonstration of a D-Wave quantum machine was met with indignation from the scientific community who continued to believe that the development of true quantum computers was many years away (e.g., Pontin, 2007). There was also no easy way to verify that the D-Wave machine was performing quantum operations because the most common method was to simulate the machine's behavior on a more powerful and vetted machine. In the case of the D-Wave machine, this required access to a vetted quantum computer to test the quantum-ness of the D-Wave machine: a conundrum. In 2011, an event involving D-Wave brought this first era to an end.

5.2 Quantum computing patents and publications after May 2011

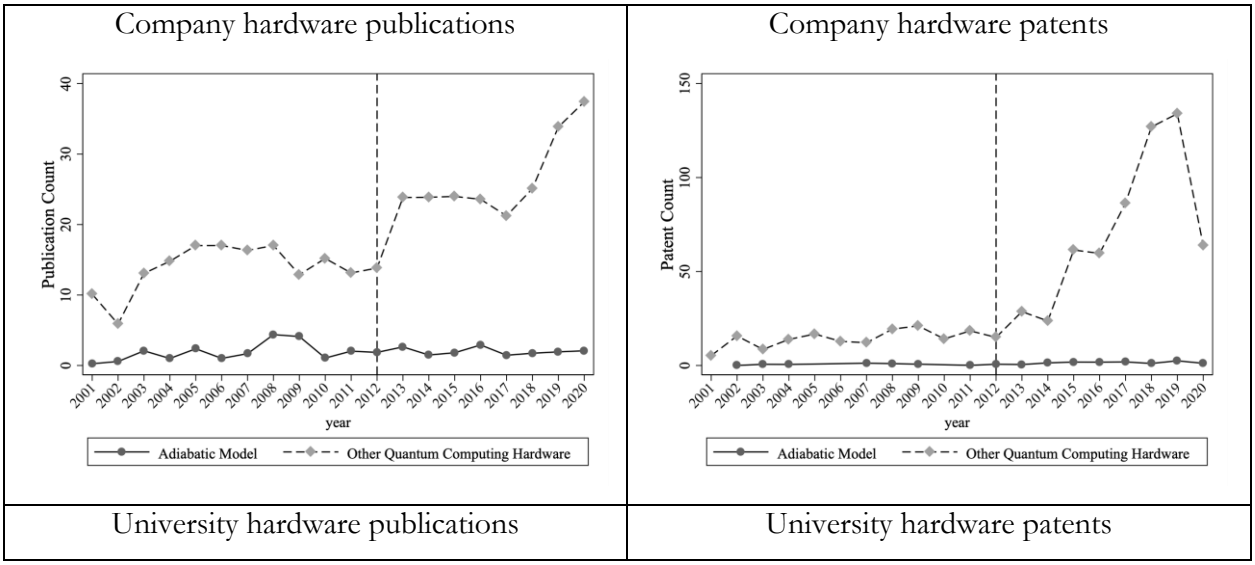
To our knowledge, the main newsworthy event in quantum computing in 2011 was the lease of D-Wave's adiabatic machine to Lockheed Martin. We interpret this as a reduction in demand uncertainty as a large company was willing to invest substantial resources into learning more about possible practical applications of quantum technology.

The May 2011 lease to Lockheed Martin was not viewed as a transaction of a commercially viable product. It remains controversial as to whether that D-Wave machine should even be classified

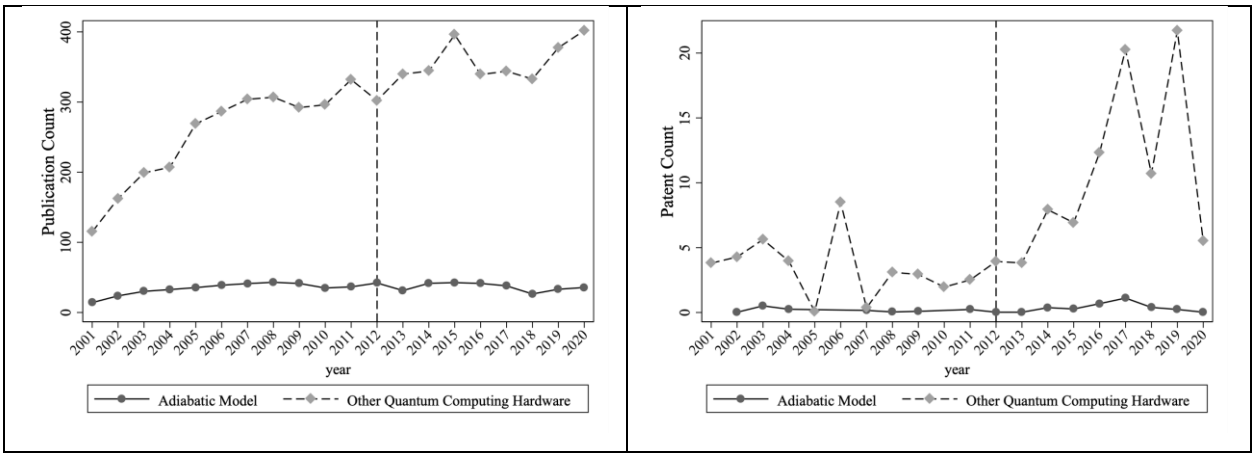
as a quantum computer (e.g., Jones, 2013; Quantum Zeitgeist, 2024[22]). Lockheed Martin acquired a D-Wave machine as part of their Skunk Works division as an engineering novelty that had the potential to contribute to quantum computing innovation efforts. Thus, we view this event as having reduced some demand uncertainty about what constitutes a minimal value proposition for potential customers.

Although technological uncertainty remained substantial (Merali, 2011; Hsu, 2013), an alternative interpretation of this event is that it reduced technological uncertainty, as Lockheed Martin's interest showed that a quantum machine was far enough along to be useful. We argue that this alternative interpretation is unlikely because the increase in patents and publications after 2011 was not driven by innovation in the same area of quantum computing as D-Wave's *adiabatic* machine. Instead, the increase was in *non-adiabatic* quantum computing technologies. Figure 4 compares raw numbers of hardware patents and publications by companies and universities in adiabatic and non-adiabatic quantum innovation. It is clear that there was an increase in other, non-adiabatic, quantum computing hardware, and it is hard to see much of an increase in adiabatic computing.

Figure 4. Adiabatic did not drive the rate increase after the 2011 D-Wave event (raw data).



[22] https://quantumzeitgeist.com/quantum-annealing-vs-gate-based-quantum-computing-round-2



To understand how the reduction in demand uncertainty influenced company and university innovation in quantum hardware and software, we turn to our SDID specification. We focus on a 10-year window around the 2011 event, which we interpret as a reduction in demand uncertainty. The first year in our post period is 2012.

Company patents and publications: Figure 5 shows a sharp increase in company publications and a modest increase in patents in hardware after the 2011 event, in line with our themes 1 and 4 in Section 3.4. Figure 5 is the SDID-generated graphical representation of this estimator. The dotted line is the SDID-selected counterfactual out of our designed group of candidate controls as described in Section 4.3. The solid line is the treated category, here the number of publications and patents in quantum computing hardware. The dark shape at the bottom of the graph represents the time period weights the SDID estimators add to generate an appropriate counterfactual, and so identifies the part of the trend where the comparison group was adjusted. The difference in levels between treated and control categories is a feature of the SDID estimator as explained in Arkhangelsky, Athey, Hirshberg, Imbens and Wager (2021). In addition, SDID produces the ATT estimate which we show at the bottom right corner of the SDID graph. We also include an interpretation of the ATT in percentage change. SDID does not offer other typical regression results, such as the goodness of fit.

In Figure 5.a, we also show the change in company publications and patents separate for publications and patents authored solely by companies from publications and patents that also include collaboration with universities. As per Section 3.4., theme 2, collaboration with universities in producing hardware publications appears to play a significant role. Most of the increase in company involvement in hardware publications is in collaboration with universities (an increase of

21.4% which represents an additional 5.527 publications), although non-collaborative contributions also increase by 13.3% or an additional 1.087 publications.

Figure 5.a. SDID, Company Hardware (pre- and post-2011) – split by collaboration with universities

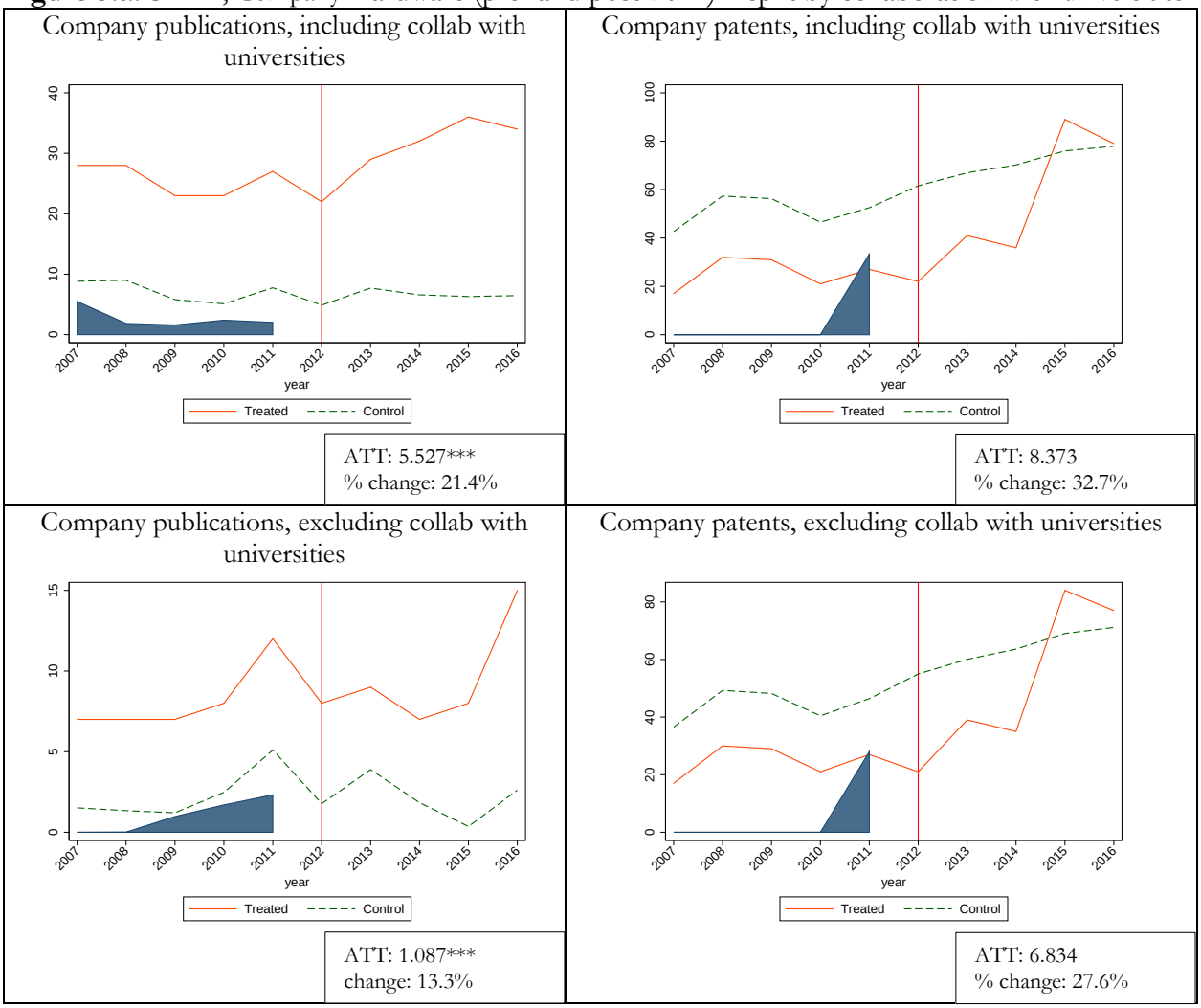
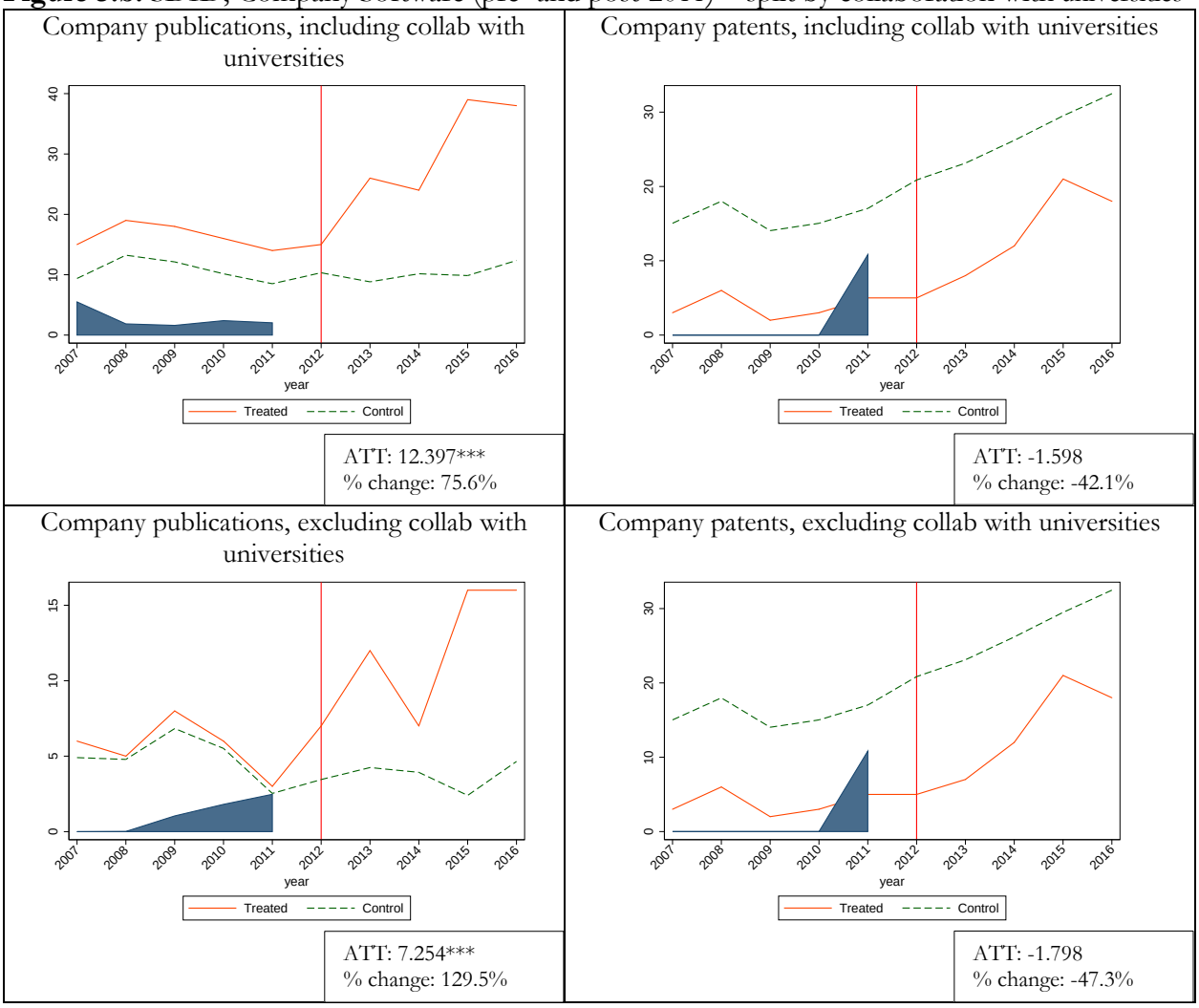


Figure 5.b presents similar analysis for company software publications and patents. It shows a large percent increase in software publications after 2011, both collaborative with universities (75.5% increase or 12.397 additional publications) and non-collaborative (129.5% increase or 7.254 additional publications), in line with theme 1. However, there is no increase in software patenting, in line with theme 4. It is likely too early to see IP in software at this stage when there is still significant hardware uncertainty.

