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Patent Pledge and Technological Innovation: The "Good Faith" of Tesla

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Abstract

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Keywords Patent pledge; Intellectual property strategy; Ecosystem; Invention diffusion; Electric Vehicles; Tesla

JEL Classification O30, O32, O34

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Abstract

On June 12, 2014, Tesla declared that it would refrain from initiating patent litigation against any party that, in *good faith*, seeks to utilize its technology. The stated intention behind this move was to stimulate the market for electric vehicles. This research presents the first empirical analysis of the impact of patent pledge for pledgor's entire patent portfolio as a corporate strategy on both the pledgor's innovation and follow-on innovations. The result indicates that adopting this strategy increased technology similarity for innovations associated with Tesla's innovation and raised Tesla's patenting activity, suggesting an expansion of ecosystem surrounding Tesla. Nonetheless, no significant impact has been observed on Tesla's innovation activities and the extensive margin of follow-on innovations, which may be attributed to the *good faith* condition that distinguishes Tesla's patent pledge from a patent expiration or mandatory royalty-free licensing. This paper offers implications for managers considering incorporating patent pledge in their strategic toolkit to augment their firm's ecosystem. Meanwhile, policymakers should also treat firms' patent pledge carefully, including evaluating the social implications of the conditions attached to their patent pledge.

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1. Introduction

Tesla's CEO, Elon Musk, made an announcement on June 12, 2014, in a blog post titled *"All Our Patent Are Belong To You"* on Tesla's official website. Musk states that all Tesla patents[12], which have been disclosed in the past and will be released in the future starting from June 12, 2014, can be used by anybody without royalties or the need for complex contracts, as long as they are used in *good faith*[3]. The significance of employing its patents in a *good faith* manner as a "defensive termination" was underscored in Tesla's declaration. Although Tesla declared its intention to refrain from legal proceedings against anyone that utilized its patents in *good faith*, the legal framework pertaining to patent infringement is intricate. Disputes may potentially emerge regarding the interpretation of Tesla's patents or the delineation of the concept of *good faith* use. For instance, in 2023, Tesla initiated legal action against Cap-XX, an Australian creator and manufacturer of supercapacitors, for patent infringement[4]. Tesla contended that Cap-XX breached the *good faith* condition by initiating a patent infringement lawsuit against Maxwell Technologies in 2019, shortly after Tesla's acquisition of the company, which rendered Maxwell Technologies' patents the property of Tesla and

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[1] "Tesla Patents" means all patents owned now or in the future by Tesla (other than a patent owned jointly with a third party or any patent that Tesla later acquires that comes with an encumbrance that prevents it from being subject to this Pledge).

[2] Tesla's patent pledge is effective after the transfer of its patents, eliminating the concern associated with the change of patent ownership (Schultz and Urban, 2012). https://www.tesla.com/en_GB/legal/additional-resources#patent-pledge

[3] According to Tesla's interpretation, a party is "acting in good faith" for so long as such party and its related or affiliated companies have not:

- asserted, helped others assert or had a financial stake in any assertion of (i) any patent or other intellectual property right against Tesla or (ii) any patent right against a third party for its use of technologies relating to electric vehicles or related equipment;
- challenged, helped others challenge, or had a financial stake in any challenge to any Tesla patent; or
- marketed or sold any knock-off product (e.g., a product created by imitating or copying the design or appearance of a Tesla product or which suggests an association with or endorsement by Tesla) or provided any material assistance to another party doing so.

[4] https://www.reuters.com/legal/tesla-sues-australias-cap-xx-over-ev-battery-technology-2023-07-17/

technically safeguarded by Tesla's defensive termination[5] if no relevant encumbrance term was attached to Tesla's acquisition of Maxwell Technologies.

This paper first offers literature that could shed light on Tesla's rationale in adopting this strategy. The rationale is analyzed from ecosystem's point of view, especially for electric vehicle ecosystem (Chen et al., 2017), arguing that Tesla intends to stimulate the growth of an ecosystem centering around Tesla by leveraging the patent pledge to encourage the advent of complementary innovations (Adner, 2006; Adner and Kapoor, 2010; 2016; Jacobides et al., 2018; Teece, 2018). Moreover, this paper also summarizes the existing literature assessing the impact of royalty-free licensing (Gaessler et al., 2025; Watzinger et al., 2020; Sampat and Williams, 2019; Galasso and Schankerman, 2015; Moser and Voena, 2012; Murray and Stern, 2007) and patent pledges (de Rassenfosse and Palangkaraya, 2023; Contreras et al., 2018; Hall and Helmers, 2013) on follow-on innovations, emphasizing the distinct context between these discoveries and Tesla.

This paper analyzes innovation based on patent data from PATSTAT and other firm-level control data from Compustat and SDC Platinum. The research period is 2009 – 2019. The methodology adopted by this research is Difference in Differences (DID) with synthetic DID for robustness checks. The findings indicate that the technological similarity (Jaccard Similarity and Cosine Similarity) between Tesla's patents and subsequent innovations rise significantly following Tesla's announcement of patent pledge, suggesting an expansion of ecosystem with Tesla as the focal firm. Furthermore, Tesla augment its patenting activity (number of granted patent application) while maintaining a relatively consistent level of innovation intensity (number of patent families), indicating Tesla's aim to extend the reach

[5] *Tesla, inc. v. CAP-XX, Ltd., 23-cv-00334* (E.D. Texas, July 14, 2023); *CAP-XX, Ltd. V. Maxwell Technologies, Inc.*, 19-cv-01733, 2020 WL 2914497 (D.Delaware, June 3, 2020).

of its innovations to additional patent offices' jurisdiction. Moreover, the significant increase in subsequent inventions at the extensive margin (number of forward citations), as indicated by prior work analyzing the influence of royalty-free licensing imposed by policy or legislation, is not observed, suggesting that follow-on innovators respond variably to royalty-free licensing (patent pledge) in different contexts.

The conclusions from this research are mainly threefold. Firstly, companies could opt to pledge their patents royalty-free to promote the development of complementary innovations, so fostering the growth of an ecosystem centered around these firms. This approach may be especially beneficial when the technology constraints impeding ecosystem growth are very modular. Then, policymakers need to assess the implications of the conditions attached to the patent pledges made by firms, especially by incumbents. Incumbents could use conditional patent pledge as a way to shape the future technological trajectory in their favor under the banner of open innovation with additional publicity benefit. Finally, future study on patent pledges, royalty-free licenses for patents, and open-source software should delineate the extent of freedom or openness, as legally granted free licenses typically impose less restrictions than those freely provided by corporations i.e. *good faith* condition by Tesla. Different restrictions imposed may result in varying behaviors among subsequent innovators. Schilling (2022) asserts that it is more beneficial to view the technological system as a continuum ranging from wholly proprietary to wholly open, rather than in a binary framework (closed or open). Contreras (2023) and Ehrnsperger and Tietze (2019) provide framework to classify patent pledges for their level of openness for analytical purposes. This research outlines consequences for managers about the adoption of patent pledge as a corporate strategy and for policymakers in comprehending the motivations of enterprises that utilize royalty-free licensing and in integrating it into their policy toolkits.

2. Theory

2.1. Ecosystem for Electric Vehicles

Substitutions between new (i.e. lithium battery) and old technologies (i.e. combustion engine) depend not only on their inherent capabilities, but also on their embedded ecosystems, including the innovation from complementors (Adner, 2006; Adner and Kapoor, 2010; 2016; Jacobides et al., 2018; Teece, 2018). Meanwhile, auto firms have also consistently been the focal point of an ecosystem that necessitates providers of complementary innovations, products, or services. These providers may be from different industries and are not required to adhere to contractual agreements; however, they maintain substantial interdependence (Jacobides et al., 2018; Chen et al., 2017). Therefore, the survival of auto firms is contingent upon the existence of a flourishing ecosystem that is characterized by a variety of roles and roles played by multiple participants, as opposed to a simple firm-supplier relationship. According to Jacobides et al. (2006), Baldwin (2015), and Hannah (2016), technological bottlenecks, which are components that are either in limited supply, high cost, or of poor quality, are the primary impediments to the development of a nascent ecosystem. The case on ecosystem for electric vehicles presented by Chen et al. (2017) illustrates that the primary and secondary constraints for electric vehicles were battery and charging, respectively, from 2007 to 2015. Nevertheless, from 2015 to 2017, the primary impediment was charging, while the second was the battery (Chen et al., 2017). Tesla made significant strides in battery innovation from 2007 to 2012, including the implementation of mature laptop cell technology to reduce battery costs. However, innovations cannot be translated into profits unless complementary assets are in place (Tripsas, 1997; Teece, 1986; 2006). Tesla not only continued to innovate but also developed complementary assets for its battery technologies by investing in its first gigafactory in 2014 in collaboration with Panasonic, a world-leading battery manufacturer, after effectively developing advanced battery technology for electric vehicles. Therefore, Tesla's remaining major impediment was charging. Since late 2012, Tesla has been in the process of constructing a rapid charging network and has already developed its fast-charging technology. It is imperative for Tesla to resolve the charging bottleneck, as the diffusion of electric vehicles is greatly influenced by the powerful network effect between charging facilities and adoption of electric vehicles (Li et al., 2017; Springel, 2021). Tesla's V1 Supercharger demonstrated competitiveness against major rival standards, including the first-generation CHAdeMO and Combined Charging System (CCS), in various technological aspects such as maximum power output (90 kW for Tesla's V1 Supercharger compared to 50 kW for CHAdeMO 1.0 and CCS 1.0)[6]. However, coordination efforts from other players are essential to the adoption of Tesla's Supercharger. For instance, in addition to modifying the connector, other automakers need to adjust their Battery Management System (BMS) to ensure the safety and efficiency of utilizing new charging technologies. Hardware manufacturers, including those producing batteries and semiconductors, must advance their technologies by incorporating superior materials in semiconductors to enhance power conversion efficiency, minimize energy losses,

[6] By early 2018, four major EV charging standards were competing globally: https://www.reuters.com/article/business/plug-wars-the-battle-for-electric-car-supremacy-idUSKBN1FD0QM/. However, in North America, Tesla's Supercharger emerged as the dominant standard (Bhargava et al., 2021). Tesla has rebranded its charging standard as the North America Charging Standard (NACS), which has been adopted by other automakers including Ford and General Motors. More details can be found on Tesla's website: https://www.tesla.com/en_GB/blog/opening-north-american-charging-standard and https://www.tesla.com/NACS.

and increase the energy storage capacity of batteries, thereby ensuring the efficacy, stability, and safety of faster charging. Furthermore, grid operators must adapt to Tesla's Supercharger technology by implementing effective load management and intelligent scheduling strategies to ensure a stable power supply to charging infrastructure and prevent grid overload.

The emergence of ecosystem is more likely to result from modularization and the consequent reduction of frictional transaction costs, as argued by Baldwin (2008), Langlois (2003), and Jacobides and Winter (2005). Consequently, the modularity of charging technologies and the reduced costs of follow-on innovations and investment in complementary assets could significantly contribute to the expansion of the market through patent pledge of all of Tesla's technology, including its charging technologies, from 2014 onwards. A positive feedback cycle between Tesla's establishment of charging stations and the sale of cars could be established with network externalities brought by charging stations. Consequently, the purported objective of Tesla's patent pledge to promote the expansion of the electric vehicle market can also be interpreted as the expansion of an ecosystem that surrounds Tesla. Meanwhile, Tesla is also reducing the cost of imitators or innovators who try to develop substitutes for Tesla’s products. Hence, it would be reasonable to see an increase in technology similarity between Tesla’s innovation and its follow-on innovation.

In addition, the California Air Resources Board amended its Zero Emissions Vehicle (ZEV) credit system in 2013, granting nearly double the credits to long-range ZEVs capable of charging 80 percent of their range in under fifteen minutes compared to those that are not. Considering the substantial impact of credit revenue on Tesla's financials (Niedermeyer, 2019), this policy modification could incentivize Tesla to accelerate development and implementation of its supercharging technologies by providing royalty-free access for the development of complementary facilities and technologies, thereby encouraging broader adoption and indirectly enhancing Tesla's credit revenue. Furthermore, Tesla might gain advantages by establishing itself as the de facto standard setter for the industry in multiple contexts. For example, Tesla imposes a markup on electricity fees for consumers of its supercharging network in order to cover overhead expenses, such as management and maintenance fees. Thus, although a unified charging standard can enhance consumer surplus, the quantity of charging stations, and the adoption of electric vehicles (Li, 2023), Tesla may leverage its monopolistic power once its supercharging network becomes the de facto standard for all electric vehicles after market saturation.

In the blogpost[7], Elon Musk states that “We believe that applying the open source philosophy to our patents will strengthen rather than diminish Tesla’s position in this regard[8].” Nonetheless, open-source has a variety of business models. Companies may opt to make their whole source code and development processes publicly accessible, allowing anybody to examine, change, and distribute them, as exemplified by the Linux Kernel. In alignment with the prior discussion on ecosystems, IBM's commitment to refrain from enforcing its patents against implementations of Linux was motivated not by generosity, but by a desire to promote the extensive adoption of Linux, which would ultimately benefit IBM as a vendor of Linux servers and a provider of associated consulting services (Merges, 2004; Wen et al., 2016). Alternatively, corporations may choose for partially open source systems, such as Android, which includes a fundamental open source framework but incorporates certain private features or components. Tesla imposes a *good faith* condition on its openness to retain

[7] http://www.tesla.com/blog/all-our-patent-are-belong-to-you.
[8] Several systems on Tesla Model S, Model X and Model 3 are open sourced: https://www.tesla.com/en_GB/legal/additional-resources#open-source

a certain level of control to ensure the trajectory of follow-on innovations does not deviate to a path that Tesla does not want. Hence, the *good faith* condition resembles Sun Microsystem's Java Community Process, which prevents fragmentation of the core platform due to unregulated development by the software community while encouraging a wider software community to enhance Java and create complementary applications by granting everyone access to Java’s source code without fees.