Figure 5.b. SDID, Company Software (pre- and post-2011) – split by collaboration with universities



According to Arora et al. (2021a), the increase in company innovation should be driven by the involvement of established or large corporations. In Appendix C, Table C.1. (a and b), we show evidence to this effect by splitting our analysis between large companies and others. We proxy large companies by companies in the S&P 500 and S&P Global 100. The results show that the increase in company patents and publications is mainly driven by these large public companies.

University patents and publications: In contrast to industry, Figure 6.a shows that university hardware publications do not increase after 2011. Hardware patenting does increase but off a low base. Collaboration with companies does not play a major role in the modest hardware patent increase – a change of 5.355 additional patents (178.5% increase) when including collaboration with companies and a change of 3.991 patents (181.4% increase) when excluding collaboration with companies. Figure 6.b, however, shows a significant increase in software

publications, in line with theme 3, but no change in software patenting. Part of the increase is due to collaboration with companies, but not all. When including company collaboration, university scientists increase software publications by 27.5% (97.806 publications). When excluding company collaboration, the increase in the rate is only slightly lower (25.8% which is the equivalent of 89.280 publications).

Figure 6.a. University SDID Hardware (pre- and post-2011) – split by collaboration with companies

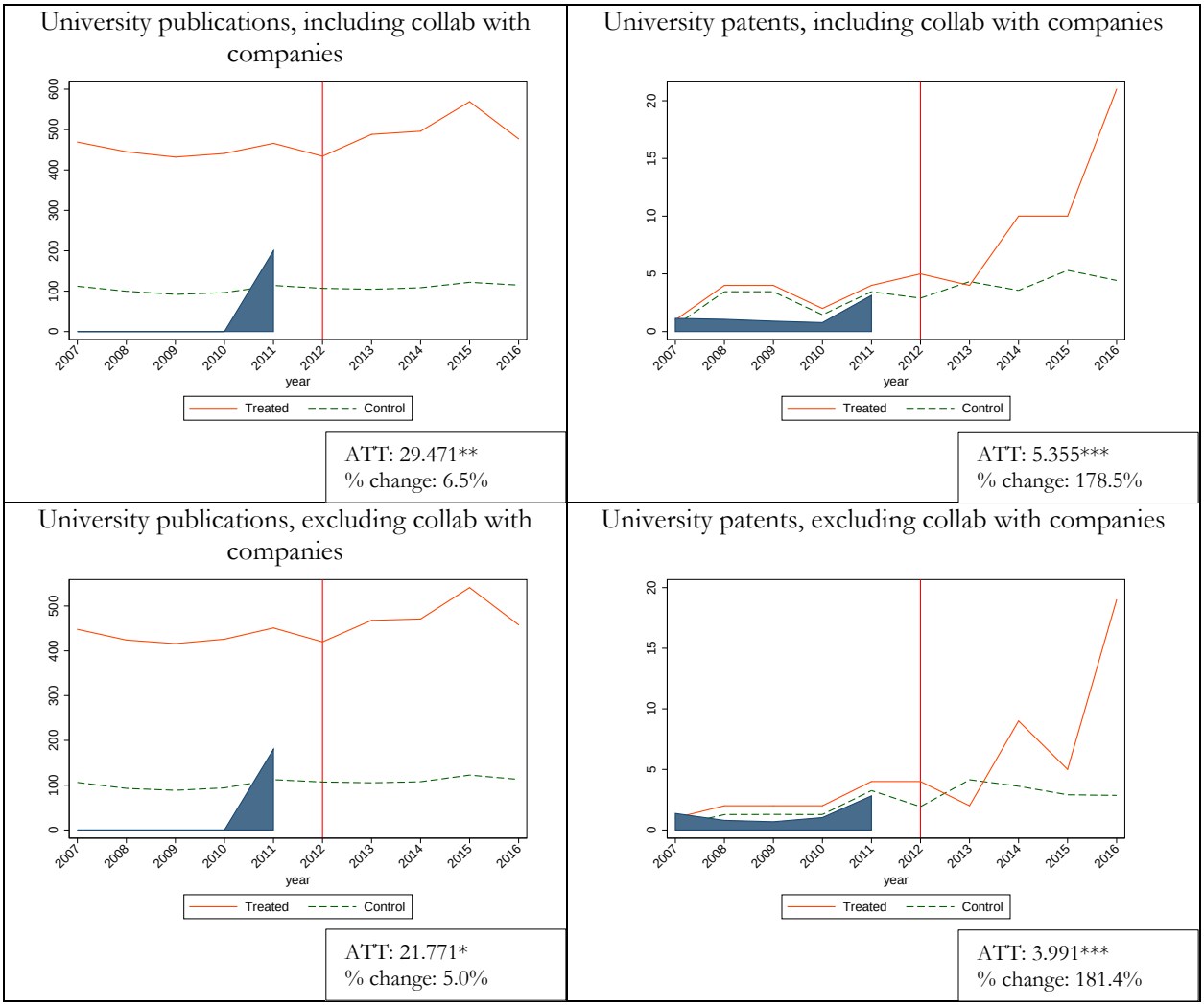
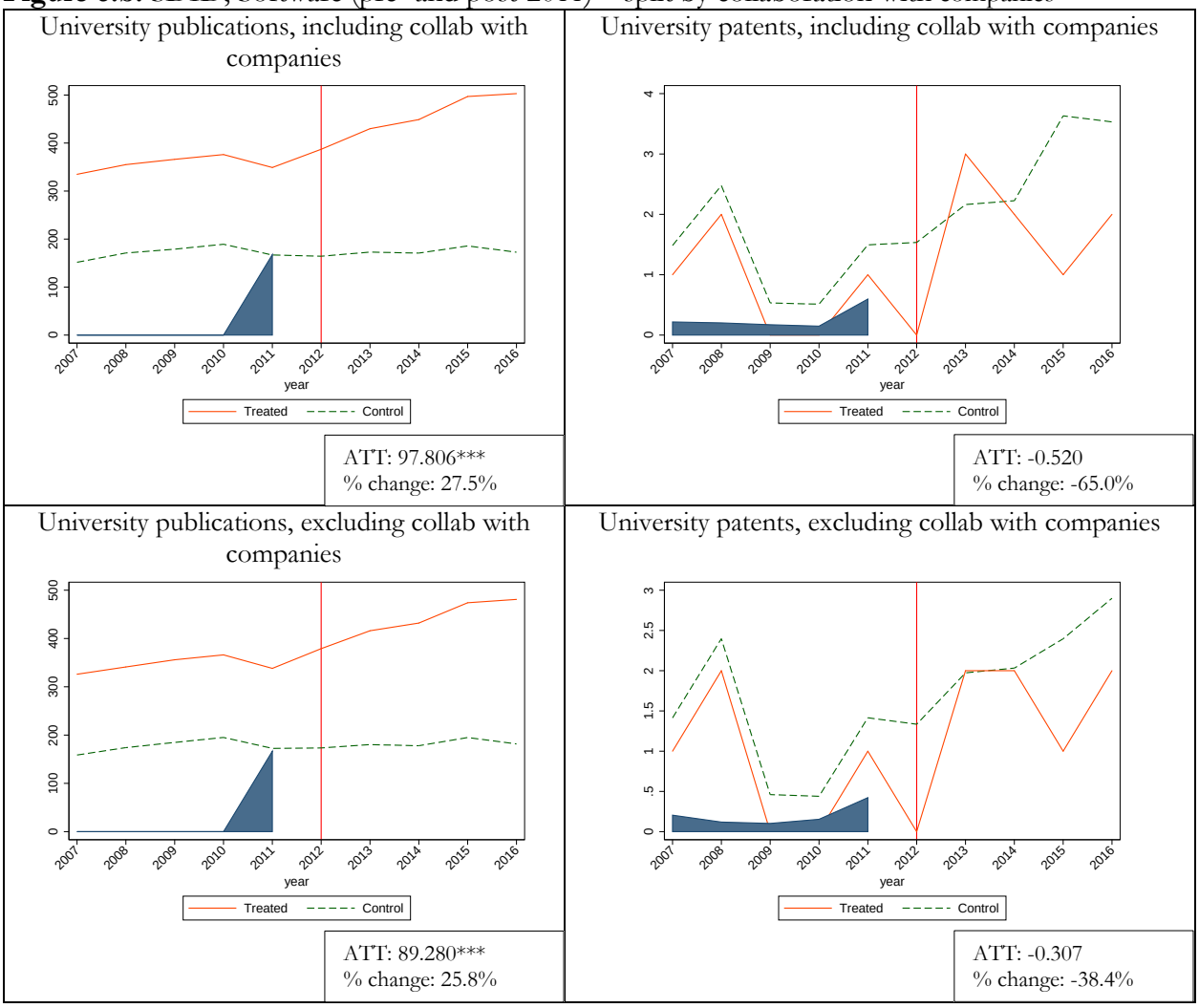


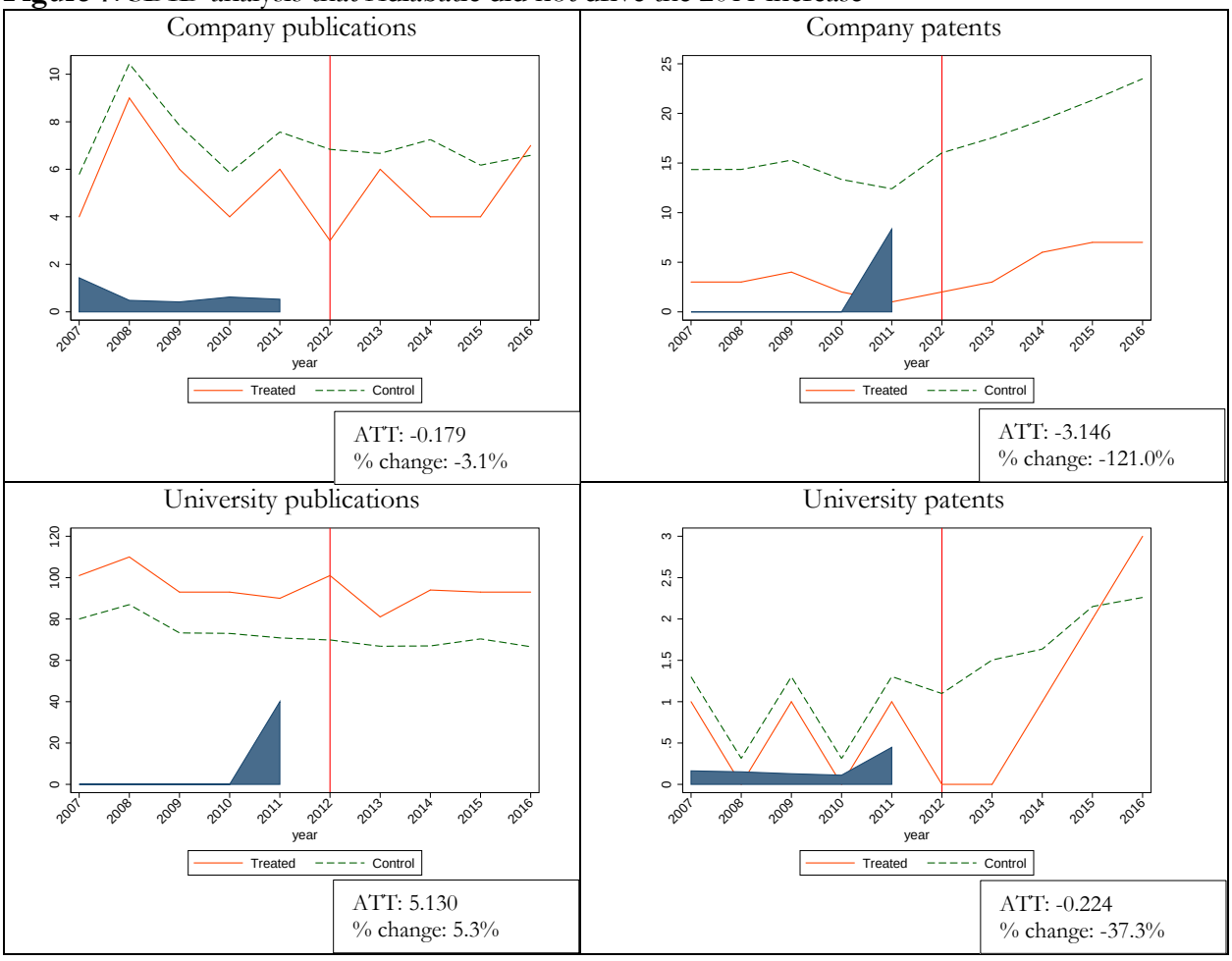
Figure 6.b. SDID, Software (pre- and post-2011) – split by collaboration with companies



Not driven by a reduction in technological uncertainty

To assess whether the changes post-2011 are likely driven by a reduction in demand uncertainty and not a reduction in technological uncertainty, we verify whether the increase in innovation we observe is driven by the D-Wave adiabatic approach to quantum computation, or not. Figure 7 repeats our main analysis for companies and universities, restricted to adiabatic hardware innovations, showing no increase for this quantum trajectory. Appendix C, Table C.3. show that these results persist when splitting our analysis by large companies and all other.