2.2. Compulsory Royalty-free Licensing and Patent Pledge

Numerous empirical studies have been conducted to examine the impact of royalty-free licensing on innovations. A case similar to Tesla studied by Watzinger et al. (2020), has revealed that the breakup of the Bell Lab and the 1956 Consent Decree, which required Bell Lab to grant royalty-free licenses for all its patents, stimulated innovation in various sectors across the United States, excluding the telecommunications industry where Bell Lab primarily operates. Other literatures investigate royalty-free licensing or patent invalidation suggest similar effect on follow-on innovations. Gaessler et al. (2025) and Galasso and Schankerman (2015) uncover that patent invalidation increase follow-on innovations by 16 percent and 50 percent on average based on EU and US data respectively. The study conducted by Sampat and Williams (2019) examine the impact of gene patent grants on subsequent innovation and concludes that there is no discernible effect. Moser and Voena (2012) uncover that the Trading with the Energy Act, which requires several patent removals, leads to a 20 percent boost in follow-on innovation. Murray and Stern (2007) discover that the citation rate for a published technology decreased by 9% to 17% after the technology is granted a patent. Hence, Gilbert (2022) suggests that compulsory royalty-free licensing is generally conducive to innovation.

While there are similarities, the cases of royalty-free licensing in most of the aforementioned literature are different from Tesla's patent pledge. Tesla's patent pledge is effectively equal to a compulsory royalty-free licensing with a *good faith* condition attached. Ehrnsperger and Tietze (2019) dissect patent pledges into three dimensions: accessibility, compensation, and condition. Tesla's patent pledge is equivalent to compulsory royalty-free licensing in terms of the dimension of accessibility and compensation – accessible to general public without any monetary compensation. However, the attachment of *good faith* – an indirect non-assertion clause, could potentially lead to different behavior of follow-on innovators for Tesla's patents compared to those for the compulsory cases. de Rassenfosse and Palangkaraya (2023) study the effect of patent pledges on follow-on innovations based on 1213 U.S. patents pledge between 2005 and 2017. They discover that patent pledges do accelerate more innovation and the effect is stronger for patent pledges that are more open according to the framework provided by Ehrnsperger and Tietze (2019). While de Rassenfosse and Palangkaraya (2023) include patent pledges from Tesla in their study, only 184 patents of Tesla filed in the US are incorporated, which is a small fraction of Tesla's patent portfolio[9]. Hence, its result may not be able to extrapolate to Tesla's patent pledge and

[9] According to author's search based on USPTO data, the number of Tesla patents published before 12th June 2014 is 420 (excluding 7 co-owned patents according to Tesla's patent pledge). The data de Rassenfosse and Palangkaraya (2023) use for Tesla is from the patent pledge data maintained by Ehrnsperger (2019): https://www.repository.cam.ac.uk/items/9571edb4-f8f5-4f7c-bac9-a2b2bf26c3d1. Ehrnsperger (2019) extracts Tesla's pledged patent data from https://www.tesla.com/en_gb/legal/additional-resources#patent-list in 2019. The US patents contained in the list by Ehrnsperger (2019) include 79 patents published after its announcement for patent pledge. Thus, only a quarter of patents published before Tesla's announcement eligible under the patent pledge (105) is included in the list.

a firm-level analysis for all patents of Tesla covers wider range in time and space potentially leading to additional or different insights is warranted.

In contrast to the findings of the aforementioned literature, investigations on the "Eco-Patent Commons (EcoPC)", a situation that resembles Tesla's, arrive at different conclusions. The EcoPC was a pioneering non-profit project organized by a selected group of major industrial companies. Its objective was to offer "green technology" patents for widespread and royalty-free utilization in tackling environmental issues. Contreras et al. (2018) found that EcoPC did not stimulate more innovation. Although EcoPC may be perceived as a form of strategic conduct by corporations, it possesses distinct characteristics that set it apart from Tesla's patent pledge. The initiation of EcoPC involved a number of prominent global corporations such as IBM and Nokia, which may result in challenges when it comes to coordinating and enforcing EcoPC. In addition, contributors to EcoPC only donate patents that are distant from their own portfolios, as opposed to Tesla's practice which covers patents pertaining to Tesla's core business (Hall and Helmers, 2013).

Moreover, it is essential to highlight concerns and risks linked to follow-on innovators citing royalty-free license patents conferred by legislation and pledged patents by Tesla. Due to Tesla's *good faith* provision, innovators may be required to grant Tesla or other companies in the electric vehicle sector royalty-free access to innovations derived from Tesla's technology, thereby mitigating the risk of potential litigation from Tesla. This arrangement reflects an implicit reciprocity mechanism, which aligns with the concept of *Collective Invention* as outlined by Robert Allen (1983). Thus, unlike policy or legally mandated royalty-free licensing, any patent rights acquired by a party utilizing Tesla's intellectual property under the Patent Pledge will likely be superfluous. Moreover, some managers may worry that any future profit derived from technologies built upon Tesla's could face more risks of appropriation by Tesla. These may dissuade prospective innovators from licensing Tesla's patents except for those who intend to establish a long-term relationship with Tesla either as a competitor, a collaborator, or both.

According to Aghion et al. (2005), royalty-free licensing or its equivalent can be seen as a way to reduce monopolistic power and promote competition. If the pledgor/licensor is at the forefront of technology, increased competition could result in more innovation from both the follow-on innovators given the lowered barrier of entry and the pledgor/licensor for increased pressure for staying at the technological frontier (Aghion et al., 2005).

3. Data and Sample

3.1. Dependent Variables and Independent Variable

The independent variable for this study is a binary variable named *did* as the treatment variable for the Difference in Differences estimation. The innovation variables used in this study are based on patent data obtained from PATSTAT Online for each firm. These variables include the annual number of patent applications that are eventually granted, which serves as a measure of the intensity of innovation. Additionally, the ratio of the number of patent claims to the number of patent applications (only for granted patents) are used as measures of the quality/scope of innovation. Moreover, the annual number of patent citations (only for granted patents) and the number of patent families (distinct innovations) – DOCDB patent families according to PATSTAT - that cite the pledgor's patent at least once each year are used as measures for the combined effect of patent quality and the extensive margin of the patent pledge. Furthermore, the annual Cosine Similarity and Jaccard Similarity of the CPC

(Cooperative Patent Classification) code between the granted patent and its forward cited patent are calculated based on the application year for forward cited patents as measures of the technology similarity between patents. The log transformations for patent data and all other variables are all performed in the manner of $\log(Y)$ without $\log(1+Y)$ treatment for zero values to avoid the biased estimation highlighted by Chen and Roth (2023). However, a robustness check for $\log(1+Y)$ transformation is also included in Appendix A, which leads to the same conclusion as the main results.

3.2. Control Variables

This study also accounts for a range of business and industry parameters that could potentially influence a firm's future innovation productivity, especially for innovation quantity and quality. The variables are calculated for firm i throughout its fiscal year t. Similar to Jia and Tian (2018) and Chemmanur et al. (2014), the control variables used in the analysis are as follows: firm size (represented by the natural logarithm of the book value assets -- *lnat*), firm age (calculated as the difference between the fiscal year and the founding year obtained from the firm's website -- *lnage*), investments in intangible assets (measured by R&D expenditures divided by total assets -- *rdint*), profitability (measured by return on assets -- *roa*), asset tangibility (represented by net PPE scaled by total assets - *ppea*), leverage (*leverage*), capital expenditures (*capexasset*), growth opportunities (measured by Tobin's Q -- *tobinq*), financial constraints (measured by the Kaplan and Zingales (1997) five-variable KZ index -- *kzindex*), market power (measured by the Lerner Ratio, defined as operating income after depreciation divided by sales -- *lerner*), and institutional ownership (*instown*). In order to address the non-linear impacts of competition in the product market on innovations (Aghion et al., 2005), the squared Lerner Ratio (*lernersq*) is also incorporated. The control variables are obtained from Compustat (North America), with the exception of institutional ownership, which is obtained from SDC platinum.

3.3. Sample selection

As per the official instructions of PATSTAT Online[10], the database includes the vast majority of applications that were submitted three years prior to the present edition. Since I obtained our patent data from the PATSTAT 2023 Spring and PATSTAT 2023 Autumn versions, the most recent year included in the data is 2020. Due to the unprecedented occurrence of the Covid-19 pandemic in 2020, firms experienced varying impacts on their innovation efforts. For instance, pharmaceutical companies like AstraZeneca significantly increased their research and development activities, while car manufacturers such as Tesla and Toyota temporarily halted innovation and daily operations. Therefore, the most recent year considered for this study is 2019. Tesla successfully completed its initial public offering (IPO) and became listed on the Nasdaq stock exchange in 2008. As a result, the earliest data that is accessible for all control variables pertaining to Tesla is from 2008. Due to the lack of complete control variable data for Tesla in 2008 and the impact of the financial crisis, the earliest year that can be considered is 2009. Therefore, the designated timeframe for conducting an examination at the level of individual firms is from 2009 to 2019.

Due to the lack of interconnectivity between PATSTAT, Compustat, and SDC platinum, the innovation variables and control variables must be calculated and extracted independently, requiring manual matching. Therefore, only a restricted number of companies

[10] PATSTAT Online does not provide access to textual information of patents including patent abstract or full-text description. Hence, textual analysis based on elements including patent abstract or patent claims is not implementable.

can be selected. I intend to include sufficient number of control groups and strike a balance between effective construction of matching of Tesla by including a certain number of firms that are relatively similar to Tesla and an acceptable level of violation of SUTVA when analyzing based on standard Difference in Differences. Therefore, a set of control firms that possess different attributes of Tesla could facilitate the analysis based on Synthetic Difference in Differences. Thus, the control firms can be classified as three groups. The first group refers to firms that are most likely affected by Tesla's patent pledge should be included in the control group. Hence, all firms that can be classified within the same industry or the same product market as Tesla, based on the two-digit SIC code, from 2009 to 2019 according to the Text-based Network Industry Classifications (TNIC) data constructed by Hoberg and Phillips (2010; 2016), are included. Furthermore, all firms on Compustat (North America) with a SIC code of 3711, which represents the standard industry classification for Motor Vehicles and Passenger Car Bodies, such as Tesla and Toyota, are also included. Toyota announced in early 2015 that it permitted the royalty-free use of about 5,610 patents pertaining to hydrogen fuel cell vehicles (FCVs) until 2020. Given that Toyota implemented this policy shortly after Tesla's statement, it is plausible to infer that this constitutes Toyota's response to Tesla's declaration. However, Toyota implemented this strategy at the business unit level, whereas Tesla embraced it at the firm level by pledging all of its patents freely without term limits apart from *good faith* condition. Consequently, since all variables are gathered at the firm level, Toyota is omitted from the sample.[11] Nonetheless, Toyota's initiative underscores the necessity of incorporating hydrogen FCVs players in the

[11] Toyota's patent pledge is classified as a different type of patent pledge by Ehrnsperger and Tietze (2019) as a *conditional restricted patent pledge* compared to Tesla's *conditional open patent pledge*. The reason is that Toyota put restrictions on access and users have to negotiate individual royalty-free license agreements with Toyota. https://global.toyota/en/detail/4663648

assessment. Thus, the second group refers to firms recognized by the European Patent Office/International Energy Agency (2023) and The Intellectual Property Office (2021) as top innovators in hydrogen technologies are also added to the control groups to represent a group of firms that could be indirectly affected by Tesla's patent pledge. Lastly, since Tesla is generally reckoned as a high-tech firm and it has been added to Nasdaq 100 from 2013, all firms that belong to the Nasdaq 100 index in 2023 are included in the third group[12]. All firms belong to the above groups have complete data for the period 2009 to 2019 on Compustat are included in the analysis to establish a balanced panel. In the end, a total of 70 (excluding Tesla) firms are selected with the first group, second group, and third group comprised of 14 firms, 12 firms, and 48 firms respectively (there are small overlaps between these three groups). The summary statistics for control variables is presented in table 1.

Table 1. Summary Statistics for Controls used in Analysis

VarName	N	Mean	SD	Median	Max	Min
rdint	756	0.0905	0.0886	0.0645	0.5380	0.0023
lnage	759	3.6269	0.8128	3.5264	5.1475	0.0000
lnat	759	9.7390	1.7974	9.7858	13.5694	3.8490
roa	754	0.1257	0.1154	0.1280	0.4710	-0.9257
ppea	759	0.1687	0.1324	0.1224	0.7151	0.0108
leverage	755	0.2399	0.1798	0.2159	0.9938	0.0000
capexasset	755	0.0390	0.0338	0.0282	0.2774	0.0038
tobinq	663	2.8530	2.2102	2.1150	13.5848	0.3753
lerner	759	0.1232	0.3530	0.1486	0.6822	-5.8179
lernersq	759	0.1396	1.5028	0.0271	33.8478	0.0000
kzindex	606	-13.2392	41.2083	-5.2830	114.3361	-695.1763
instown	759	0.7222	0.2482	0.7964	1.0000	0.0000

Note: Control variables are utilized solely for the analysis for Tesla's innovation behavior (section 5.3) due to their significant explanatory influence on dependent variables, as indicated by prior literature (Jia and Tian, 2018; Chemmanur et al., 2014). Linde and Pepsico are removed from the analysis due to the absence of the institutional ownership variable from SDC Platinum during the entire research period.

[12] Google has also initiated a non-assertion patent pledge classified as *conditional open patent pledge* by Ehrnsperger and Tietze (2019) similar to Tesla's. However, only dozens of patents related to information technology are pledged during the research period, which only comprised of a tiny portion of Google's patent portfolio. Hence, Google is retained in the control group and its removal has no impact on the regression results. https://www.google.com/patents/opnpledge/patents/

To maintain consistency, these two companies are removed from all main analyses. The incorporation of these two companies in the analysis for technology similarity (Section 5.1) and follow-on innovations (Section 5.2) has minimal effect on the results and does not alter the conclusion. Nevertheless, these two companies are incorporated in the robustness checks for hypotheses 1 and 2 utilizing synthetic DID, whose validity enhances with an increase in data volume.

4. Empirical Setup

The selected methodology for this study is Difference in Differences (DID). Many analytical approaches can be employed, including the classic Two-Way Fixed Effect (TWFE), synthetic DID, and Propensity Score Matching DID (PSM-DID). In addition, the synthetic difference-in-differences (DID) method proposed by Arkhangelsky et al. (2021) is based on synthetic controls. This approach necessitates an adequate number of pre-intervention and post-intervention periods to prevent overfitting and false correlations, as emphasized by Abadie (2021). Therefore, due to the limited duration of the pre-intervention era (2009-2013) and the post-intervention period (which may be even shorter if variables are forwarded), the use of synthetic DID is not the best option for this study. However, given the natural advantage of synthetic DID in quantitative case studies, which is suitable for this study in the case of Tesla, synthetic DID is conducted as a robustness check for all the results yielded in the main analysis using TWFE. The synthetic DID results are presented in appendix B, leading to same conclusion as the main analysis performed under TWFE. PSM-DID is also not implementable in this study as the number of treated groups is one – tesla, which does not have enough variations for calculating propensity scores. Hence, convergence cannot be achieved in the statistical software (STATA) when PSM-DID analysis is conducted.

Thus, the methodology for this study is standard TWFE:

$$Innovation_{i,t} = \beta \cdot PP_{i,t} + \delta \cdot Controls_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t}$$

The term $Innovation_{i,t}$ represents variables related to innovation, such as the number of patent applications made by each firm annually. The variable $PP_{i,t}$ is a binary variable that takes the value of 1 when patent pledge is occurring, and 0 otherwise. The term $Controls_{i,t}$ denotes control variables that vary over time. μ_i represents the fixed effect of the company, while δ_t represents the fixed effect of time. The term $\varepsilon_{i,t}$ refers to idiosyncratic errors.

5. Main Results

Since R&D expenditure and other innovation inputs take time to translate into patents, this study includes a forward analysis of all innovation variables, using data adjusted forward by one and two years.

5.1. Impact on Technology Similarity

Similar to Hedge et al. (2023), Bloom et al. (2013), and Jaffe (1986), this paper uses Jaccard Similarity and Cosine Similarity for the CPC code between focal patents and their forward cited patents as a measure for technology similarity. Since CPC code has different levels, the Jaccard Similarity and Cosine Similarity for CPC code in Subgroup level is analyzed given Subgroup level is the most detailed level for technology classification.

5.1.a. Jaccard Similarity

The Jaccard Similarity between patents and their forward cited patents is computed as:

$$Jaccard\ Similarity = \frac{A \cap B}{A \cup B}$$

Where Set A refers to the focal patent's CPC classifications in Subgroup level and Set B refers to one of its forward cited patents' CPC classifications also in the Subgroup level. After retrieved the value for Jaccard Similarity for the focal patents and each pair of their forward cited patents, the value is averaged for each individual firms in our sample annually per the application year of the forward cited patents to yield the final result.

The result from table 2 indicates that for CPC code in Subgroup level, the Jaccard Similarity for patents and their forward cited patents has increased 3.82 percent and 4.47 percent with statistically significant in 1 percent for no forward patents and forward 1-year patents respectively and robust to the result for event study and the Honest DID (Rambachan and Roth, 2023) testing for parallel trend assumption and linear pre-trend with 5 percent level of sensitivity analysis (Figure 1 and Figure 2). Figure 3 illustrates that the result for dependent variable forwarded two years does not pass the parallel trend assumption.

Table 2. Effects on Technology Similarity (Measured by Jaccard Similarity)

	(1) Current		(2) Forward 1Y		(3) Forward 2Y	
Patent Pledge	0.0382^{***}	(0.0061)	0.0447^{***}	(0.0040)	0.0383^{***}	(0.0032)
Constant	0.1913^{***}	(0.0116)	0.1622^{***}	(0.0107)	0.1304^{***}	(0.0047)
Fixed Effects	Yes		Yes		Yes	
N	742		683		616	
r2_a	0.2857		0.2188		0.1945	

Note: Standard errors in parentheses
Source: PATSTAT Compustat SDC_Platinum
$^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$

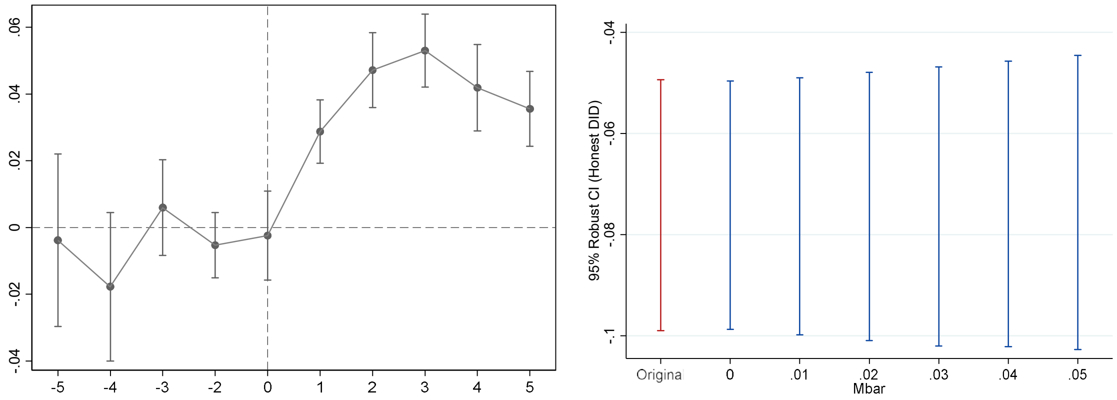


Figure 1. Event Study and Honest DID result for Jaccard Similarity

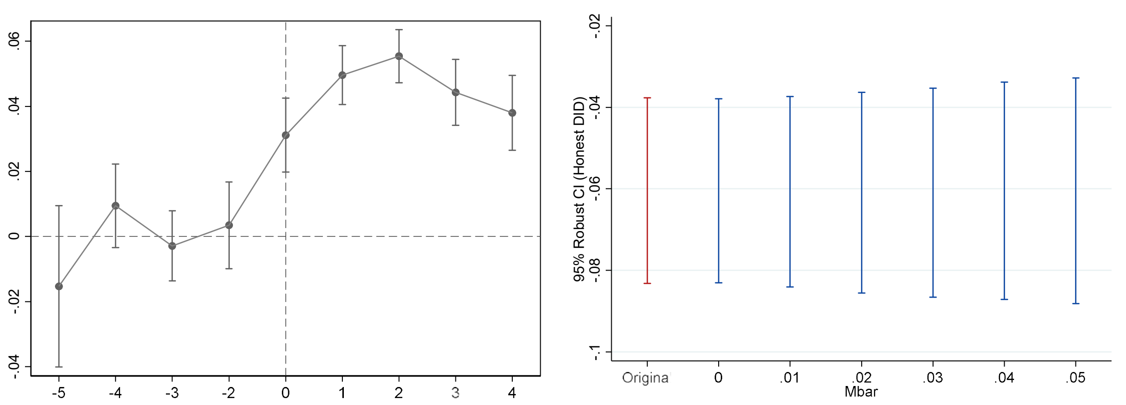


Figure 2. Event Study and Honest DID result for Jaccard Similarity – Forward 1-year

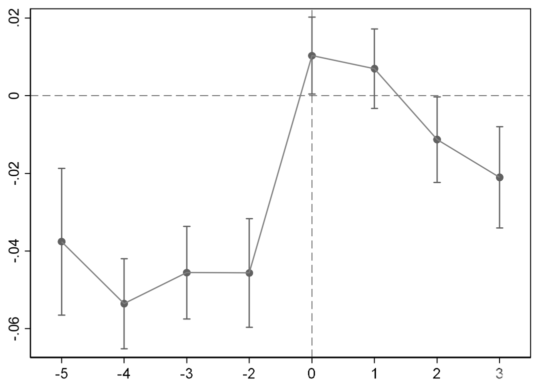


Figure 3. Event Study result for Jaccard Similarity – Forward 2-years

Same set of analysis is also conducted for granted patents applied before Tesla's announcement. Table 3 shows a stronger increase of 4.95 percent with the passage of parallel trend testing and linear pre-trend for the no forward case (Figure 4). Meanwhile, the results for forward 1 year and forward 2 years cases do not pass the parallel trend test (Figure 5).

Table 3. Effects on Technology Similarity for Granted Patents Applied before the Announcement of Strategy (Jaccard Similarity)

	(1)		(2)		(3)	
	Current		Forward 1Y		Forward 2Y	
Patent Pledge	0.0495***	(0.0063)	0.0532***	(0.0045)	0.0448***	(0.0029)
Constant	0.1902***	(0.0117)	0.1608***	(0.0108)	0.1289***	(0.0048)
Fixed Effects	Yes		Yes		Yes	
N	739		680		613	
r2_a	0.3706		0.3303		0.3741	

Note: Standard errors in parentheses
Source: PATSTAT Compustat SDC_Platinum
* $p < .10$, ** $p < .05$, *** $p < .01$

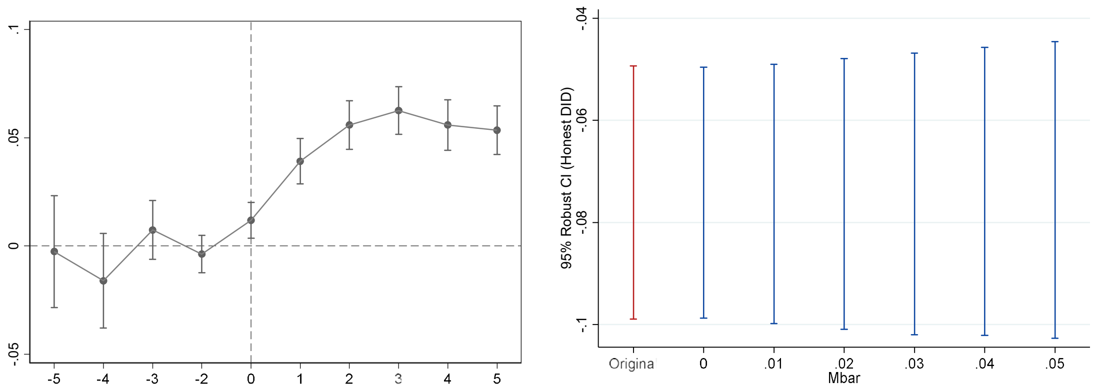


Figure 4. Event Study and Honest DID result for Jaccard Similarity of Granted Patents before Strategy

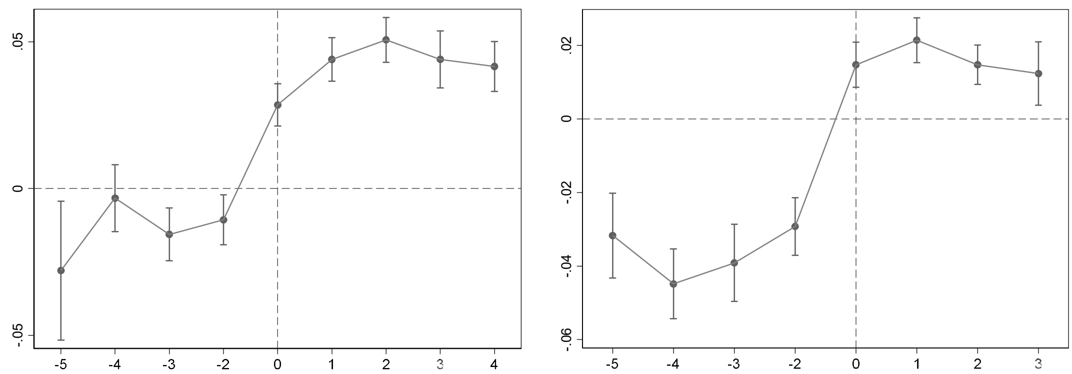


Figure 5. Event Study result for Jaccard Similarity of Granted Patents before Strategy – Forward 1 year and Forward 2-years

5.1.b. Cosine Similarity

Additionally, more in-depth analysis is performed to further investigate technology similarity by using cosine similarity, which is widely used to measure the proximity of two vectors.

The Cosine Similarity is calculated as:

$$Cosine\ Similarity = \frac{N_f N_c'}{(N_f N_f')^{1/2} * (N_c N_c')^{1/2}}$$

Where f represents focal patents and $c = 1, \ldots \ldots, C$ represents any patents of the focal patent's forward cited patents. Here N_k is a vector with each element indicating patent k's fraction of CPC assignments in each of the groups down to subgroup level of CPC code. For example, $N_k = (N_{k1}, N_{k2}, \ldots \ldots N_{k273071})$ for all 273071 Subgroup CPC groups (full CPC code) according to the 2024.01 version of CPC. After retrieved for the Cosine Similarity value for each pair, they are averaged under firm-level for all firms in our sample annually per the application year of the forward cited patents to generate the final result.

The regression results below illustrate that for all levels of CPC, the technology similarity measured by Cosine Similarity increased by around 4.11 percent to 5.61 percent when patent data is not forwarded and forwarded one year with statistically significant in 1 percent (table 4). In addition, the corresponding result of event study and the Honest DID (Rambachan and Roth, 2023) demonstrates the robustness for the regression results according to figure 6 and figure 7.