Figure 7. SDID analysis that Adiabatic did not drive the 2011 increase



In summary, after 2011, there was an increase in company publications in hardware and software, a modest increase in patenting in hardware, and an increase in university publications in software. Collaboration with universities played an important role in the company increase in publications. The direction of research did not change toward the technology with the first successful commercial transaction, suggesting that—to the extent that the D-Wave lease was the catalyst for these changes-—they were driven by reductions in demand uncertainty, rather than technological uncertainty. In 2016, an event also reduced technological uncertainty, bringing this second era to an end.

5.3. Quantum computing patents and publications after May 2016

As discussed in Section 3.1, technological uncertainty during an incubation stage refers to uncertainty about a feasible quantum computing design (Agarwal et al., 2017). Thus, an event that makes engagement with a feasible prototype possible at a large scale reduces some technological

uncertainty. In our view, such an event occurred on May 4th, 2016, when the IBM Quantum team launched IBM Quantum Experience, a Cloud service that offered access to IBM's five-qubit quantum processor and matching simulator. Within the first week of launch, 7,000 users registered. By the second week, 17,000+ more users registered. As of May 2021, IBM had over 325,000 users and the numbers continued to grow. [23]

The IBM Quantum Cloud launch was not unexpected. The possibility of such a project was mentioned at a ThinkQ conference in December 2015, where MIT professor Isaac Chuang asked dozens of researchers if they would be interested in having access to a small-scale, Cloud-based IBM quantum processor. Everyone raised their hands. Four months later, the resulting service matched the announcement description. Anyone could run their own quantum computing experiments, but access was targeted towards researchers and developers as the program's user interface required some understanding of quantum mechanics.[24] The IBM Cloud launch was followed by several other similar services, such as Alibaba's quantum computing Cloud, Rigetti's Forest, and D-Wave's the Leap Quantum Cloud Service in 2018, and Xanadu Cloud, Honeywell's System Model H1, and Amazon Braket in 2020.[25]

As before, we focus on a 10-year window around the May 2016 event, which we interpret as a reduction in technological uncertainty. The first year in our post period is 2017.

Corporate patents and publications: Figure 8.a shows an increase in hardware patents after 2016 (179% equivalent to 87.717 additional patents), in line with theme 4. This increase appears to be largely driven by patents that are not collaborative with universities (179.6% change equivalent to 84.724 patents) since there are so few such collaborative patents. Hardware publications also increase, clearly driven by collaboration with universities (6.1% increase equivalent to 1.829 publications), in line with themes 1 and 2.

[23] https://research.ibm.com/blog/quantum-five-years
[24] https://research.ibm.com/blog/quantum-five-years
[25] Other events include the publication of Biamonte et al's (2017) paper, "Quantum machine learning", in *Nature*, and the launch of a quantum computing focused stream at the Creative Destruction Lab with an associated increase in the number of quantum startups.

Figure 8.a. SDID Hardware (pre- and post-2016) – split by collaboration with universities

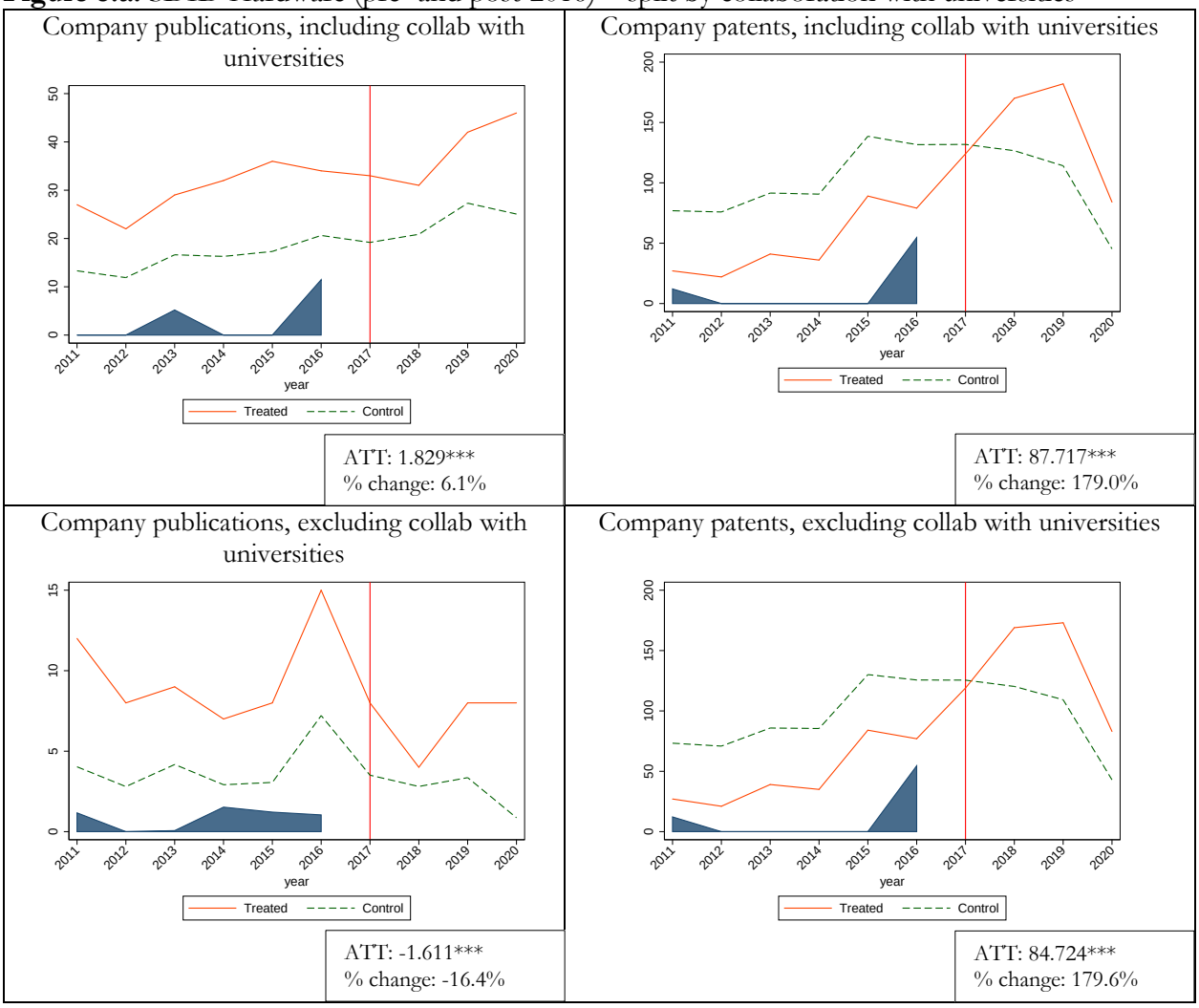
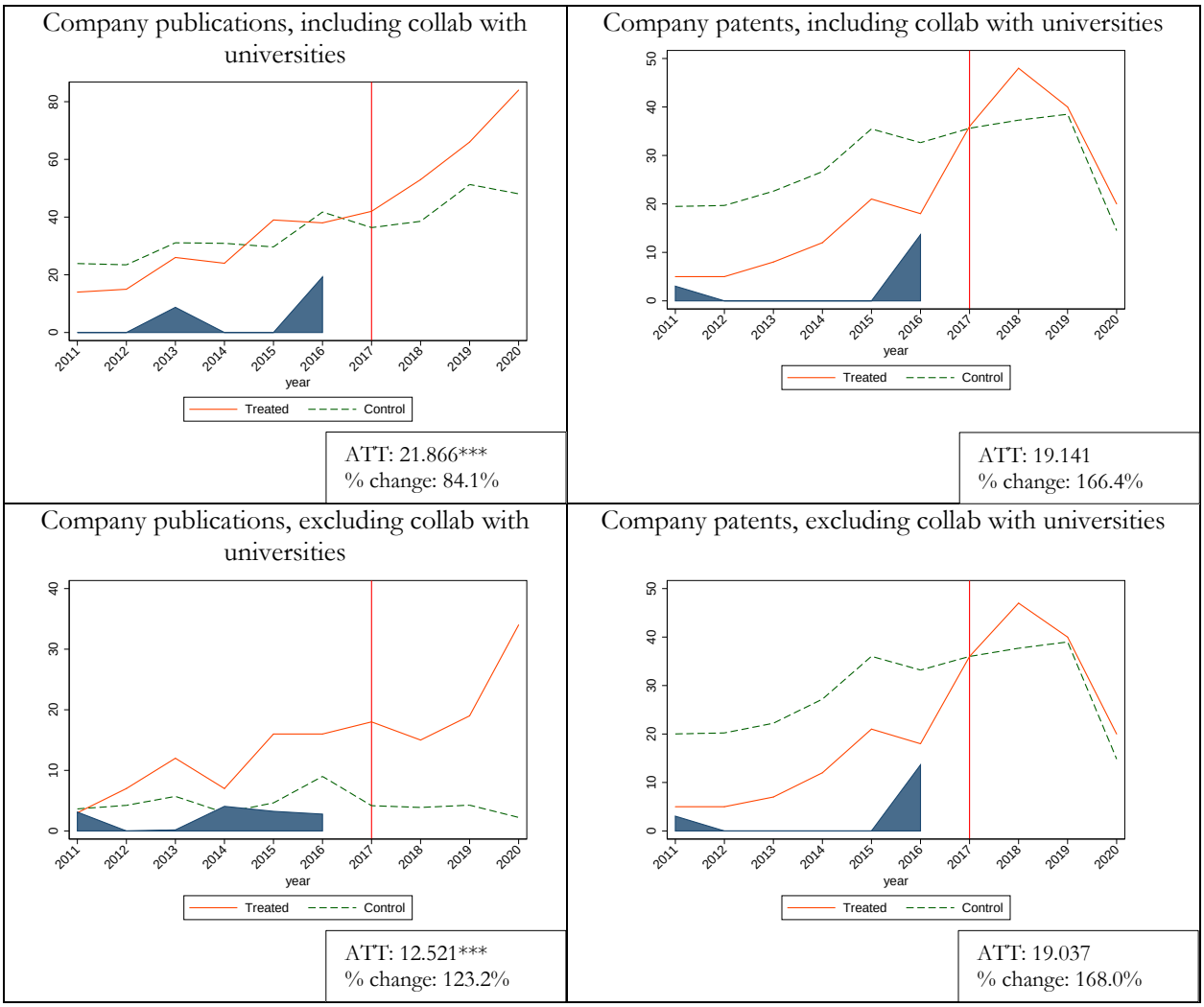


Figure 8.b shows a sharp increase in company software patents and publications after 2016. For publications, this increase is particularly strong for collaborations with universities. When accounting for collaboration with university, we estimate an 84.1% increase, equivalent to 21.886 additional publications. When excluding collaboration with university, the increase is reduced to an additional 12.521 publications, however the percentage change is large (123.2%) since most company software publications are collaborative. To the extent that this change was driven by a reduction in technological uncertainty, it suggests that the reduction in uncertainty led to another boost in collaborative software work between companies and universities. Given that software is an important complement to the hardware that many companies were building and patenting, this suggests that companies encouraged university researchers to develop a relatively low capital cost complement to quantum computing hardware.

Figure 8.b. SDID Software (pre- and post-2016) – split by collaboration with universities



As before, we find that the increase in company innovation efforts is driven by large companies (Arora et al., 2021a). We include these results in Appendix C, Table C.2.

University patents and publications: Figure 9a and 9b examine university patents and publications. As after 2011, there is little increase in university hardware or software patenting. Unlike after 2011, university hardware publications decline after 2016. However, there is a substantial increase in university software publications in both a relative and absolute sense (31.3% increase, equivalent to 136.552 additional publications), in line with theme 3. As after 2011, after 2016 collaboration with companies represent only a small subset of this increase (30.1% increase when excluding collaboration with companies, equivalent to 126.542 additional publications). We interpret these results to suggest that a reduction in technological uncertainty moved focus even

more on innovation in software as the complementary technology to hardware, as described in Section 3.

Figure 9.a. SDID, University Hardware (pre- and post-2016) – split by collaboration with companies

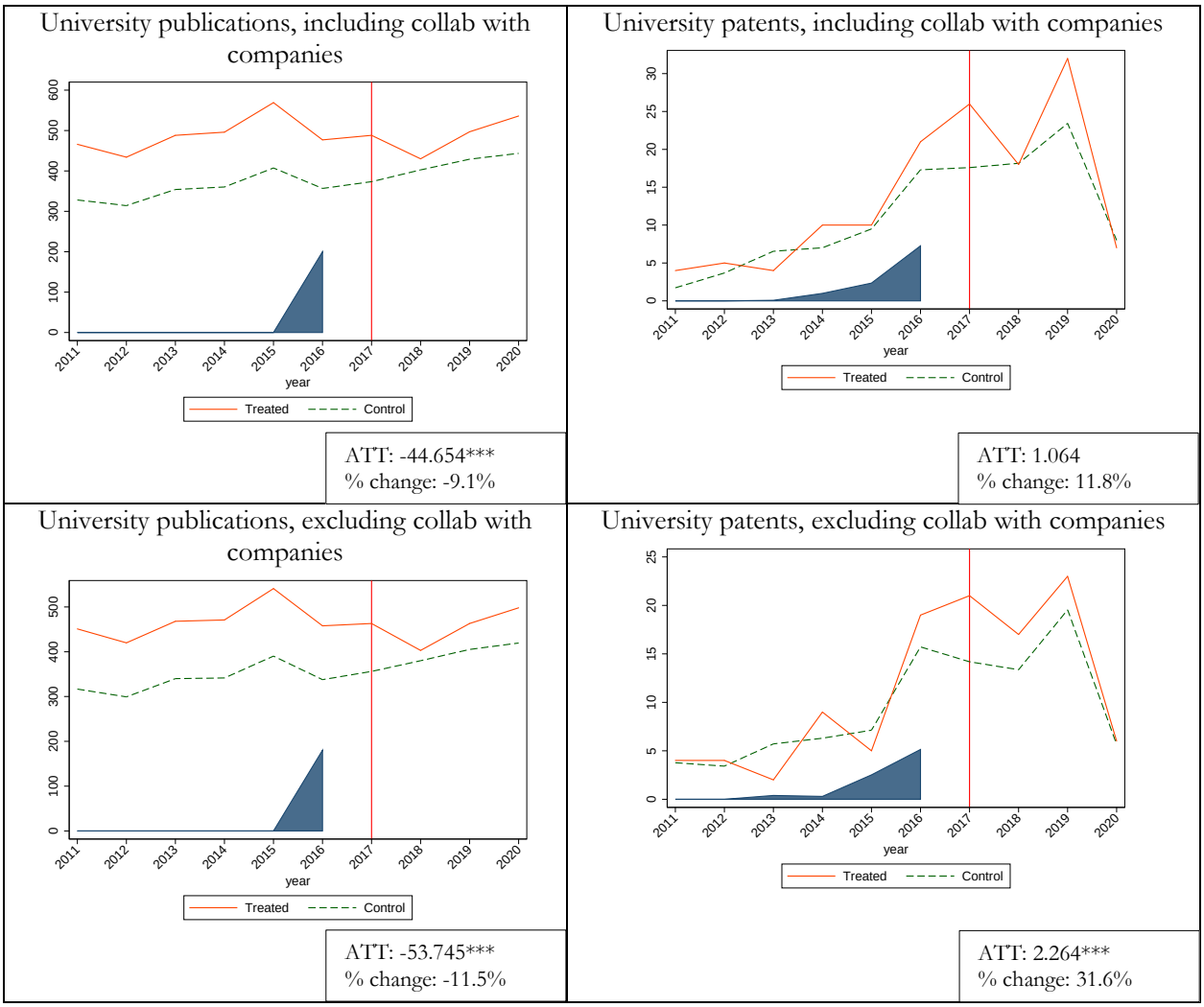
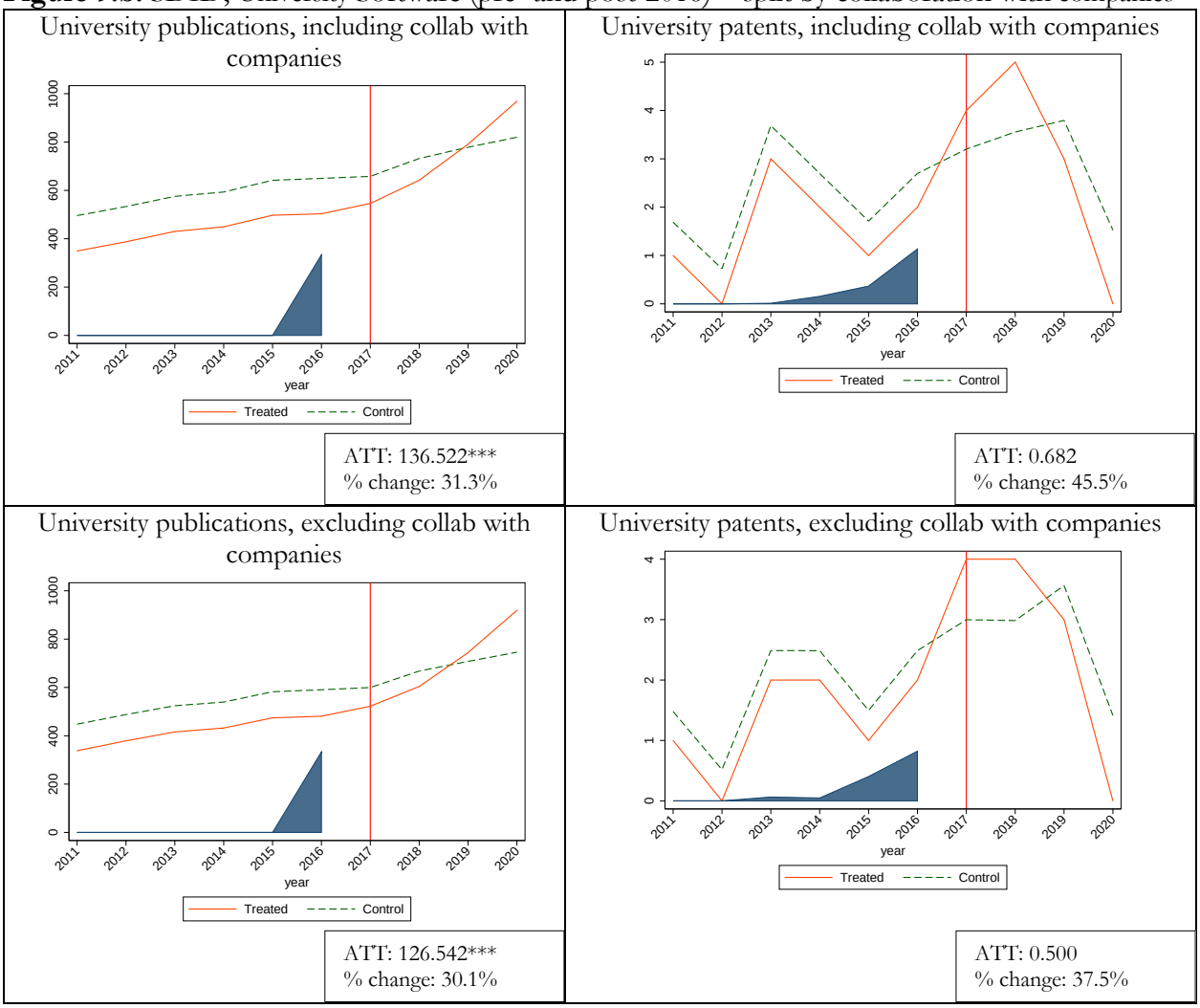


Figure 9.b. SDID, University Software (pre- and post-2016) – split by collaboration with companies



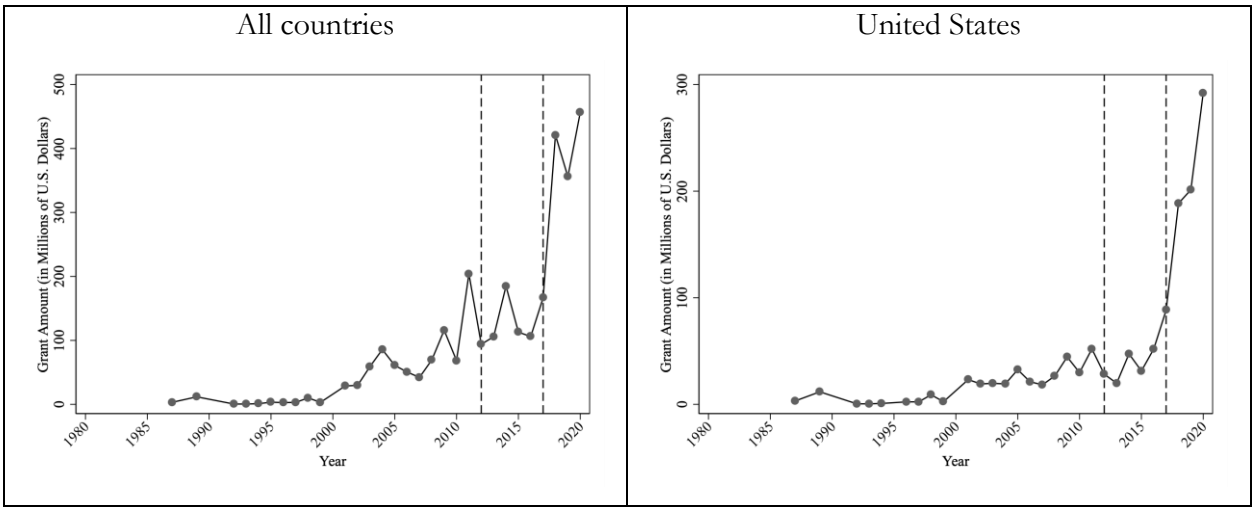
Overall, after 2016, companies increasingly focused on hardware patents that were not collaborative with university researchers, and hardware and software publications that were often collaborative. University researchers increased their innovation in software publications, a necessary complementary technology for quantum hardware to generate value.

The role of government funding

Figure 10 shows annual grant funding to quantum computing over time, demonstrating a steady increase with a change in the trajectory, particularly in the United States, around 2016. Government funding appears to have followed, rather than led, the apparent decrease in technological uncertainty that occurred in 2016. Furthermore, in December 2018, the United States enacted the National Quantum Initiative Act (NQI), a plan to advance quantum technologies and, in particular,

quantum computing. The grant amounts shown in Figure 10 include hundreds of millions in funding for quantum R&D under the NQI umbrella, including the National Science Foundation (NSF), DARPA, and the Department of Energy (DOE). Therefore, while some of the increases in university and company innovation after 2016 was likely government funded, it is unlikely that the government funding itself caused the change in trajectory. Instead, it was likely other events around the same time, that we interpret as a reduction in technological uncertainty, that caused both the increase in grant funding and the increase in innovation of various kids.

Figure 10. Grant amounts in quantum computing (in millions of U.S. dollars)



5.4. Feedback loop

The themes identified in Section 3.4 that have been guiding our empirical analysis thus far build on the assumption that quantum computing is an enabling technology. In particular, theme 3's emphasis on open innovation by universities in software along with theme 4's emphasis on IP protection in hardware assume a feedback loop for innovation between hardware and software. Therefore, we should also empirically observe evidence of a feedback loop between innovation efforts in hardware and software.

We look for this feedback loop in the informative paper trail provided in the references in patents and publications. If frontier developments in hardware inform frontier development in software and vice versa, then we should observe a reference pattern where software innovation cites most recent hardware developments and most recent hardware innovation efforts cite the latest developments in software. In Figure 11, we plot heat maps of share of references counts between all

combinations of hardware and software patents and academic publications, with the exception of patent references in academic publications. We identity academic publications referenced in patents using data from Marx and Fuegi (2020, 2022), which match USPTO patents to the publications in MAG and create patent-paper linkages. We identify publications referenced in other academic publications from MAG, and patents referenced in other patents from PatentsView. To our knowledge, data on patent references in academic publications is not available. In Figure 11, the x-axis represents the publication year of the focal academic publications or patents, and the y-axis represents the publication year of the reference patents or academic publications. In all cases, we observe that most recent academic publications and patents in hardware and software reference recently published academic publications and patents in hardware and software, suggesting a feedback loop.

Figure 11.a. (a) Hardware publications share of references to other hardware publications, (b) Software publications share of references to other software publications, (c) Hardware publications share of references to software publications, and (d) Software publications share of references to hardware publications.

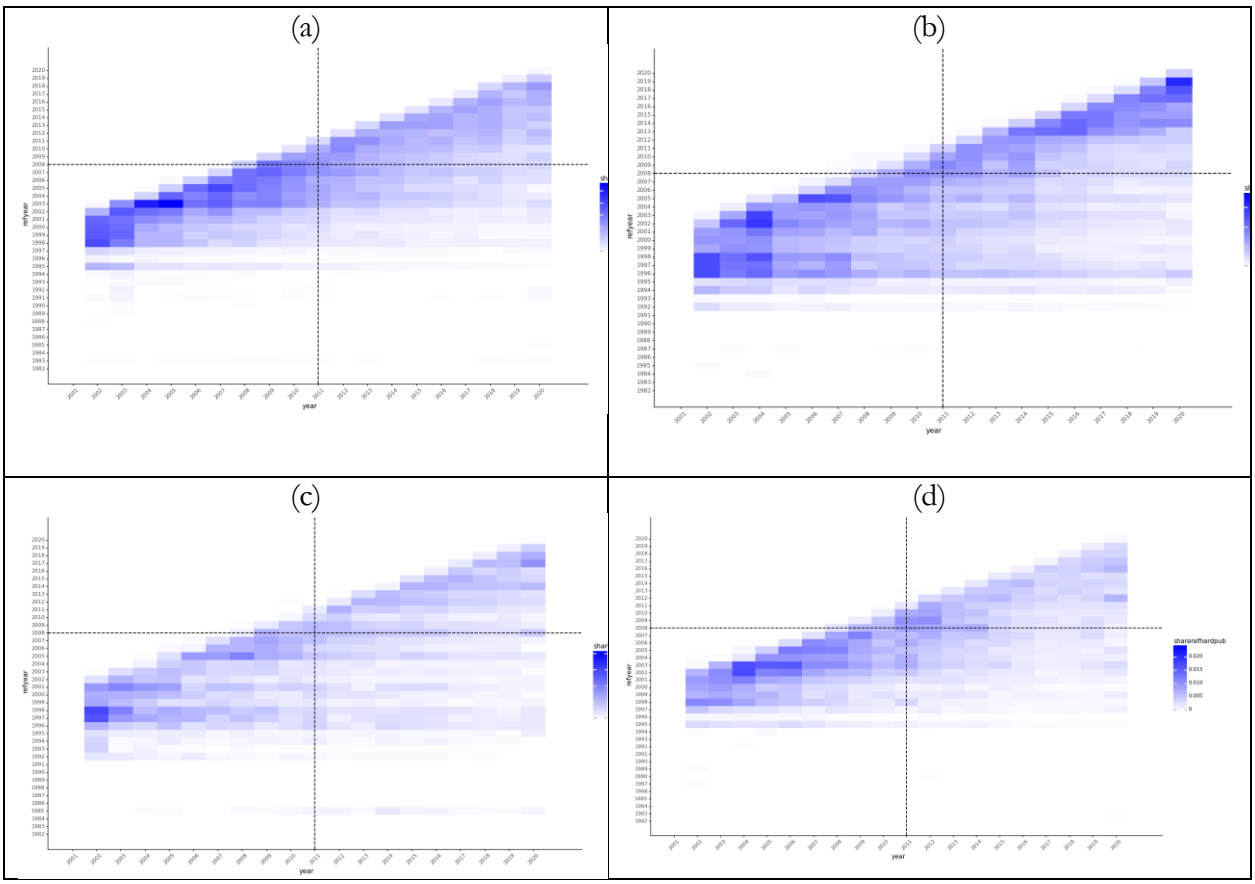


Figure 11.b. (a) Hardware patents share of references to hardware publications, (b) Software patents share of references to software publications, (c) Hardware patents share of references to software publications, and (d) Software patents share of references to hardware publications.