Table 4. Effects on Technology Similarity (Measured by Cosine Similarity)

	(1) Current		(2) Forward 1Y		(3) Forward 2Y	
Patent Pledge	0.0411***	(0.0064)	0.0561***	(0.0044)	0.0484***	(0.0036)
Constant	0.2532***	(0.0106)	0.2295***	(0.0115)	0.1962***	(0.0058)
Fixed Effects	Yes		Yes		Yes	
N	742		683		616	
r2_a	0.2415		0.1760		0.1380	

Note: Standard errors in parentheses
Source: PATSTAT Compustat SDC_Platinum
* $p < .10$, ** $p < .05$, *** $p < .01$

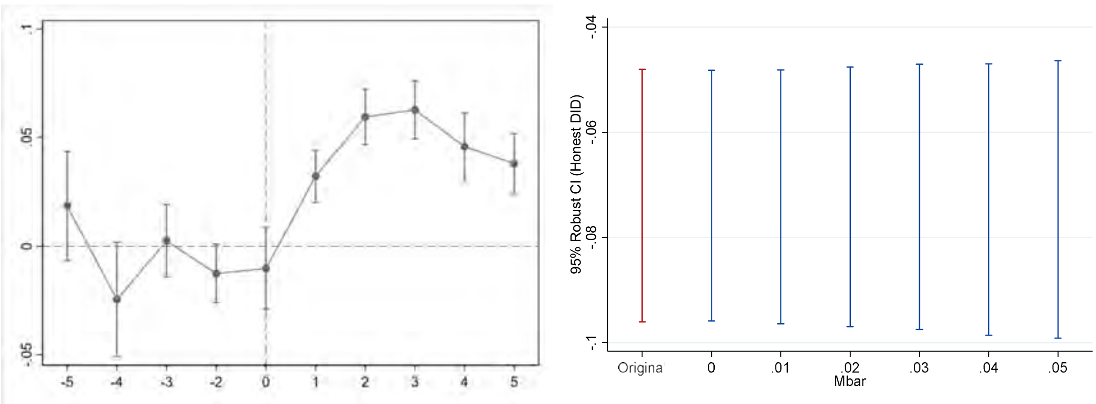


Figure 6. Event Study and Honest DID result for Cosine Similarity

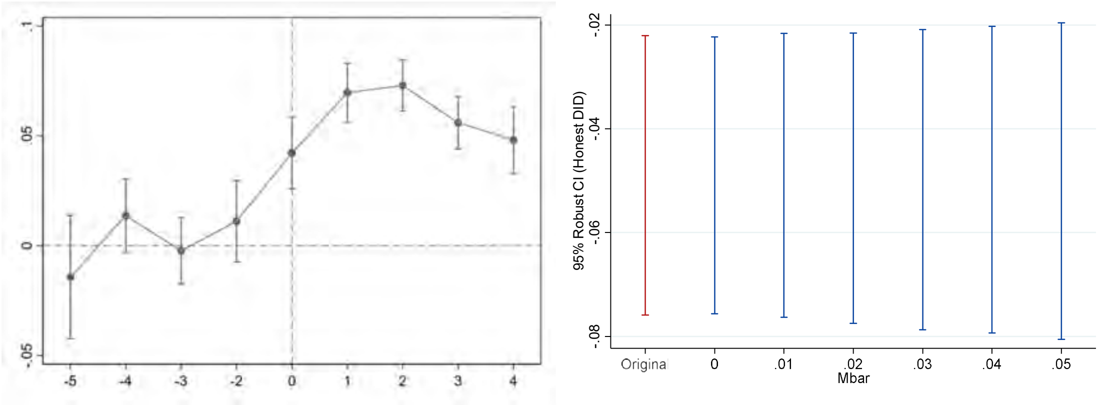


Figure 7. Event Study and Honest DID result for Cosine Similarity – Forward 1-year

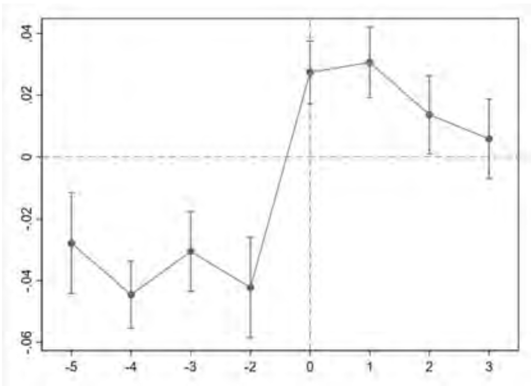


Figure 8. Event Study result for Cosine Similarity – Forward 2-years

As the same for Jaccard Similarity, same package of analysis is also performed for granted patents applied before the announcement of the patent pledge. Table 5 and figure 9 in combined indicate an increase of 5.71 percent in technological similarity. In the meantime, figure 10 suggests a violation of parallel trend for forward 1 year and forward 2 years results.

Table 5. Effects on Technology Similarity for Granted Parents Applied before the Announcement of Strategy (Cosine Similarity)

	(1) Current		(2) Forward 1Y		(3) Forward 2Y	
Patent Pledge	0.0571***	(0.0064)	0.0693***	(0.0046)	0.0603***	(0.0035)
Constant	0.2520***	(0.0106)	0.2275***	(0.0114)	0.1944***	(0.0060)
Fixed Effects	Yes		Yes		Yes	
N	739		680		613	
r2_a	0.3490		0.2993		0.3097	

Note: Standard errors in parentheses
Source: PATSTAT Compustat SDC_Platinum
* $p < .10$, ** $p < .05$, *** $p < .01$

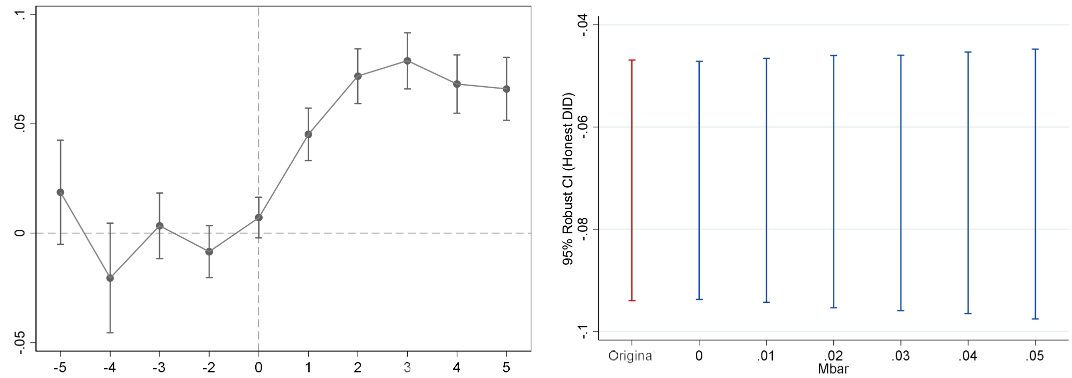
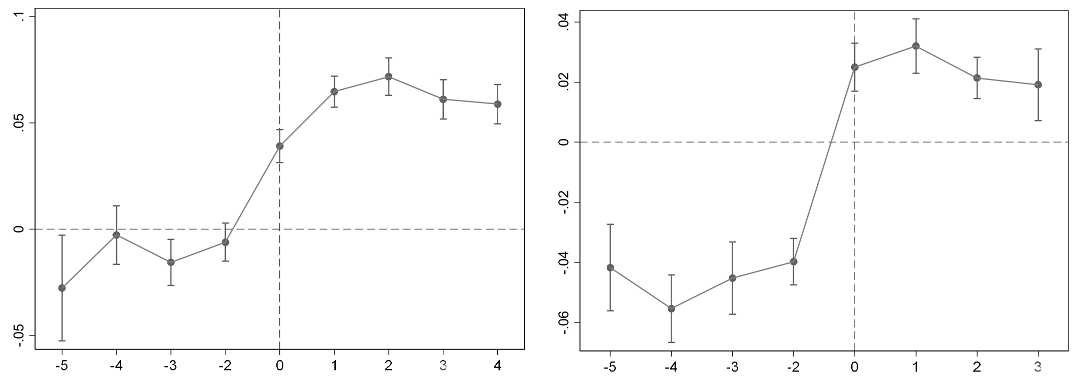


Figure 9. Event Study and Honest DID result for Cosine Similarity of granted patents before patent pledge



(i) Forward 1 year (ii) Forward 2-years

Figure 10. Event Study result for Cosine Similarity of granted patents before patent pledge – Forward 1 year

Therefore, the results from the measure of both Cosine Similarity and Jaccard Similarity indicates that the technology similarity between Tesla's patents and their forward cited patents has increased since the implementation of the patent pledge strategy.

5.2. Influence on the Extensive Margin of Follow-on Innovations

The natural logarithm of the annual number granted patents cite Tesla's patents at least once (total) and annual number of innovations – patent families - which cite Tesla's patents at least once (distinct) are regressed using TWFE to investigate the implication of this strategic behavior on extensive margin. The regression result demonstrates that Tesla's patent pledge strategy negatively impacted the extensive margin on follow-on innovations by from 14.16 percent (table 6) to 17.46 percent (table 7). However, the event study illustrates that the parallel assumption is violated, which renders the regression result invalid (figure 11).

Table 6. Effects on Tesla's Patents' (granted) Forward Citations (Total)

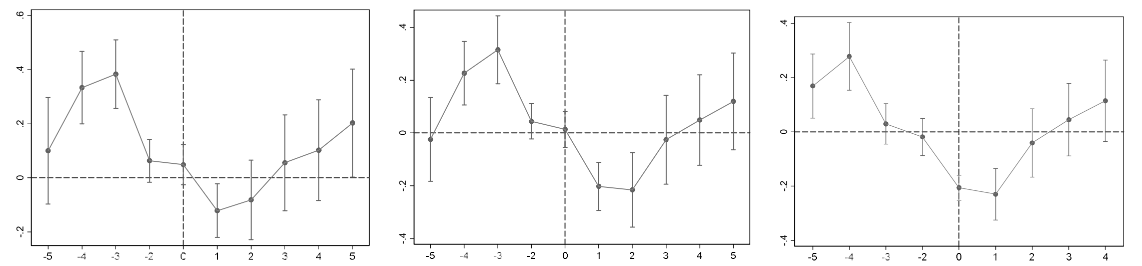
	(1) Current		(2) Forward 1Y		(3) Forward 2Y	
Patent Pledge	-0.1416^{**}	(0.0690)	-0.1345^{*}	(0.0718)	-0.0050	(0.0709)
Constant	4.8479^{***}	(0.0714)	5.3945^{***}	(0.0630)	6.1182^{***}	(0.0634)
Fixed Effects	Yes		Yes		Yes	
N	740		680		614	
r2_a	0.8018		0.7181		0.5459	

Note: Standard errors in parentheses
Source: PATSTAT Compustat SDC_Platinum
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 7. Effects on Tesla's Patents' (granted) Forward Citations (Distinct)

	(1) Current		(2) Forward 1Y		(3) Forward 2Y	
Patent Pledge	-0.1556^{**}	(0.0656)	-0.1746^{**}	(0.0677)	-0.0519	(0.0676)
Constant	4.2030^{***}	(0.0634)	4.8071^{***}	(0.0548)	5.4071^{***}	(0.0653)
Fixed Effects	Yes		Yes		Yes	
N	740		680		614	
r2_a	0.8453		0.7821		0.6730	

Note: Standard errors in parentheses
Source: PATSTAT Compustat SDC_Platinum
* $p < .10$, ** $p < .05$, *** $p < .01$



(i) Total Number of Forward Citation (ii) Distinct Number of Forward Citation (iii) Distinct Number of Forward Citation (Forward 1 year)

Figure 11. Event Study result for extensive margin of Tesla –

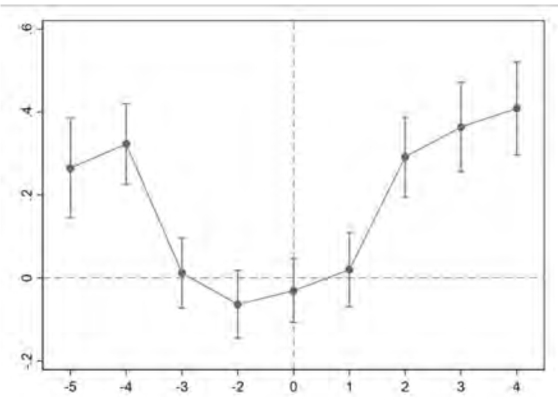
Moreover, the analysis is performed not only for granted patents applied during the whole research period, but also conducted for granted patents applied before the announcement date for the patent pledge. The significant increase in extensive margin from the regression result (table 8 and table 9) is invalidated by the event study testing for parallel trend assumption (figure 12).

Thus, nothing conclusive has been reached in terms of the extensive margin of Tesla's patent pledge strategy.

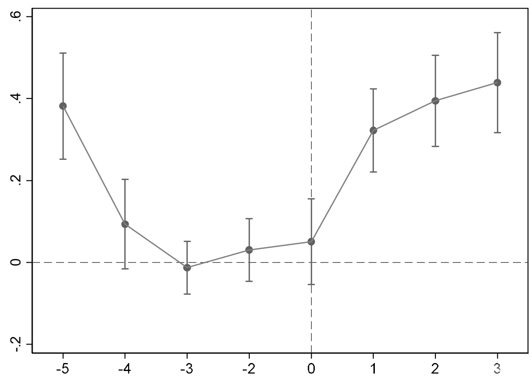
Table 8. Effects on Tesla's Granted Patents' (Applied before the Announcement of Strategy) Forward Citations (Total)

	(1) Current		(2) Forward 1Y		(3) Forward 2Y	
Patent Pledge	0.0585	(0.0438)	0.1019^{**}	(0.0428)	0.2248^{***}	(0.0468)
Constant	4.8141^{***}	(0.0683)	5.3722^{***}	(0.0507)	6.0954^{***}	(0.0458)
Fixed Effects	Yes		Yes		Yes	
N	744		684		617	
r2_a	0.8162		0.7367		0.5569	

Note: Standard errors in parentheses
Source: PATSTAT Compustat SDC_Platinum
$^{*} p < .10$, $^{**} p < .05$, $^{***} p < .01$



(i) Total Number of Forward Citation (Forward 1-Year)



(ii) Total Number of Forward Citation (Forward 2-Years)

Figure 12. Event Study result for extensive margin of Tesla before patent pledge –

Table 9. Effects on Tesla's Granted Patents' (Applied before the Announcement of Strategy) Forward Citations (Distinct)

	(1)		(2)		(3)	
	Current		Forward 1Y		Forward 2Y	
Patent Pledge	0.0608	(0.0507)	0.0611	(0.0448)	0.1507***	(0.0437)
Constant	4.2091***	(0.0670)	4.8192***	(0.0502)	5.4017***	(0.0529)
Fixed Effects	Yes		Yes		Yes	
N	744		684		617	
r2_a	0.8322		0.7559		0.5957	

Note: Standard errors in parentheses
Source: PATSTAT Compustat SDC_Platinum
* *p* < .10, ** *p* < .05, *** *p* < .01

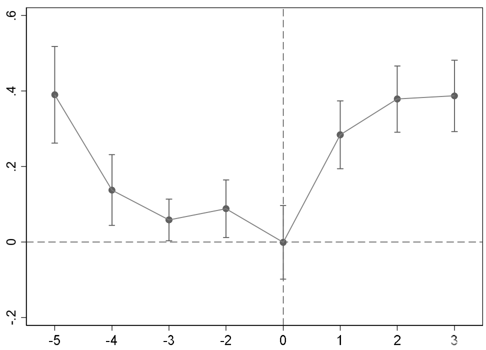


Figure 13. Event Study result for extensive margin of Tesla before patent pledge – Distinct Number of Forward Citation (Forward 2-Years)

5.3. Alternations in Tesla’s Innovation Behavior

Firstly, the natural logarithm of the number of patent application (granted) each year is regressed using TWFE. The results from table 10 suggest that the patent pledge strategy has increased Tesla’s granted patenting around 130% with outcome variable forwarded two years with 5% significance level satisfied.