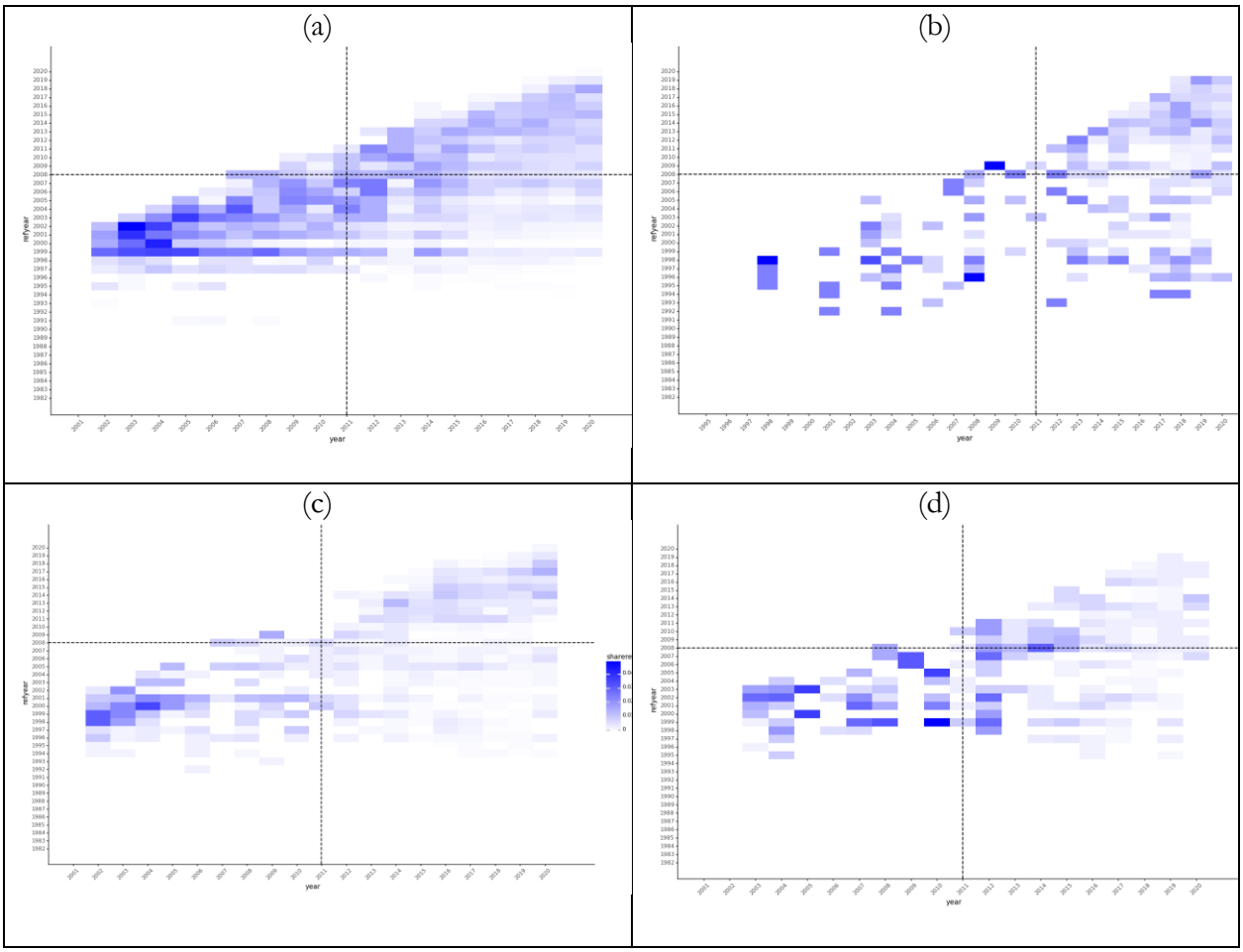
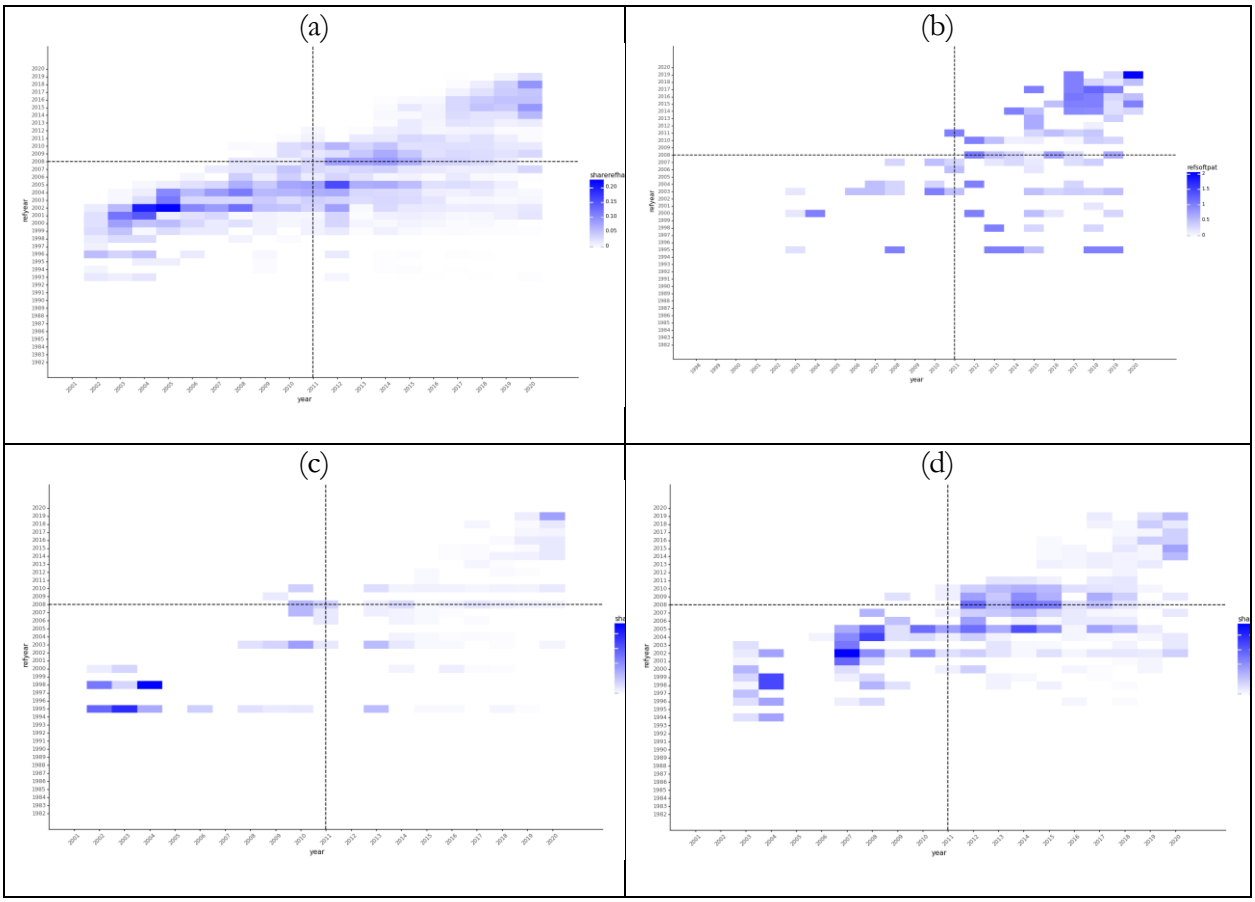


Figure 11.c. (a) Hardware patents share of references to other hardware patents, (b) Software patents share of references to other software patents, (c) Hardware patents share of references to software patents, and (d) Software patents share of references to hardware patents.



6. Discussion and conclusion

We document early innovation efforts in quantum computing, an emerging enabling technology. We focus on uncovering factors that impact the evolution of a quantum computing industry during the incubation stage. It is rare to have rich data on industry formation starting with the earliest incubation stage. Most studies on the emergence of new industries document later stages, after the technology becomes commercially viable (Gort and Klepper, 1982; Utterback and Suarez, 1993; Agarwal and Bayus, 2002). It is important to understand how economic actors interact during the incubation stage because this phase shapes the technology's trajectory and hence the magnitude of potential value creation (Moeen and Agarwal, 2017).

Quantum computing falls under the category of industries triggered by scientific discoveries (Agarwal, Moeen and Shah, 2017). The initial idea of quantum computational devices was speculated in a lecture of Nobel Prize winning physicist Richard Feynman (1982). Until 2011, quantum

computing innovation efforts unfolded primarily in the realm of open science through collaborative efforts between university and company scientists. During this period, scientists focused on theoretically demonstrating that quantum computing was possible and useful. The 2011 unanticipated commercial lease of a D-Wave's quantum machine to Lockheed Martin likely reduced demand uncertainty and led to a substantial increase in company quantum hardware publications. University scientists increased publications in the complementary software domain. There was likely a reduction in technological uncertainty following the 2016 launch of the IBM Cloud services. This was followed not only by an even higher output in open science, but also by an increase in company patenting, particularly in hardware. By the end of our period of study in 2020, there was still substantial demand and technological uncertainty. Quantum computing remained in its incubation stage with considerable uncertainty as to whether the technology will prove commercially viable. However, despite this uncertainty, quantum computing has attracted economically meaningful investments.

The patterns of publishing and patenting in each era are consistent with the four themes we identified in the existing literature on the incubation phase of an industry, on university and company innovation, and on enabling technologies. They suggest that incubation-stage technological development requires the joint efforts of both company and university scientists, in line with Agarwal et al. (2017) and Arora et al. (2021a). Moreover, collaboration between these economic actors is essential (Rosenberg (1982, 1994). Nonetheless, our findings indicate that such collaboration, especially for enabling technologies, is not guaranteed. Companies' incentives to innovate are hindered by value capture concerns (Teece, 2018; Gambardella et al., 2021). Lowering demand uncertainty and in particular technological uncertainty likely incentivizes companies to secure IP protection for promising hardware designs. This IP, as complementary assets, appears to boost companies' potential to capture value from open science software innovation, a necessary step towards the feedback loop path of enabling technology development. In other words, our findings suggest that not only demand and technological uncertainties impact the evolution of the technology, but also ecosystem uncertainty (Adner and Kapoor, 2010; Moeen et al., 2020) can hold back enabling technology innovation.

It is plausible that a reduction in demand uncertainty influenced innovation actions that subsequently reduced technological uncertainty, thus suggesting a strategy for navigating the incubation phase. Prior to the reduction in demand uncertainty, there was little company involvement in hardware open science innovation, a necessary ingredient of a successful incubation stage. This increase in involvement may have helped reduce technological uncertainty (Fleming and Sorenson, 2004; Rosenberg, 1982), ultimately leading to IBM's Cloud event, which likely served as a milestone

that facilitated further reductions in technological uncertainty, potentially followed by additional reductions in demand uncertainty. This possibility aligns with the findings of Moeen, Agarwal, and Shah (2017), which suggest an interaction between demand and technological uncertainty during the incubation stage. However, it is important for us to acknowledge that it is not possible to assert that the increase in quantum computing innovation was a result of first reducing demand uncertainty. We do not observe what would have happened had there been no apparent reduction in demand uncertainty.

In summary, our analysis attempts several contributions. First, we contribute to research on industry emergence and evolution (Agarwal, Moeen and Shah, 2017; Moeen and Agarwal, 2017; Moeen, Agarwal and Shah, 2017) by documenting how changes in demand and technological uncertainty during the incubation stage shape company and university scientists' innovation efforts. We also show evidence consistent with the hypothesized negative consequence of the decrease in corporate investments in open science for technological advancement (e.g. Arora et al., 2021a, b, c), particularly for the advancement of enabling technologies. Last, we contribute to our knowledge of enabling technologies and, more broadly, general purpose technologies (Bresnahan and Trajtenberg, 1995; Teece, 2018; Rathje and Katila, 2021) by documenting factors that influence economic actors' incentives to contribute to the advancement of such technologies.

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Appendix A

HDP

Table A.1. List of topics with top words in terms of probability.

Topic	**Top 20 words**
	Category: Methods of Building Qubits (Hardware)
1	ion, atom, trapped_ion, trap, optic, laser, atomic, experiment, rydberg, quantum_information, quantum_computing, cool, lattice, control, coherence, motion, crystal, scalable, neutral_atom, excitation
2	superconducting_qubit, qubit, coupling, resonance, superconducting, circuit, frequency, microwave, cavity, control, quantum_electrodynamics, coherence, tunable, readout, k_qubit, flux, oscillator, drive, quantum_information, measurement
3	quantum_dot, spin, qubit, charge, coupling, electron, silicon, spin_qubit, control, electron_spin, quantum_computing, coherence, semiconductor, diamond, k_electron, exchange, solid_state, donor, gate, device
4	photon, optic, entanglement, photon_quantum_computing, experiment, polarization, coherence, quantum_information, detection, application, continuous_variable, quantum_computing, quantum_communication, fiber, device, integrate, measurement, waveguide, frequency, quantum_network
5	device, superconducting, layer, chip, substrate, fabrication, material, qubit, cryogenic, circuit, surface, temperature, quantum_computing, electrode, signal, semiconductor, dielectric, waveguide, integrate, josephson_junction
6	qubit, memory, processor, device, store, coupling, signal, control, storage, set, apparatus, cell, analog, register, pulse, braketnotation, operation, programmable, information, single_flux
7	quantum_dot, electron, coupling, semiconductor, exciton, quantum_well, optic, phonon, dot, energy, gaas, laser, device, resonance, electronic, wire, emission, confine, control, nanostructure
8	superconducting, current, josephson_junction, flux, qubit, superconducting_quantum_interference_device, junction, magnetic, charge, device, josephson, loop, coupling, phase, measurement, experiment, tunnel, ring, circuit, macroscopic
9	model, spin, lattice, chain, ground_state, hamiltonian, body, phase, local, coupling, spin_chain, simulation, heisenberg, magnetic_field, ising, quantum_phase_transition, disorder, dimensional, ise, site
10	cavity, atom, atomic, quantum_electrodynamics, adiabatic, coupling, passage, entanglement, photon, transfer, k_atom, resonance, optic, emission, three_level, decay, quantum_information, spontaneous, laser, raman
11	spin, nuclear_magnetic_resonance, experiment, nmr, quantum_computing, pulse, nuclear_spin, k_qubit, quantum_information, algorithm, coupling, molecule, resonance, qubit, coherence, implement, sequence, magnetic_field, polarization, nucleus
12	detection, signal, frequency, readout, microwave, amplifier, device, resonance, noise, sensor, josephson, resolution, application, ratio, measurement, improve, performance, parametric, sensitivity, receiver
13	material, magnetic, surface, graphene, defect, device, application, topological, topological_insulator, quantum_computing, electronic, spintronic, spin, carbon, gap, superconductivity, nanotube, crystal, metal, transport
	Category: Models of Manipulating Qubits for Computation (Hardware)
14	adiabatic_quantum_computing, hamiltonian, adiabatic, energy, model, approximation, evolution, problem, theory, ground_state, parameter, time_dependent, exact, operator, perturbation, numerical, gap, schrodinger, nonlinear, oscillator
15	anyon, topological, topological_quantum_computing, statistical, phase, fractional, quantum_hall, non_abelian, model, theory, majorana, charge, superconducting, fermion, anyonic, excitation, majorana_fermion, quasiparticle, dimensional, experiment, magnetic_field
16	circuit, reversible, design, gate, logic, synthesis, quantum_circuit, quantum_computing, adder, quantum_cost, application, low_power, binary, reduce, ternary, optimize, arithmetic, synthesize, technology, multiplier