This result is corroborated with parallel trend assumption not violated under standard treatment of event study and the Honest DID approach proposed by Rambachan and Roth (2023) for testing linear pre-trend (figure 18).

Table 10. Effects on Tesla's Patent Application (granted)

	(1) Current		(2) Forward 1Y		(3) Forward 2Y	
Patent Pledge	0.8468	(0.5671)	1.2865*	(0.6566)	1.3015**	(0.6296)
Constant	7.6847**	(3.0054)	10.4107***	(3.2629)	10.7777***	(2.9712)
Control Variables	Yes		Yes		Yes	
Fixed Effects	Yes		Yes		Yes	
N	587		527		465	
r2_a	0.1710		0.2156		0.2498	

Note: Standard errors in parentheses
Source: PATSTAT Compustat SDC_Platinum
* $p < .10$, ** $p < .05$, *** $p < .01$

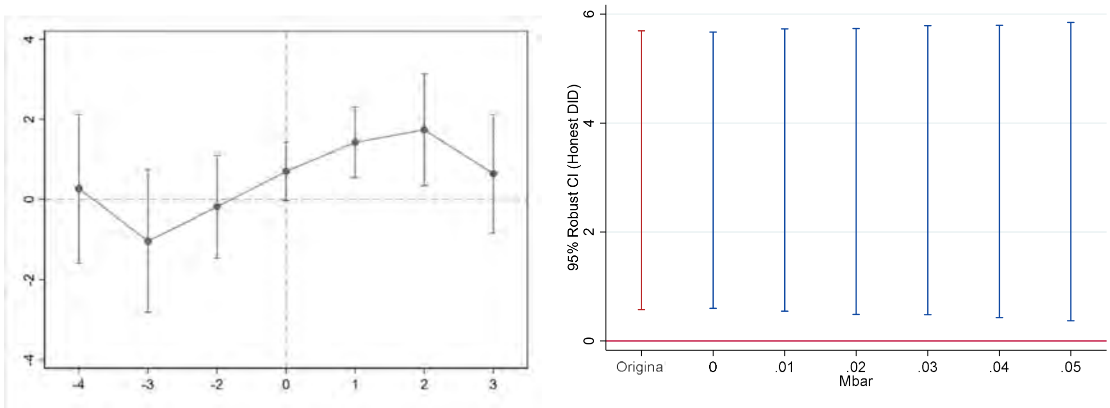


Figure 14. Event Study and Honest DID result for Patenting Intensity of Tesla – Granted Patent Applications (Forward 2-Years)

Apart from using granted patent application as a measurement for innovation intensity, a more credible proxy for measuring innovation is patent family as patent family contains more than one patent which can be regarded as the same invention. Hence, the natural logarithm of the number of patent families which contain at least one granted patent during the research period each year is regressed using TWFE. The results from table 11 suggest that the number of inventions by Tesla does not vary significantly following the implementation of this strategy.

Table 11. Effects on Tesla's Patent Family Application (granted)

	(1) Current		(2) Forward 1Y		(3) Forward 2Y	
Patent Pledge	0.3396	(0.4927)	0.8363	(0.5435)	1.0398*	(0.5422)
Constant	5.7454**	(2.7274)	7.9450**	(3.0914)	8.1501***	(2.5996)
Control Variables	Yes		Yes		Yes	
Fixed Effects	Yes		Yes		Yes	
N	587		527		465	
r2_a	0.0779		0.0952		0.0764	

Note: Standard errors in parentheses
Source: PATSTAT Compustat SDC_Platinum
$^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$

The aforementioned result illustrates that Tesla increased its patenting activity but did not increase its innovation activity after implementing patent pledge strategy. Then, patent quality defined as the annual number of claims divided by annual number of granted patents and the natural logarithm of the annual number of total forward citations and distinct forward citations from published patents and patent families respectively are regressed to assess whether Tesla has increased its patent's quality after pledged its patents freely. The results (table 12, table 13, and table14) indicate that Tesla's individual patents have not varied too much in terms of quality by this strategy.

Table 12. Effects on Tesla's Patents' (granted) Quality/Scope

	(1)		(2)		(3)	
	Current		Forward 1Y		Forward 2Y	
Patent Pledge	-2.8868	(2.7714)	-1.0698	(2.9871)	-3.1787	(2.2747)
Constant	29.0298^{**}	(12.5073)	8.7424	(15.9162)	13.3849	(11.3895)
Control Variables	Yes		Yes		Yes	
Fixed Effects	Yes		Yes		Yes	
N	587		526		464	
r2_a	0.0732		0.0966		0.0423	

Note: Standard errors in parentheses
Source: PATSTAT Compustat SDC_Platinum
$^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$

Table 13. Effects on Tesla's Patents' (granted) Forward Citations (Total)

	(1)		(2)		(3)	
	Current		Forward 1Y		Forward 2Y	
Patent Pledge	0.1549	(0.2765)	-0.1299	(0.3239)	0.0034	(0.3237)
Constant	5.2218^{***}	(1.6680)	5.1658^{***}	(1.9373)	6.2671^{***}	(1.5374)
Control Variables	Yes		Yes		Yes	
Fixed Effects	Yes		Yes		Yes	
N	589		529		468	
r2_a	0.7394		0.6042		0.4569	

Note: Standard errors in parentheses
Source: PATSTAT Compustat SDC_Platinum
$^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$

Table 14. Effects on Tesla's Patents' (granted) Forward Citations (Distinct)

	(1)		(2)		(3)	
	Current		Forward 1Y		Forward 2Y	
Patent Pledge	-0.0096	(0.2426)	-0.3064	(0.2910)	-0.1167	(0.3018)
Constant	4.2727^{***}	(1.5095)	4.1904^{**}	(1.8233)	5.7215^{***}	(1.3968)
Control Variables	Yes		Yes		Yes	
Fixed Effects	Yes		Yes		Yes	
N	589		529		468	
r2_a	0.8020		0.7126		0.6236	

Note: Standard errors in parentheses
Source: PATSTAT Compustat SDC_Platinum
$^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$

6. CONCLUSION

This study uncovered that Tesla's embrace of this patent pledge strategy led to an increase in technology similarity for follow-on innovations that are associated with Tesla's innovation. This suggests that Tesla's follow-on innovations focus more on technology areas where Tesla is operating, potentially leading to expansion of an ecosystem that centered around Tesla's innovation. Furthermore, given Tesla's main business practices focus on electric vehicles during the research period, this strategy could have also contributed to the growth of electric vehicles market. In addition, Tesla's patenting activity also increased drastically by about 130% given its innovation activity is relatively stable since the implementation of this strategy suggesting that Tesla tried to expand the impact of its innovation and extend the effect of this strategy to larger areas.

Nevertheless, this study has not identified a strong effect on Tesla's innovation activities including innovation intensity and quality following the implementation of the strategy of patent pledge. Moreover, the notable increase in extensive margin that was detected in the compulsory royalty-free licensing for Bell labs patents and other cases mandated by policy or legislation is not found by this study. Thus, this research strengthens that the analysis for patent pledge should not be viewed as 0 or 1 dichotomous event but from a continuous framework such as the dimension of wholly proprietary system to wholly open system (Schilling, 2022). The royalty-free licensing imposed on firms by policy and legislation, patent invalidation, and patent lapse are similar to the wholly open system. Meanwhile, open patent pledge, open source and other equivalence to royalty-free licensing initiated by firms with certain conditions such as Tesla's *good faith* condition and Sun Microsystem's Java Community Process falls into the purview of free-licensing, which suggests a lesser degree of openness compared to wholly open system (Schilling, 2022). Hence, the future research on the impact of royalty-free licensing or open-source initiative should articulate clearly the degree of freedom or openness rather than simply treat it as a binary case – 0 or 1 – before delving further. A good starting point could be the framework established from Intellectual Property (IP) law literature. Ehrnsperger and Tietze (2019) propose taxonomies for patent pledges and licensing based on three dimensions: accessibility, compensation, and conditions. Tesla's pledge can be classified as a conditional open patent pledge, as it is freely available to the unrestricted public contingent upon a non-assertion clause – *good faith*. Meanwhile, patent validation or compulsory royalty-free licensing such as the 1956 Decree imposed on Bell lab (Watzinger et al., 2020) is equivalent to an unconditional open patent pledge, which is technically more open than Tesla's patent pledge. The other good starting point could be the framework proposed by Contreras (2023). Contreras (2023) classified patent pledges as three types i) Unilateral Covenant: Tesla; ii) Bilateral Commitment: SDO membership agreements; iii) Public License: Open COVID Pledge. However, more nuanced classification for conditions attached to patent pledges is warranted including the restrictions for follow-on users, legal effectiveness of patent pledges following ownership changes, etc.

This paper offers the first empirical assessment of the use of patent pledge applicable to pledgor's entire patent portfolio as a corporate strategy. Furthermore, this could potentially offer valuable insights to Competition Authorities. The significance of innovation in the development of Competition Policies is increasingly prominent in contemporary times. Although prior literature has demonstrated the effectiveness of compulsory royalty-free licensing in stimulating follow-on innovations, its impact on the extensive margin of subsequent innovations may be diminished if it is used by an incumbent firm with defensive termination terms. Firms may occasionally voluntarily issue patent pledges claiming to address specific issues, exemplified by the Open COVID Pledge involving Microsoft, IBM, Intel, and others, aimed at expediting the development and dissemination of essential medical devices, protective equipment, and biomedical products crucial for resolving the immediate crisis. Regulators should consider the conditions linked to the patent pledge, as these may have enduring consequences once the technological trajectory is influenced by the pledge. Further investigation is needed to determine whether Tesla's patent pledge enhances or diminishes its market power, particularly as the expansion of its ecosystem may attract both complementors—such as auto parts suppliers for EV—and rivals like NIO and XPeng which were founded six months after Tesla's patent pledge announcement. Moreover, the growing discourse and academic interest in ecosystem competition among technology giants (Lianos and Jacobides, 2021), especially in the context of digital platforms, could be meaningfully extended to automotive companies like Tesla. Thus, a collaborative initiative among different authorities, including competition authorities and environmental agencies, concerning matters of royalty-free licensing or patent pledges is increasingly vital due to the dormant crisis incubated by worsening global climate conditions.

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Appendix:

A. Robustness Checks for Outcome Variables with log transformation from $\log(Y)$ to $\log(Y+1)$

A.1. Influence on Follow-on Innovations

The results below suggest that the two different log transformation yield same significant result for forward 1-year distinct number of forward citations with similar results (-14.86% and -15.5% respectively). However, a statistically significant result is yielded for total number of forward citations (no forward) suggesting a -17.09% decrease, which contrasts with the main results showing no statistical significance. Nevertheless, all these results failed the parallel trend tests based on event study, leading to the same conclusion on extensive margin as shown in the main results in section 5.2.

Effects on Tesla's Patents' (granted) Forward Citations (Total)

	(1) Current		(2) Forward 1Y		(3) Forward 2Y	
Patent Pledge	-0.1709^{**}	(0.0747)	-0.1335^{*}	(0.0722)	-0.0064	(0.0724)
Constant	4.6277^{***}	(0.0863)	5.3571^{***}	(0.0616)	6.0341^{***}	(0.0671)
Fixed Effects	Yes		Yes		Yes	
N	759		690		621	
r2_a	0.7977		0.7193		0.5611	

Note: Standard errors in parentheses
Source: PATSTAT
* $p < .10$, ** $p < .05$, *** $p < .01$

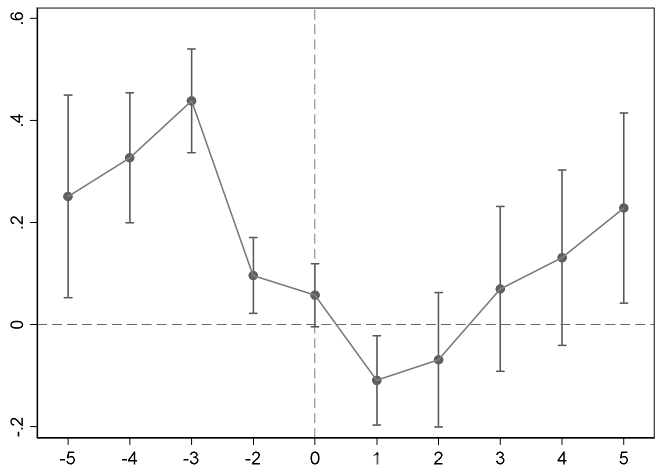


Figure: Event Study result for extensive margin of Tesla – Total Number of Forward Citation

Effects on Tesla's Patents' (granted) Forward Citations (Distinct)

	(1)		(2)		(3)	
	Current		Forward 1Y		Forward 2Y	
Patent Pledge	-0.1410^{*}	(0.0711)	-0.1486^{**}	(0.0682)	-0.0406	(0.0680)
Constant	4.1073^{***}	(0.0775)	4.8303^{***}	(0.0559)	5.3796^{***}	(0.0645)
Fixed Effects	Yes		Yes		Yes	
N	759		690		621	
r2_a	0.8348		0.7790		0.6813	

Note: Standard errors in parentheses
Source: PATSTAT
* $p < .10$, ** $p < .05$, *** $p < .01$

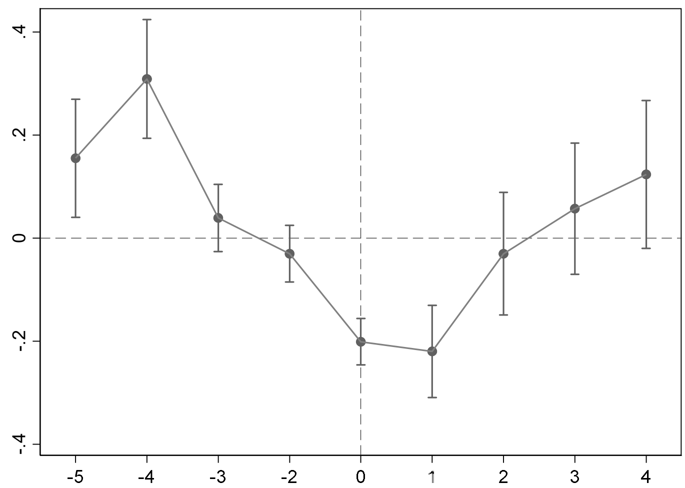


Figure: Event Study result for extensive margin of Tesla – Distinct Number of Forward Citation (Forward 1-Year)

A.2. Alternations in Tesla's Innovation Activities

A.2.1. Patenting Intensity

The log $(Y + 1)$ transformation for the number of granted patent applications supports the conclusion on patenting intensity of the main results. The results below suggest a slightly lower figure for forward 2-years case (125.46%) compared to its counterpart in main results (132.7%) statistically significant, both of which pass the tests for parallel trend & linear pre-trend and placebo test. However, it is worth mentioning that the forward 1-year case's result for robustness check is not statistically significant as its counterpart in the main results whose result does not pass the test for linear pre-trend.

Effects on Tesla's Patent Application (granted)

	(1) Current		(2) Forward 1Y		(3) Forward 2Y	
Patent Pledge	0.7761	(0.5342)	1.2099*	(0.6328)	1.2546**	(0.6059)
Constant	7.2704**	(2.8386)	9.7627***	(3.0140)	10.1567***	(2.7417)
Control Variables	Yes		Yes		Yes	
Fixed Effects	Yes		Yes		Yes	
N	587		527		465	
r2_a	0.1780		0.2214		0.2552	

Note: Standard errors in parentheses
Source: PATSTAT Compustat SDC_Platinum
* $p < .10$, ** $p < .05$, *** $p < .01$

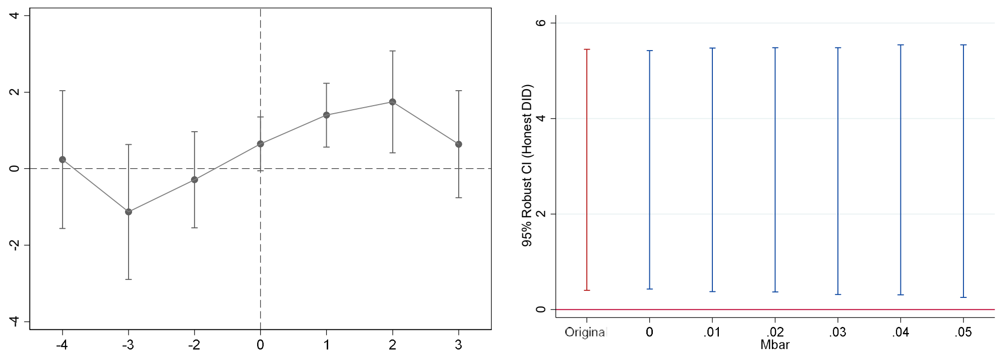


Figure: Event Study and Honest DID result for patenting Intensity of Tesla – Granted Patent Applications

(Forward 2-years)

A.2.2. Innovation Intensity

No statistically significant results are yielded for robustness checks for the number of patent family with at least one granted patent application, which further corroborates the conclusion from the main results.

Effects on Tesla's Patent Family Application (granted)

	(1) Current		(2) Forward 1Y		(3) Forward 2Y	
Patent Pledge	0.2977	(0.4588)	0.7621	(0.5132)	0.9868*	(0.5135)
Constant	5.3963**	(2.5519)	7.2995**	(2.8174)	7.5539***	(2.3508)
Control Variables	Yes		Yes		Yes	
Fixed Effects	Yes		Yes		Yes	
N	587		527		465	
r2_a	0.0794		0.0936		0.0782	

Note: Standard errors in parentheses
Source: PATSTAT Compustat SDC_Platinum
* *p < .10,* ** *p < .05,* *** *p < .01*

A.2.3. Patent Quality

While patent quality is measured by the number of forward citations and the average number of claims per patent, only forward citations are included in the robustness checks as the number of claims per patent is not transformed into $\log(Y)$ in the main analysis. The results below indicate no statistically significant results, corresponding to their counterparts of the main results.

Effects on Tesla's Patents' (granted) Forward Citations (Total)

	(1) Current		(2) Forward 1Y		(3) Forward 2Y	
Patent Pledge	0.1247	(0.3628)	-0.0455	(0.3667)	0.1292	(0.3133)
Constant	4.3826***	(1.6316)	5.3342***	(1.8786)	6.4800***	(1.5420)
Control Variables	Yes		Yes		Yes	
Fixed Effects	Yes		Yes		Yes	
N	599		535		471	
r2_a	0.7433		0.6074		0.4622	

Note: Standard errors in parentheses
Source: PATSTAT Compustat SDC_Platinum
* *p < .10,* ** *p < .05,* *** *p < .01*

Effects on Tesla's Patents' (granted) Forward Citations (Distinct)

	(1) Current		(2) Forward 1Y		(3) Forward 2Y	
Patent Pledge	-0.2467	(0.3183)	-0.4019	(0.3195)	-0.1397	(0.2910)
Constant	4.5501^{***}	(1.7107)	5.1906^{***}	(1.8607)	6.3766^{***}	(1.4406)
Control Variables	Yes		Yes		Yes	
Fixed Effects	Yes		Yes		Yes	
N	599		535		471	
r2_a	0.7894		0.7092		0.6229	

Note: Standard errors in parentheses
Source: PATSTAT Compustat SDC_Platinum
* $p < .10$, ** $p < .05$, *** $p < .01$

B. Robustness Checks Based on Synthetic DID

B.1. Impact on Technology Similarity

B.1.1. Jaccard Similarity

B.1.1.a. For All Granted Patent Applications during the Research Period

The results from robustness checks for Jaccard similarity based on synthetic DID corroborate the conclusion from the main analysis indicating an increase in technology similarity. The no forward case below illustrates an increase in Jaccard similarity with parallel trend not violated given the visual figure presented. This is corresponding to main analysis where standard TWFE analysis results in a statistically significant increase for no forward case with parallel trend holds.

Effects on Technology Similarity (Jaccard Similarity) (Current)

	No Forward	
Patent Pledge	0.0351^{**}	(0.0177)
Fixed Effects	Yes	
N	660	

Note: Standard errors in parentheses
Source: PATSTAT
* $p < .10$, ** $p < .05$, *** $p < .01$

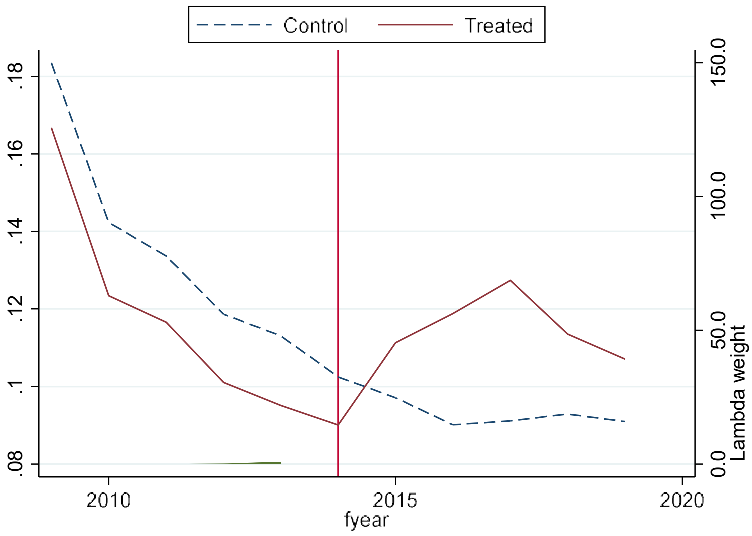


Figure: Synthetic DID for Jaccard Similarity

Effects on Technology Similarity (Jaccard Similarity) (Forward One Year)

	Forward One Year	
Patent Pledge	0.0377^{*}	(0.0219)
Fixed Effects	Yes	
N	600	

Note: Standard errors in parentheses
Source: PATSTAT
* $p < .10$, ** $p < .05$, *** $p < .01$

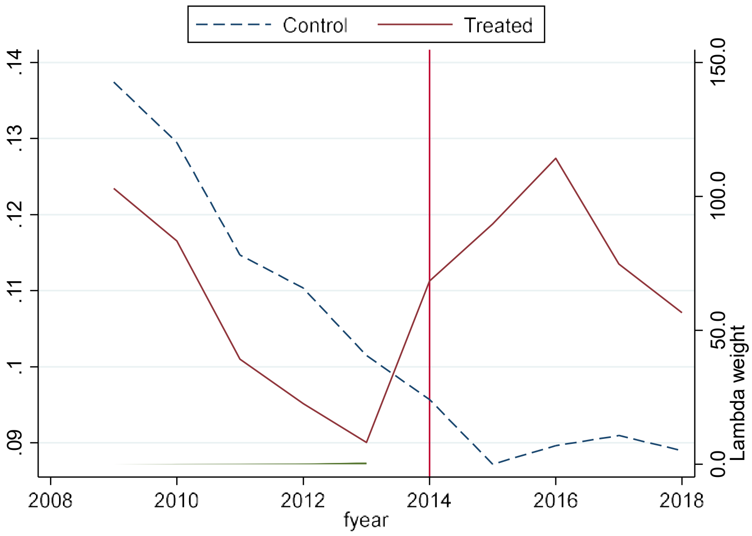


Figure: Synthetic DID for Jaccard Similarity – Forward 1-Year

Effects on Technology Similarity (Jaccard Similarity) (Forward Two Years)

	Forward Two Years	
Patent Pledge	0.0217	(0.0188)
N	540	

Note: Standard errors in parentheses
Source: PATSTAT
$^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$

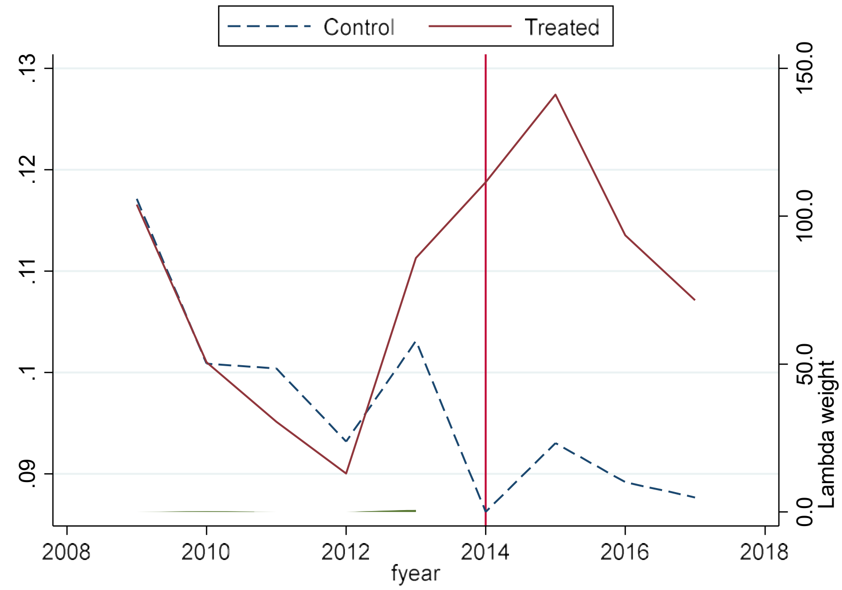


Figure: Synthetic DID for Jaccard Similarity – Forward 2-Years

B.1.1.b. For All Granted Patent Applications Applied before Tesla's Announcement

The big picture for granted patent applications before Tesla's announcement is the same for all granted patent applications during the research period. The result under no forward case is a statistically significant increase with parallel trend assumption not violated according to the corresponding figure. Thus, the conclusion reached according to the no forward case of the main results is further corroborated.

Effects on Technology Similarity (Jaccard Similarity) for Granted Patents before the Strategy (Current)

	No Forward	
Patent Pledge	0.0454^{**}	(0.0180)
Fixed Effects	Yes	
N	660	

Note: Standard errors in parentheses

Source: PATSTAT

$^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$

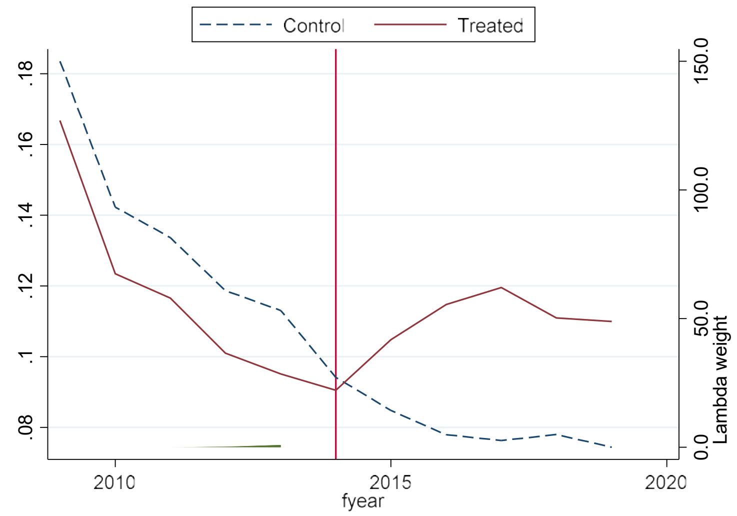


Figure: Synthetic DID for Jaccard Similarity for Granted Patents Applied before Tesla's Announcement

Effects on Technology Similarity (Jaccard Similarity) for Granted Patents before the Strategy (Forward One Year)

	Forward One Year	
Patent Pledge	0.0391*	(0.0210)
Fixed Effects	Yes	
N	600	

Note: Standard errors in parentheses
Source: PATSTAT
$^{*}\ p < .10$, $^{**}\ p < .05$, $^{***}\ p < .01$