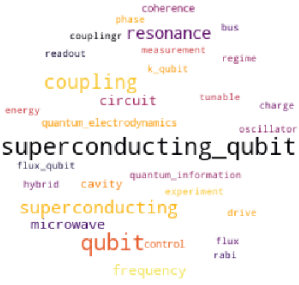
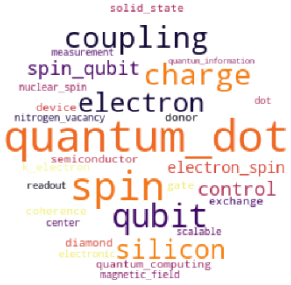
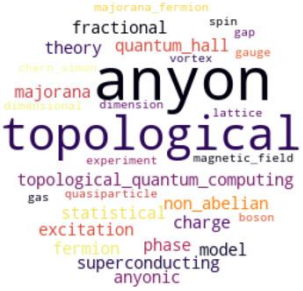
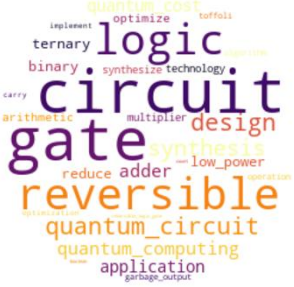
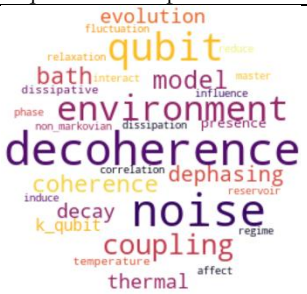
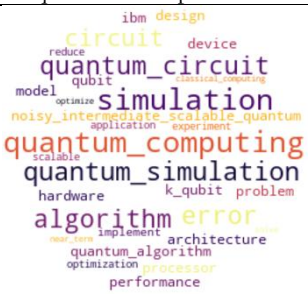
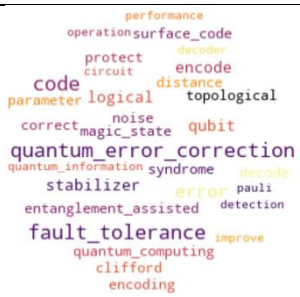
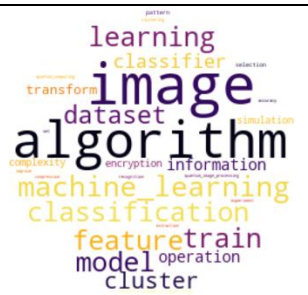
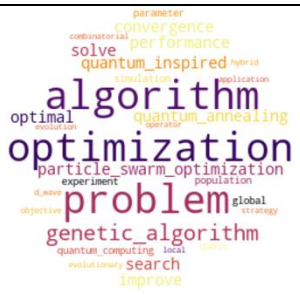
17	gate, qubit, k_qubit, operation, quantum_computing, control, quantum_gate, implement, controlled_not, universal, fidelity, set, quantum_logic, error, phase, swap, encode, experiment, logical, scalable
18	quantum_cellular_automaton, cell, device, technology, qca, design, circuit, array, architecture, transistor, quantum_dot, logic, clock, cmos, silicon, simulation, speed, nano, wire, energy
	Category: Address Obstacles to Quantum Computation (Software)
19	decoherence, noise, qubit, environment, coupling, model, coherence, bath, dephasing, decay, thermal, evolution, k_qubit, presence, dissipative, temperature, non_markovian, fluctuation, reservoir, master
20	quantum_computing, simulation, algorithm, quantum_simulation, quantum_circuit, circuit, hardware, architecture, quantum_algorithm, k_qubit, processor, error, design, device, performance, ibm, qubit, problem, model, noisy_intermediate_scalable_quantum
21	quantum_error_correction, error, fault_tolerance, qubit, encode, code, stabilizer, logical, quantum_computing, noise, surface_code, decode, protect, distance, correct, entanglement_assisted, encoding, syndrome, topological, clifford
22	measurement, qubit, optimal, experiment, error, probability, fidelity, estimation, parameter, estimate, information, cloning, preparation, probe, detection, tomography, quantum_tomography, unknown, discrimination, precision
23	entanglement, channel, measurement, k_qubit, entropy, coherence, quantum_correlation, quantum_discord, qubit, correlation, concurrence, bipartite, information, relation, capacity, mixed_state, bind, quantum_entanglement, pure_state, multipartite
24	inequality, measurement, correlation, bell, entanglement, violation, local, nonlocal, nonlocality, experiment, contextuality, theory, observable, violate, steering, k_qubit, hypergraph, quantum_mechanic, scenario, detection
25	control, pulse, sequence, optimal, feedback, design, error, coherence, dynamical_decoupling, parameter, numerical, controller, composite, transfer, operation, fidelity, optimize, decoupling, strategy, application
	Category: Applications of Quantum Computing (Software)
26	security, quantum_cryptography, key, attack, secret, information, communication, channel, message, party, eavesdrop, share, participant, server, bob, client, measurement, alice, entanglement, blind_quantum_computing
27	image, algorithm, machine_learning, feature, classification, learning, model, train, dataset, cluster, classifier, operation, information, transform, encryption, complexity, reinforcement_learning, pattern, selection, quantum_image_processing
28	optimization, algorithm, problem, genetic_algorithm, solve, quantum_inspired, search, particle_swarm_optimization, quantum_annealing, improve, convergence, performance, optimal, quantum_computing, global, experiment, qubit, population, simulation, combinatorial
29	algorithm, problem, quantum_algorithm, complexity, quantum_computing, solve, query, bind, shor, model, factor, oracle, polynomial, exponential, boolean, probability, set, polynomial_time, classical_computing, search_algorithm
30	quantum_computing, application, theory, problem, experiment, quantum_mechanic, technology, quantum_information, research, information, device, design, current, progress, model, science, classical_computing, scalable, key, offer
31	network, neural_network, model, node, quantum_network, learning, train, algorithm, layer, architecture, neuron, artificial, memory, neural, performance, pattern, weight, qubit, distribute, link
32	graph, quantum_walk, search_algorithm, search, algorithm, grover, probability, vertex, coin, discrete_time, continuous_time, step, problem, item, weight, quantum_algorithm, mark, iteration, distribution, random
33	game, player, communication, strategy, entanglement, interactive, model, prover, coin, message, round, share, complexity, zero_knowledge, problem, payoff, game_theory, auction, agent, qma
34	theory, frame, brain, model, consciousness, hole, information, black, quantum_computing, biological, reference, gravity, mind, dna, closed_timelike_curve, microtubule, space_time, mso, relativistic, cell
35	molecule, electronic, energy, calculation, quantum_computing, chemistry, chemical, vibrational, reaction, variational_quantum_eigensolver, electron, calculate, nuclear, coupling_cluster, ground_state, basis, magnetic, protein, excitation, polar
36	network, cloud, distribute, quantum_computing, communication, sensor, environment, access, post, fusion, cloud_computing, storage, wireless_sensor_network, model, energy, node, data, policy, internet, information
37	program, simulation, programming, software, code, quantum_circuit, quantum_algorithm, package, library, quantum_computing, instruction, matrix, compiler, write, mathematica, implement, operation, visualization, quantum_programming_language, algorithm

38	trajectory, event, robot, simulation, real_time, spatial, beam, learning, track, action, measurement, model, instrument, continuous, mobile, tracking, jump, stochastic, twisted, energy
39	security, signature, quantum_cryptography, attack, key, cryptosystem, algorithm, lattice, quantum_computing, cryptographic, encryption, cryptography, problem, public_key, postquantum, blockchain, assumption, hash, multivariate, break
	Category: Other topics
40	entanglement, k_qubit, channel, teleportation, quantum_teleportation, measurement, qubit, k_particle, cluster_state, operation, probability, quantum_information, control, unknown, bell_state, receiver, ghz, pair, remote, sender
41	matrix, operator, unitary, group, product, theory, generalize, dimension, set, transform, tensor, linear, hilbert, basis, map, discrete, problem, application, quantum_computing, density
42	set, permutation, generator, orthogonal, product, local_operation_and_classical_communication, subset, block, qubit, sum, member, generalize, local, basis, sequence, locc, distinguishability, maximally_entanglement, distinguish, seed
43	model, quantum_computing, measurement_based_quantum_computing, cluster_state, measurement, logic, universal, graph, probabilistic, machine, theory, semantic, logical, entanglement, fuzzy, set, operation, cluster, pattern, flow
44	phase, coherence, geometric_phase, geometric, nonadiabatic, evolution, superposition, quantum_computing, berry, drive, amplitude, oscillator, experiment, adiabatic, parameter, phase_shift, holonomic_quantum_computing, quantum_gate, holonomic, cyclic
45	braid, topological, group, model, anyon, topological_quantum_computing, theory, non_abelian, defect, fibonacci, link, polynomial, twist, lattice, universal, knot, braiding, yang_baxter_equation, abelian, unitary
46	model, machine, automata, quantum_turing_machine, quantum_finite_automaton, automaton, error, deterministic, recognize, probabilistic, equivalent, quantum_computing, complexity, ture, unbounded, width, simulation, polynomial_time, sequential, powerful
47	region, direction, model, axis, cross, sphere, plane, uniform, bloch_sphere, angle, along, bloch, virtual, qubit, rotate, around, compression, geometrical, set, hard
48	random, distribution, sample, probability, statistical, randomness, random_number_generator, index, stochastic, sampling, sequence, tree, device, carlo, monte, string, markov, binary, produce, true
49	fault, chaos, chaotic, model, map, quantum_computing, detection, imperfection, static, diagnosis, simulation, dynamical, algorithm, behavior, theory, numerical, logistic, missing_gate, forecasting, test_set
50	asymmetric, collision, ring, soliton, vortex, bose_einstein_condensate, orbital_angular_momentum, differential, nonlinear, flow, pair, symmetric, core, fluid, lattice_gas, box, cascade, simulation, macroscopic, condensate
51	matrix, delete, token, matching, cognitive, deletion, balance, machine, injection, column, aggregate, row, pole, multi_output, intent, analogue, bipolar, minimum, residue, web
52	simulation, carlo, monte, band, transport, tunneling, model, channel, quantum_monte_carlo, gate, mirror, current, device, field_effect_transistor, stoquastic, integral, sign, green, electron, wave_function
53	boson, k_particle, fermion, boson_sampling, bosonic, fermionic, energy, statistical, identical, interact, d_wave, gaussian, machine, energy_level, gibb, hong_ou_mandel, sample, quantization, body, sampler
54	voting, continuous_variable, hide, anonymous, privacy, hiding, vote, election, mix, gaussian, leader, operator_valued, voter, braunstein, green, distribute, rank, ebit, anonymity, qubit_commitment
55	measurement, qubit, parity, detection, k_qubit, fermionic, entanglement, module, nondemolition, loss, cross_kerr, weak, bus, bell_state, ancillary, quantum_non_demolition, qnd, quantum_information, analyzer, nonlinearity
56	wave, packet, duality, propagation, electromagnetic, quantum_computing, transmission, waveguide, rotate, transport, electron, nonlinear, delay, magnon, scatter, approximation, velocity, acoustic, travel, half
57	gauge, theory, lattice, scatter, dimension, quantum_field_theory, dirac, zeno, quantum_simulation, relativistic, calculation, anti, spatial, dimensional, interact, sector, k_particle, qcd, quantization, energy
58	leakage, decoherence_free_subspace, error, subspace, consensus, hierarchical, partition, elimination, comment, reduce, gadget, hilbert, casimir, non_hermitian, reduction, project, force, offer, quantum_homomorphic_encryption, encode
59	superposition, impurity, cat, schrodinger, near, fluctuation, intensity, distinct, macroscopic, macroscopically, perfect, creation, circulant, electron, superpose, basis, strongly, conjecture, amplitude, hash
60	cycle, heat, engine, thermodynamic, learning, online, pin, entropy, refrigerator, temperature, thermal, hbox, quasi, inductive, battery, friction, irreversible, otto, inference, acid

61	markov, quantum_communication, semigroup, cap, hamming, classic, bidirectional, driver, generator, direction, deterministic_security, piece, alternative, activation, dispersion, fig, pathway, partially, imperfection, barrier
62	theory, inf, matchgate, end, cyclic, router, comput, routing, sci, route, singular_value_decomposition, generalize, begin, original, knill, display, laflamme, tran, infinite, acm
63	pattern, gradient, block, tube, back, spatially, periodic, forth, global, descent, incomplete, tqc, frequency, forward, calibrate, period, flux, spatial, bandgap, enlarge
64	linear, parallel, nonlinear, model, dimensional, constant, locally, speedup, multiprocessor, driver, fractal, nutation, lll, enhance, antiparallel, embedding, nerve, formula, combination, coarse_grained
65	parallel, serial, linear, register, arm, cube, shift, simultaneously, super, massively, outperform, feedback, substantially, quadratic, pure, supersingular_isogeny_key_encapsulation, speed, parallelism, integer_linear_programming, composition
66	performance, superposition, multi_dimensional, pattern, initialize, lac, shannon, inversion, quantum_harmonic_oscillator, valence_bond_solid, wei, multiplying, array, ace, synchronous, shi, unfold, position, binary, sound
67	chain, route, hybrid, distribution, logistic, majorana_bound_state, travel, industry, vibronic, warehouse, model, resolve, end, atomic, diagram, erasure, shiba, routing, extend, gas
68	poissonian, statistical, super, multiple, systolic, communication, temperature, entanglement_assisted, simultaneous, euclidean, unconventional, topological_entanglement_entropy, access, run_time, thermofield, subradiant, sequential, region, count, reduction
69	mechanical, superinductor, percolation, wigner_function, parameter, augment, optimal_success_probability, ambiguous, solid, disorder, breakdown, affect, opto, interesting, optimization, low_loss, head, reproduce, semi_classical, nonclassicality
70	superconducting_quantum_computing, transportation, excitation, quantum_technology, ratio, micro, accidental, quantum_frequency_comb, accessible, harmonic, relationship, repetition, impractical, lock, manage, neither, low_cost, claim, energy_efficient, nest
71	graphic_processing_unit, entanglement_concentration_protocol, silicon_germanium, number_theoretic_transform, parameter, coefficient, strategy, parallelize, accelerate, compact, selection, gpu, step, vert, divergence, indirect, nonintuitive, refined, initialisation, formerly
72	poisson, measurement_induced, measurement_induced_nonlocality, criticality, variational_quantum_algorithm, hierarchy, factorization, performance, quantum_phase_transition, min, additionally, minimum, vacuum, myriad, house, reservoir, initially, universally, multimode, quantum_renormalization_group
73	viable, architecture, cavity, cell, cluster, cluster_state, create, difficult, entanglement, linear, measurement_based_quantum_computing, prior, quantum_computing, quantum_electrodynamics, quantum_error_correction, relevance, scalable, topological, topology, universal
74	quantum_computing, science, university, research, theory, researcher, technology, scientific, quantum_information, project, quantum_mechanic, scientist, physicist, institute, company, machine, material, mathematic, laboratory, group

Notes. This table presents the full list of topics and words generated by the HDP topic modeling algorithm. Phrases (e.g., bigrams and trigrams) are connected by underscores. Words are ordered by their relevance to the topics in terms of probability. We renumbered the topic IDs by categories for convenience.

Figure A.1. Example of word clouds for topics in each category. Three examples per category.

Category	Topic and word clouds		
Methods of Building Qubits (Hardware)	 Topic 1: "Trapped ions"	 Topic 2: "Superconducting"	 Topic 3: "Quantum dot"
Models of Manipulating Qubits for Computation (Hardware)	 Topic 14: "Adiabatic quantum computation"	 Topic 15: "Topological quantum computation"	 Topic 16: "Quantum gate"
Address Obstacles to Quantum Computation (Software)	 Topic 19: "Decoherence study and methodologies for addressing noise"	 Topic 20: "Quantum simulators"	 Topic 21: "Quantum error correction"
Applications of Quantum Computing (Software)	 Topic 26: "Quantum cryptography"	 Topic 27: "Quantum Machine Learning"	 Topic 28: "Quantum Optimization"

Notes. This figure presents the word clouds for the topics generated by the HDP topic modeling algorithm, and the corresponding categories labeled by our quantum computing research assistant. Phrases (e.g., bigrams and trigrams) are connected by underscores. Words that are closer to the center and larger in size are of higher relevance to the topic. Due to limited space, we only plot three topics for each category as demonstration. See Table A1 for the full list of topics and words generated by the HDP topic modeling algorithm.

Figure A.2. HDP implementation – likelihood metric.

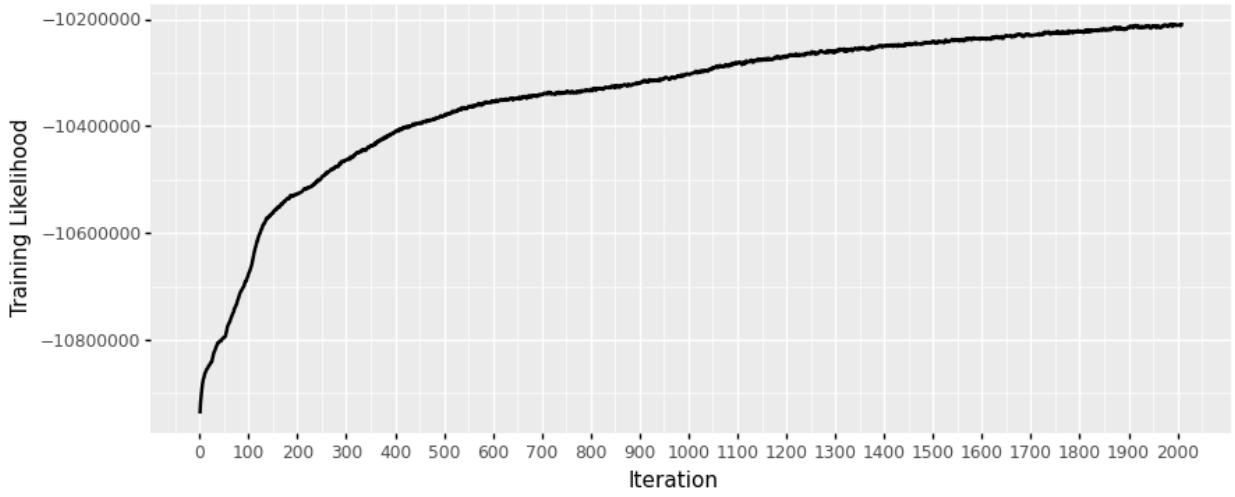
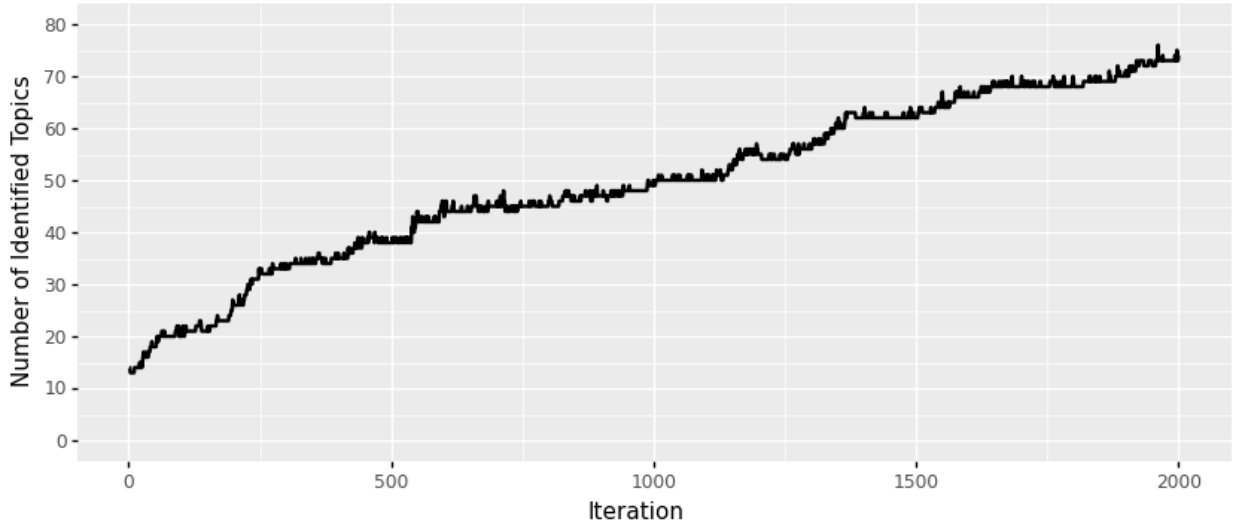


Figure A.3. HDP implementation – algorithm-identified number of topics.



Appendix B

Descriptive statistics

Table B.1. Descriptive statistics for analysis on the D-Wave event.

	Before D-Wave entry					**After** D-Wave entry				
Variable	Mean	SD	Min	Max	Obs	Mean	SD	Min	Max	Obs
	Hardware Publication									
Number of company publications, including collaboration with universities	25.80	2.59	23.00	28.00	5	30.60	5.46	22.00	36.00	5
Number of company publications, excluding collaboration with universities	8.20	2.17	7.00	12.00	5	9.40	3.21	7.00	15.00	5
Number of university publications, including collaboration with companies	450.60	16.16	432.00	469.00	5	492.80	48.85	434.00	569.00	5
Number of university publications, excluding collaboration with companies	433.00	15.56	416.00	451.00	5	471.60	43.81	420.00	541.00	5
	Software Publication									
Number of company publications, including collaboration with universities	16.40	2.07	14.00	19.00	5	28.40	10.11	15.00	39.00	5
Number of company publications, excluding collaboration with universities	5.60	1.82	3.00	8.00	5	11.60	4.51	7.00	16.00	5
Number of university publications, including collaboration with companies	356.20	15.74	335.00	376.00	5	453.20	48.31	387.00	503.00	5
Number of university publications, excluding collaboration with companies	345.40	15.71	326.00	366.00	5	436.40	42.23	379.00	481.00	5
	Control Publication									
Number of company publications, including collaboration with universities	0.48	2.74	0.00	64.00	3100	0.53	3.06	0.00	89.00	3100
Number of company publications, excluding collaboration with universities	0.16	1.08	0.00	25.00	3100	0.15	0.91	0.00	20.00	3100
Number of university publications, including collaboration with companies	21.47	89.97	0.00	2182.00	3100	25.25	118.96	0.00	3019.00	3100
Number of university publications, excluding collaboration with companies	21.15	88.44	0.00	2152.00	3100	24.87	116.88	0.00	2948.00	3100

	Hardware Patent									
Number of company publications, including collaboration with universities	25.60	6.47	17.00	32.00	5	53.40	29.01	22.00	89.00	5
Number of company publications, excluding collaboration with universities	24.80	5.59	17.00	30.00	5	51.20	27.68	21.00	84.00	5
Number of university publications, including collaboration with companies	3.00	1.41	1.00	4.00	5	10.00	6.75	4.00	21.00	5
Number of university publications, excluding collaboration with companies	2.20	1.10	1.00	4.00	5	7.80	6.76	2.00	19.00	5
	Software Patent									
Number of company publications, including collaboration with universities	3.80	1.64	2.00	6.00	5	12.80	6.69	5.00	21.00	5
Number of company publications, excluding collaboration with universities	3.80	1.64	2.00	6.00	5	12.60	6.88	5.00	21.00	5
Number of university publications, including collaboration with companies	0.80	0.84	0.00	2.00	5	1.60	1.14	0.00	3.00	5
Number of university publications, excluding collaboration with companies	0.80	0.84	0.00	2.00	5	1.40	0.89	0.00	2.00	5
	Control Patent									
Number of company publications, including collaboration with universities	17.78	39.34	0.00	733.00	15950	41.62	105.22	0.00	2323.00	15950
Number of company publications, excluding collaboration with universities	17.75	39.29	0.00	732.00	15950	41.52	105.04	0.00	2323.00	15950
Number of university publications, including collaboration with companies	0.20	0.69	0.00	17.00	15950	0.49	1.41	0.00	24.00	15950
Number of university publications, excluding collaboration with companies	0.16	0.58	0.00	13.00	15950	0.38	1.17	0.00	24.00	15950

Table B.2. Descriptive statistics for analysis on the IBM event.

	Before IBM cloud event					**After** IBM cloud event				
Variable	Mean	SD	Min	Max	Obs	Mean	SD	Min	Max	Obs
					Hardware Publication					
Number of company publications, including collaboration with universities	30.00	5.10	22.00	36.00	6	38.00	7.16	31.00	46.00	4
Number of company publications, excluding collaboration with universities	9.83	3.06	7.00	15.00	6	7.00	2.00	4.00	8.00	4
Number of university publications, including collaboration with companies	488.33	45.05	434.00	569.00	6	487.75	43.77	430.00	536.00	4
Number of university publications, excluding collaboration with companies	468.17	40.08	420.00	541.00	6	456.75	39.45	403.00	498.00	4
					Software Publication					
Number of company publications, including collaboration with universities	26.00	10.79	14.00	39.00	6	61.25	18.06	42.00	84.00	4
Number of company publications, excluding collaboration with universities	10.17	5.34	3.00	16.00	6	21.50	8.50	15.00	34.00	4
Number of university publications, including collaboration with companies	435.83	60.64	349.00	503.00	6	737.00	184.61	546.00	969.00	4
Number of university publications, excluding collaboration with companies	420.00	55.14	338.00	481.00	6	697.25	173.94	522.00	919.00	4
					Control Publication					
Number of company publications, including collaboration with universities	0.51	2.96	0.00	89.00	3720	0.59	4.08	0.00	106.00	2480
Number of company publications, excluding collaboration with universities	0.14	0.89	0.00	20.00	3720	0.13	0.89	0.00	24.00	2480
Number of university publications, including collaboration with companies	24.89	116.02	0.00	3019	3720	25.83	157.78	0.00	4029.00	2480
Number of university publications, excluding collaboration with companies	24.52	114.05	0.00	2948	3720	25.37	154.59	0.00	3945.00	2480
					Hardware Patent					
Number of company publications, including collaboration with universities	49.00	28.09	22.00	89.00	6	140.00	44.93	84.00	182.00	4
Number of company publications, excluding collaboration with universities	47.17	26.66	21.00	84.00	6	136.00	43.03	83.00	173.00	4

Number of university publications, including collaboration with companies	9.00	6.51	4.00	21.00	6	20.75	10.81	7.00	32.00	4
Number of university publications, excluding collaboration with companies	7.17	6.24	2.00	19.00	6	16.75	7.59	6.00	23.00	4
	Software Patent									
Number of company publications, including collaboration with universities	11.50	6.77	5.00	21.00	6	36.00	11.78	20.00	48.00	4
Number of company publications, excluding collaboration with universities	11.33	6.89	5.00	21.00	6	35.75	11.44	20.00	47.00	4
Number of university publications, including collaboration with companies	1.50	1.05	0.00	3.00	6	3.00	2.16	0.00	5.00	4
Number of university publications, excluding collaboration with companies	1.33	0.82	0.00	2.00	6	2.75	1.89	0.00	4.00	4
	Control Patent									
Number of company publications, including collaboration with universities	38.54	98.54	0.00	2323.00	19140	38.24	102.24	0.00	1880.00	12760
Number of company publications, excluding collaboration with universities	38.44	98.37	0.00	2323.00	19140	38.15	102.01	0.00	1879.00	12760
Number of university publications, including collaboration with companies	0.45	1.33	0.00	24.00	19140	0.48	1.69	0.00	38.00	12760
Number of university publications, excluding collaboration with companies	0.35	1.10	0.00	24.00	19140	0.39	1.41	0.00	31.00	12760

Appendix C

Additional results

The following figures repeat our results separately for large companies and others. We proxy large companies by splitting our analysis between companies in the S&P 500 and S&P Global 100, and all other. The results show that the increase in company patents and publications is largely driven by these large public companies. All estimations include all company patents and papers, regardless of whether they are collaborative with universities. As before, the increase in company publications is driven by collaboration with universities.