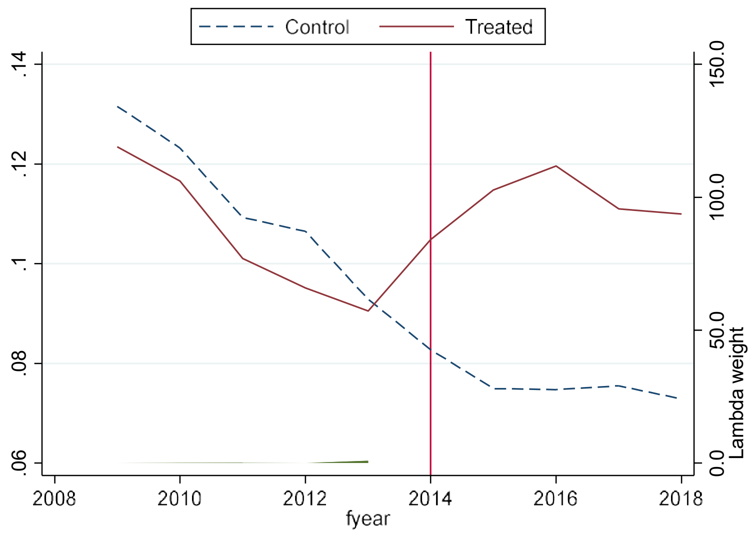


Figure: Synthetic DID for Jaccard Similarity for Granted Patents Applied before Tesla's Announcement – Forward 1-Year

Effects on Technology Similarity (Jaccard Similarity) for Granted Patents before the Strategy (Forward Two Years)

	Forward Two Years	
Patent Pledge	0.0199	(0.0137)
Fixed Effects	Yes	
N	540	

Note: Standard errors in parentheses
Source: PATSTAT
$^{*} p < .10$, $^{**} p < .05$, $^{***} p < .01$

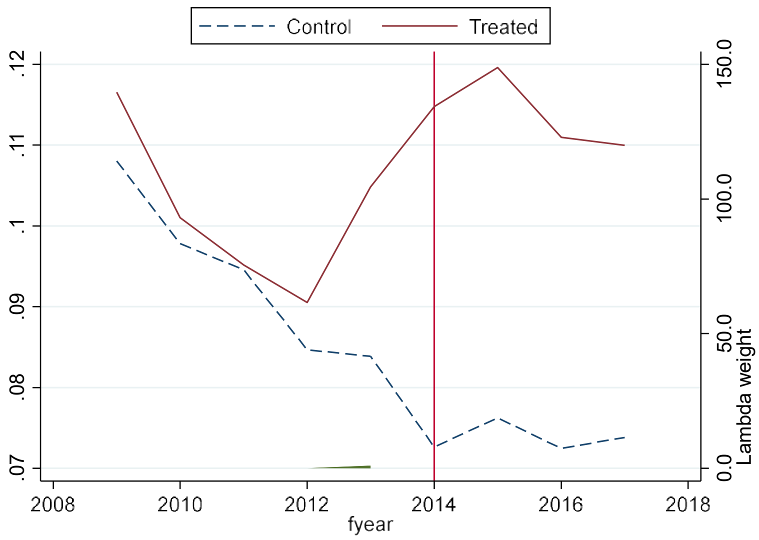


Figure: Synthetic DID for Jaccard Similarity for Granted Patents Applied before Tesla's Announcement – Forward 2-Years

B.1.2. Cosine Similarity

B.1.2.a. For All Granted Patent Applications during the Research Period

The results below show a different statistical significance level for all the three cases, which is contrast to the significant result reached by the main analysis. This could cast doubt on the main results to a certain degree. However, the robustness checks corroborate the event study in the main analysis suggesting parallel trend is not violated for no forward case based on the corresponding figure.

Effects on Technology Similarity (Cosine Similarity) (Current)

	No Forward	
Patent Pledge	0.0419*	(0.0243)
Fixed Effects	Yes	
N	660	

Note: Standard errors in parentheses
Source: PATSTAT
* $p < .10$, ** $p < .05$, *** $p < .01$

Figure: Synthetic DID for Cosine Similarity

Effects on Technology Similarity (Cosine Similarity) (Forward One Year)

	Forward One Year	
Patent Pledge	0.0487*	(0.0254)
Fixed Effects	Yes	
N	600	

Note: Standard errors in parentheses
Source: PATSTAT
* *p < .10,* ** *p < .05,* *** *p < .01*

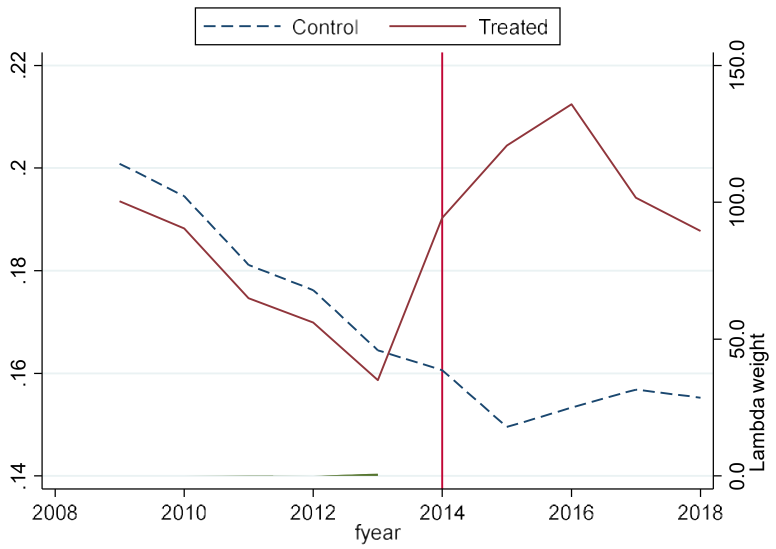


Figure: Synthetic DID for Cosine Similarity – Forward 1-Year

Effects on Technology Similarity (Cosine Similarity) (Forward Two Years)

	Forward Two Years	
Patent Pledge	0.0297	(0.0247)
Fixed Effects	Yes	
N	540	

Note: Standard errors in parentheses
Source: PATSTAT
* *p < .10,* ** *p < .05,* *** *p < .01*

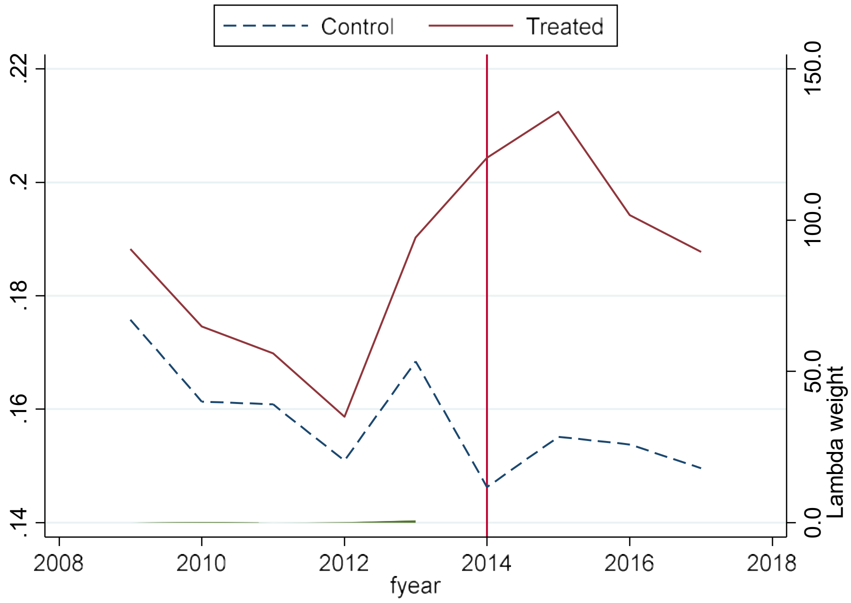


Figure: Synthetic DID for Cosine Similarity – Forward 2-Years

B.1.2.b. For All Granted Patent Applications Applied before Tesla's Announcement

When the robustness checks are confined to granted patents applied before Tesla's announcement, the results are more consistent with the main results. The no forward and forward one year's cases demonstrate statistically significant results, with no forward case's parallel trend not violated according to the figure below. Hence, the result from no forward case shows a robust conclusion on the increase in technology similarity in the same manner as its counterpart in the main analysis.

Effects on Technology Similarity (Cosine Similarity) for Granted Patents before the Strategy (Current)

	No Forward	
Patent Pledge	0.0564^{***}	(0.0216)
Fixed Effects	Yes	
N	660	

Note: Standard errors in parentheses
Source: PATSTAT

$^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$

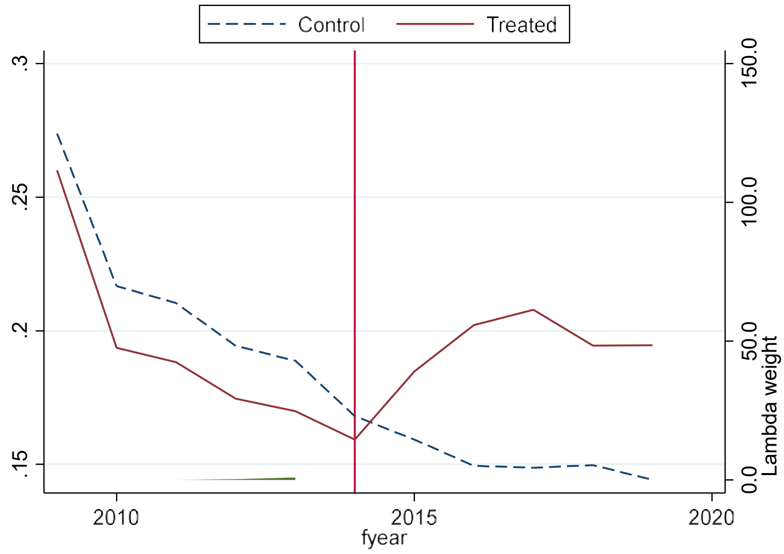


Figure: Synthetic DID for Cosine Similarity for Granted Patents Applied before Tesla's Announcement

Effects on Technology Similarity (Cosine Similarity) for Granted Patents before the Strategy (Forward One Year)

	Forward One Year	
Patent Pledge	0.0578**	(0.0235)
Fixed Effects	Yes	
N	600	

Note: Standard errors in parentheses
Source: PATSTAT
$^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$

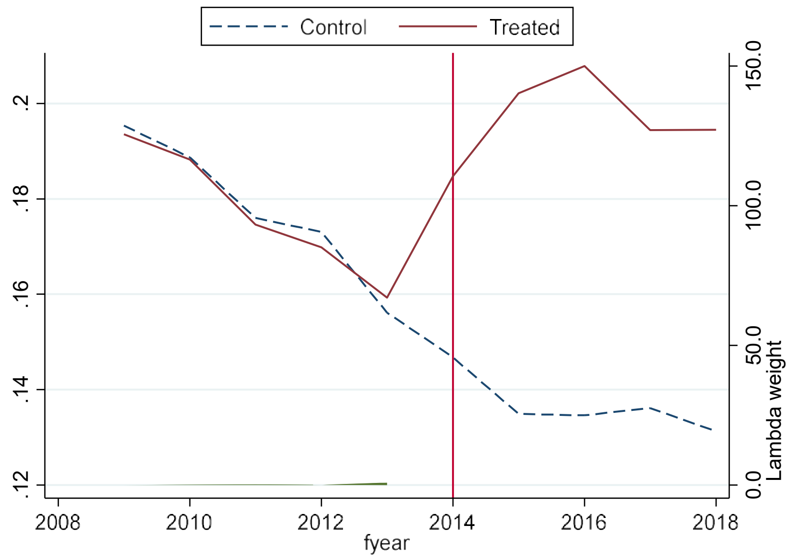


Figure: Synthetic DID for Cosine Similarity for Granted Patents Applied before Tesla's Announcement – Forward 1-Year

Effects on Technology Similarity (Cosine Similarity) for Granted Patents before the Strategy (Forward Two Years)

	Forward Two Years	
Patent Pledge	0.0339*	(0.0202)
Fixed Effects	Yes	
N	540	

Note: Standard errors in parentheses
Source: PATSTAT
$^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$

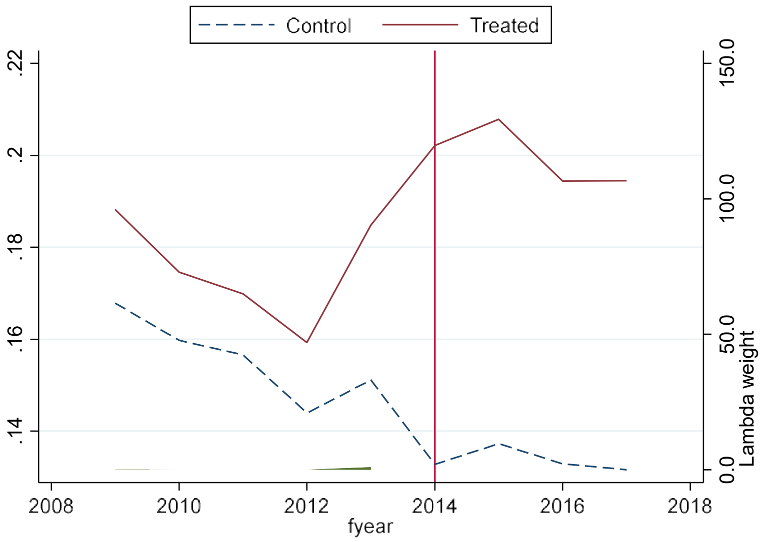


Figure: Synthetic DID for Cosine Similarity for Granted Patents Applied before Tesla's Announcement – Forward 2-Years

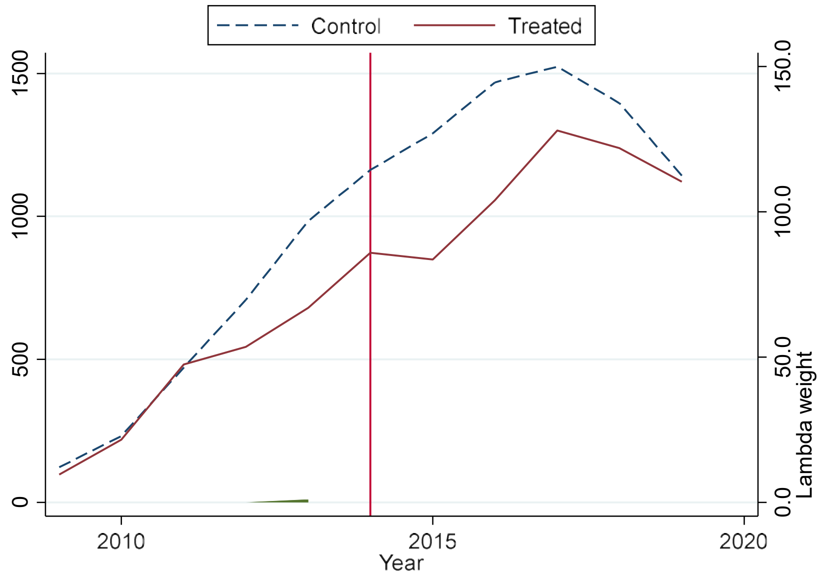
B.2. Influence on the Extensive Margin of Follow-on Innovations

Similar to main analysis, the tables below indicate no statistically significant result for the number of granted patents (total) and number of patent families with at least one granted patents (distinct) for no forward, forward one year and forward two years cases respectively. Hence, the conclusion that no strong increase in extensive margin is identified is further strengthened.