Figure C.1a. Company SDID Hardware (pre- and post-2011) – S&P 500 firms vs. non-S&P 500 firms

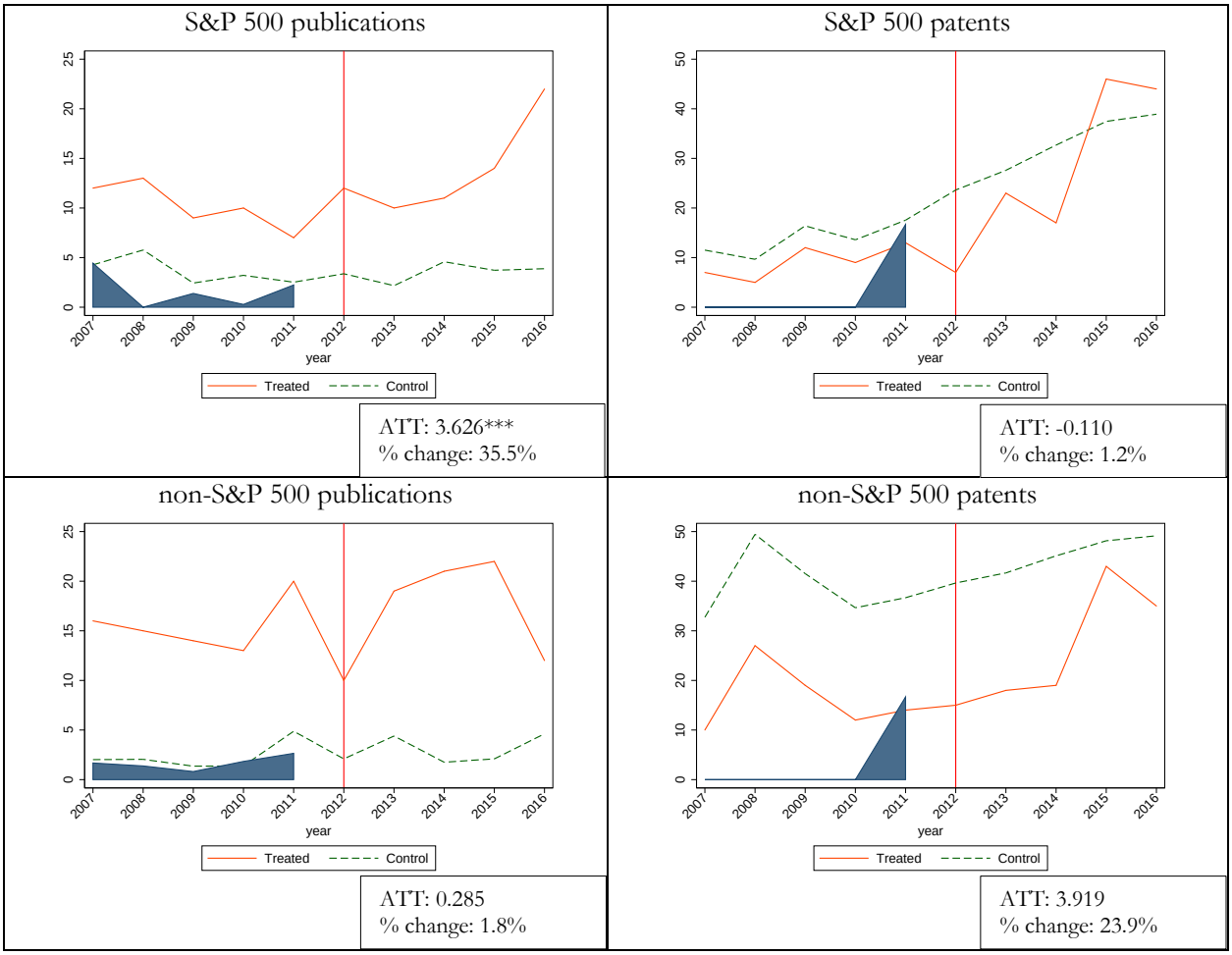


Figure C.1b. Company SDID Software (pre- and post-2011) – S&P 500 firms vs. non-S&P 500 firms

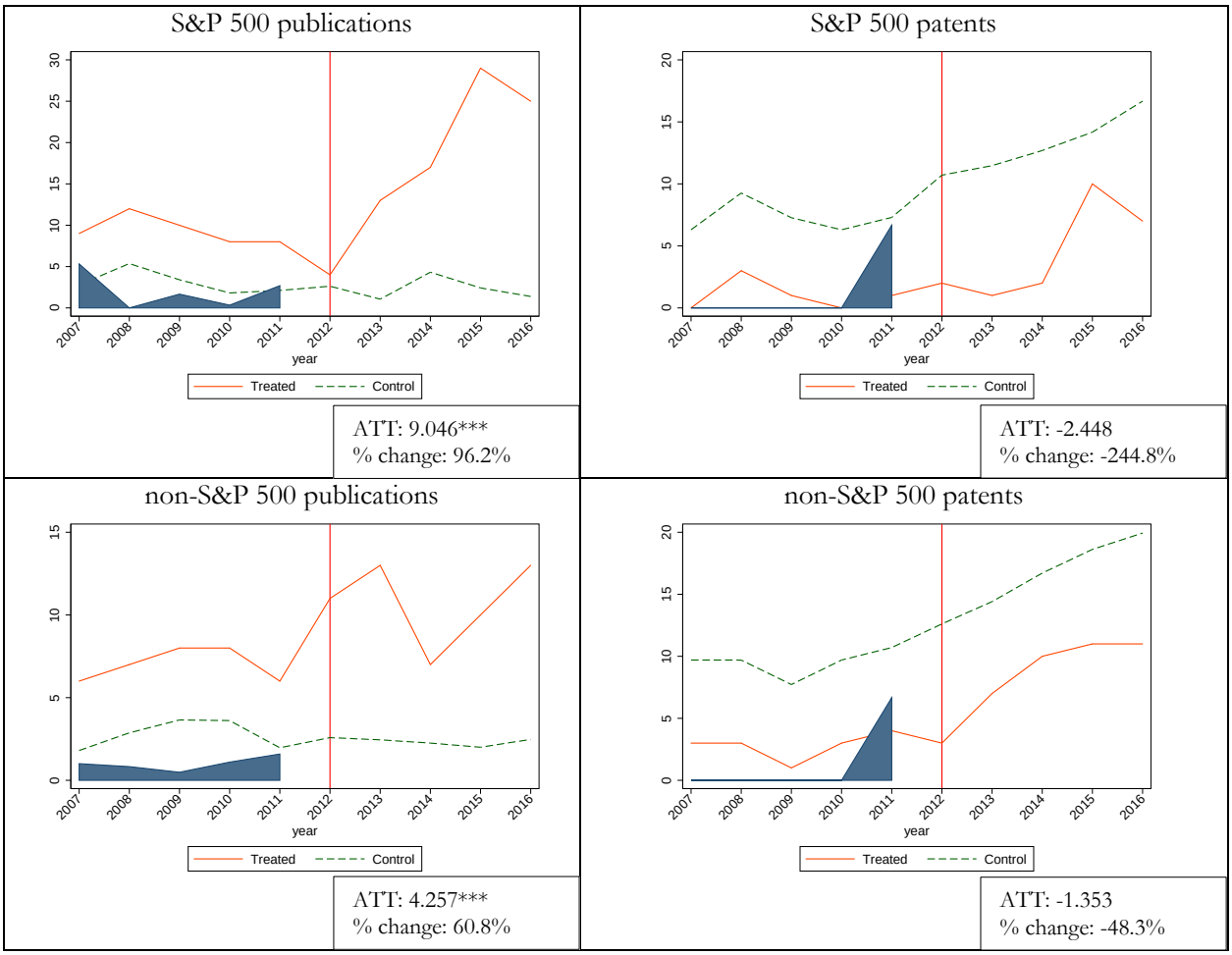


Figure C.2a. SDID Hardware (pre- and post-2016) – S&P 500 firms vs. non-S&P 500 firms

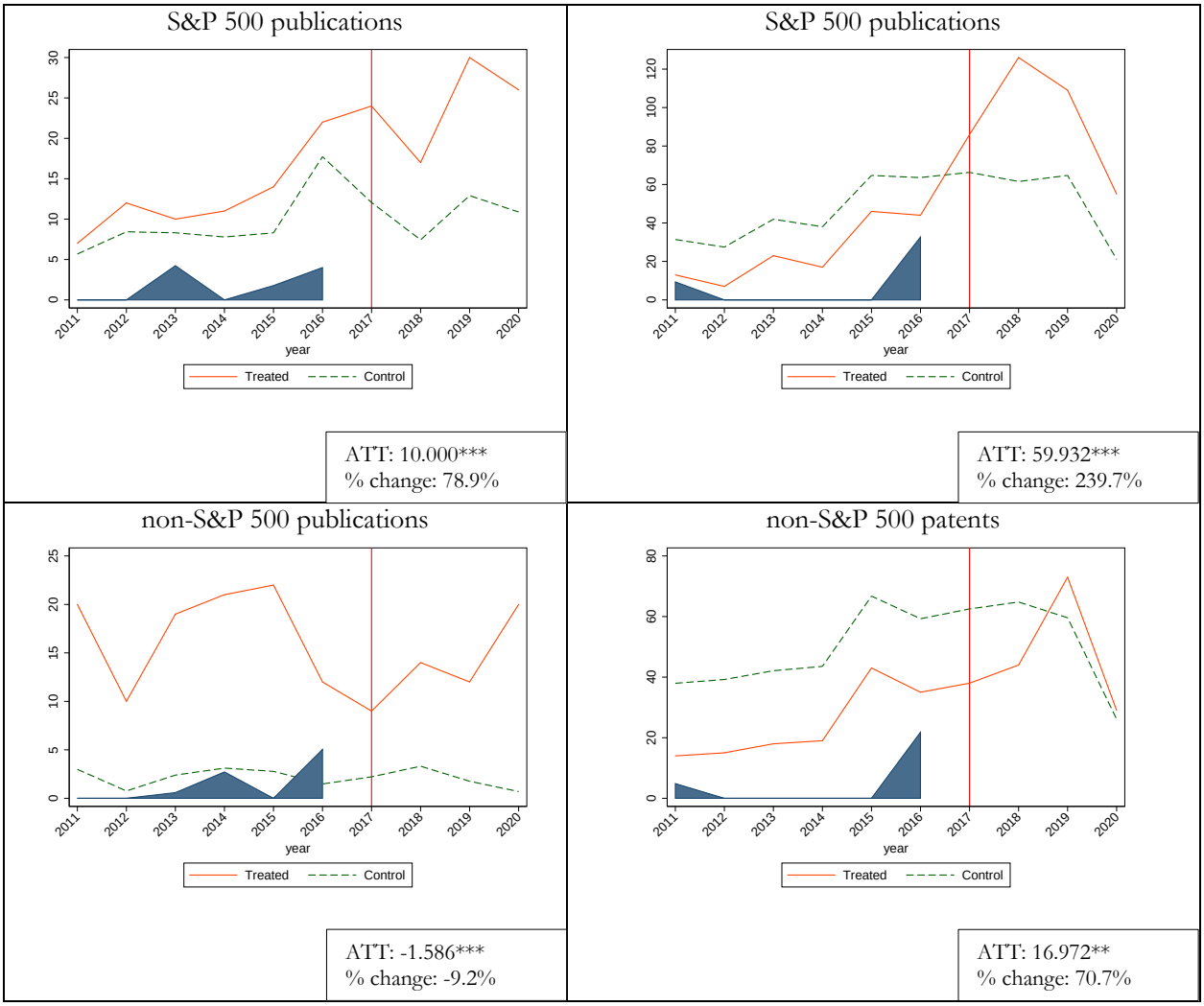


Figure C.2b. SDID Software (pre- and post-2016) – S&P 500 firms vs. non-S&P 500 firms

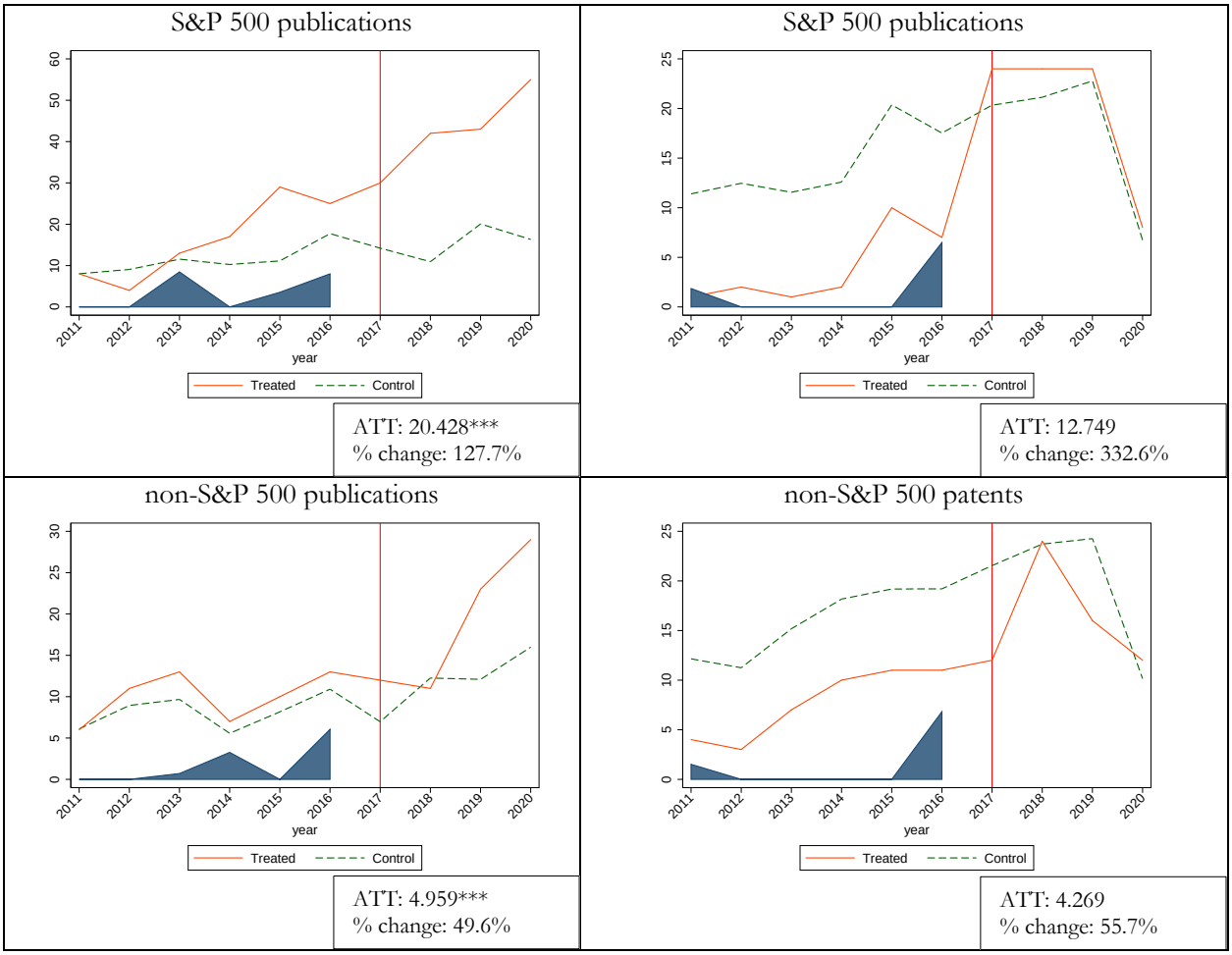


Figure C.3 S&P 500 vs. non-S&P 500 in adiabatic