Effects on Tesla's Patent Citation (Current)

	(1) Total		(2) Distinct		(3) Total (For Granted Patents Applied Before Tesla's Announcement)		(4) Distinct (For Granted Patents Applied Before Tesla's Announcement)	
Patent Pledge	46.7293	(1.5e+03)	-20.5687	(941.4935)	152.0342	(1.1e+03)	76.6302	(583.1095)
Fixed Effects	Yes		Yes		Yes		Yes	
N	781		781		781		781	

Note: Standard errors in parentheses
Source: PATSTAT
* $p < .10$, ** $p < .05$, *** $p < .01$



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Treated
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1000
500
0
150.0
100.0
50.0
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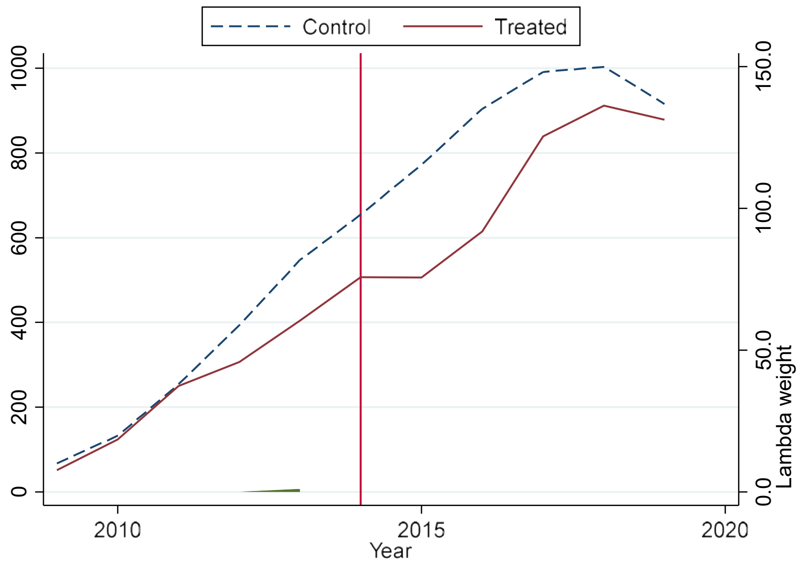
Lambda weight
2010
2015
2020
Year



Control
Treated
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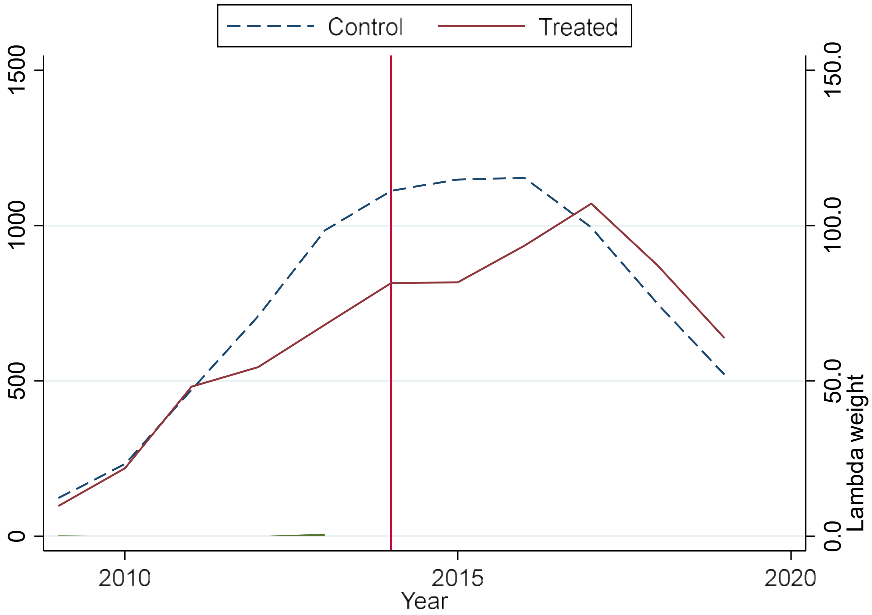
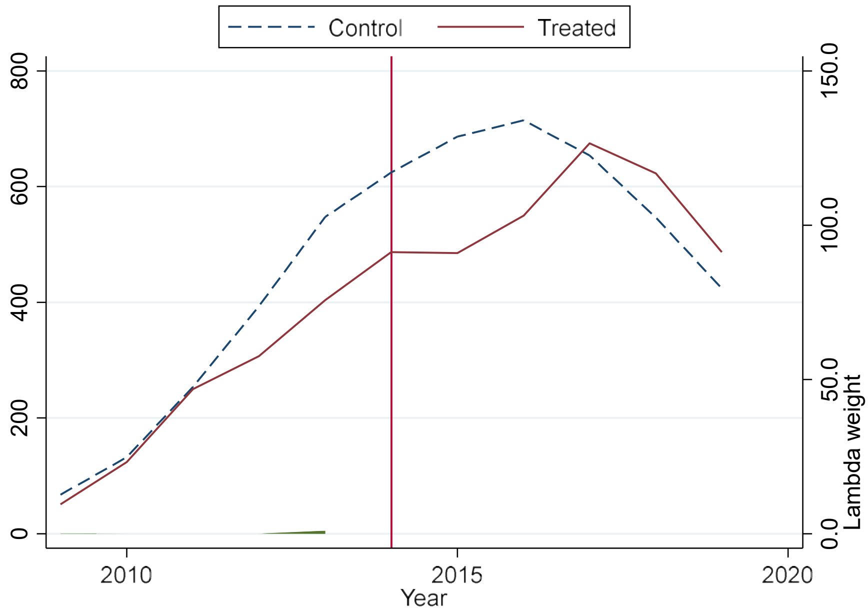
800
600
400
200
0
150.0
100.0
50.0
0.0
Lambda weight
2010
2015
2020
Year

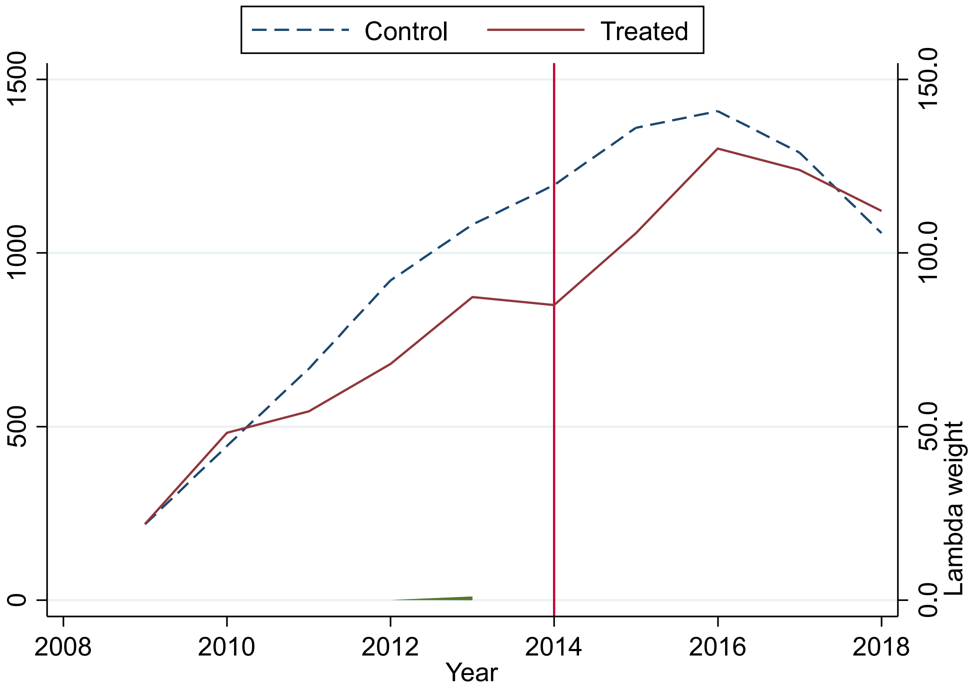




Effects on Tesla's Patent Citation (Forward One Year)

	(1) Total		(2) Distinct		(3) Total (For Granted Patents Applied Before Tesla's Announcement)		(4) Distinct (For Granted Patents Applied Before Tesla's Announcement)	
Patent Pledge	59.8780	(1.2e+03)	5.9393	(733.4282)	155.4874	(1.0e+03)	74.9763	(516.8878)
Fixed Effects	Yes		Yes		Yes		Yes	
N	710		710		710		710	

Note: Standard errors in parentheses
Source: PATSTAT
* $p < .10$, ** $p < .05$, *** $p < .01$


Control
Treated
1500
1000
500
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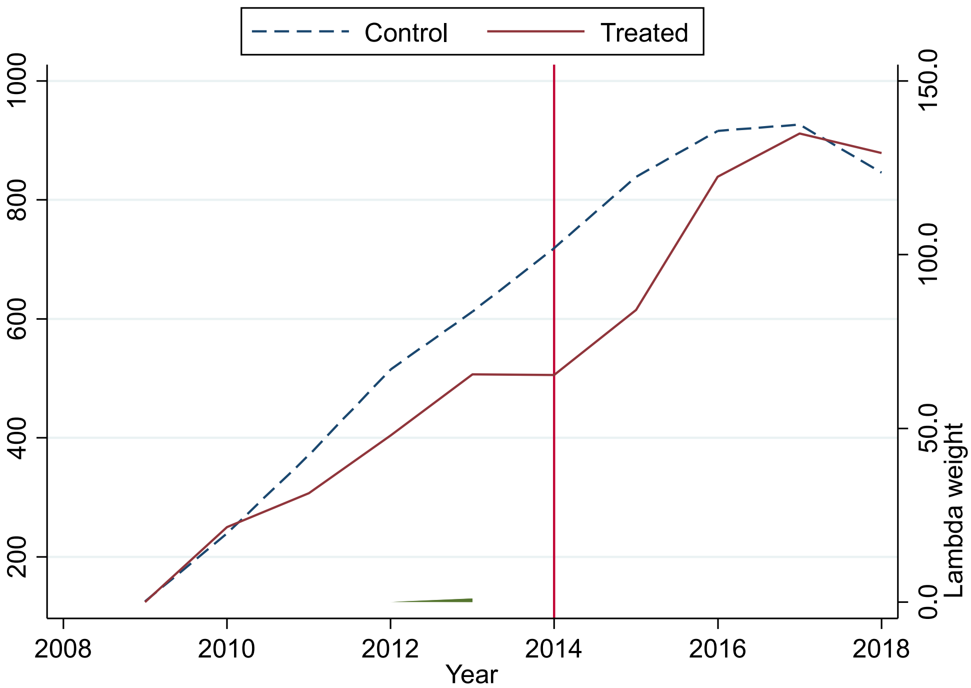
150.0
100.0
50.0
0.0
Lambda weight
2008
2010
2012
2014
2016
2018
Year


Control
Treated
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200
150.0
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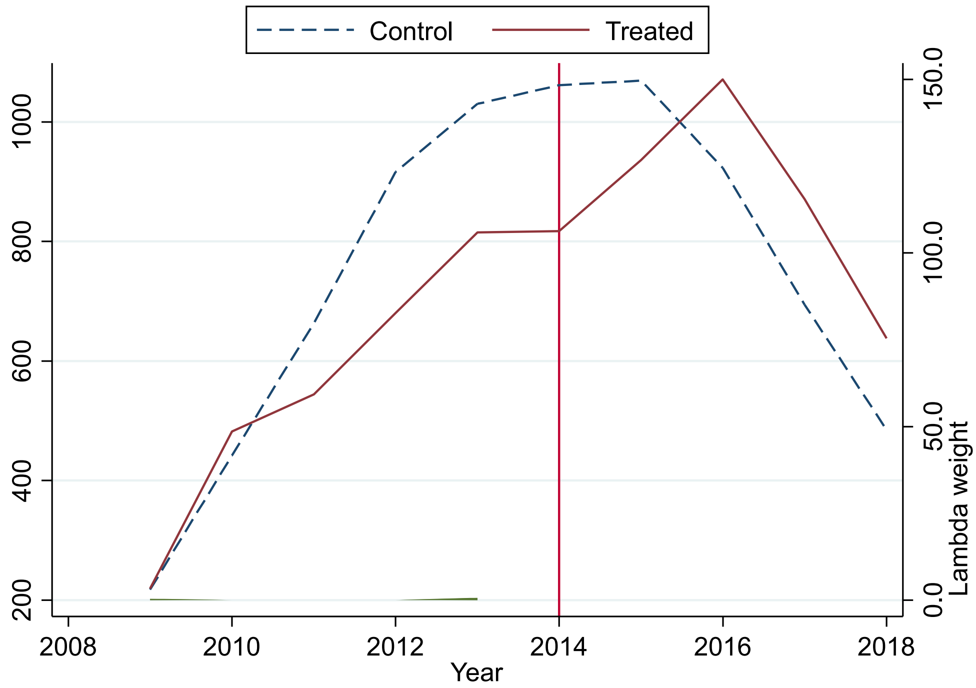
50.0
0.0
Lambda weight
2008
2010
2012
2014
2016
2018
Year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Treated
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200
150.0
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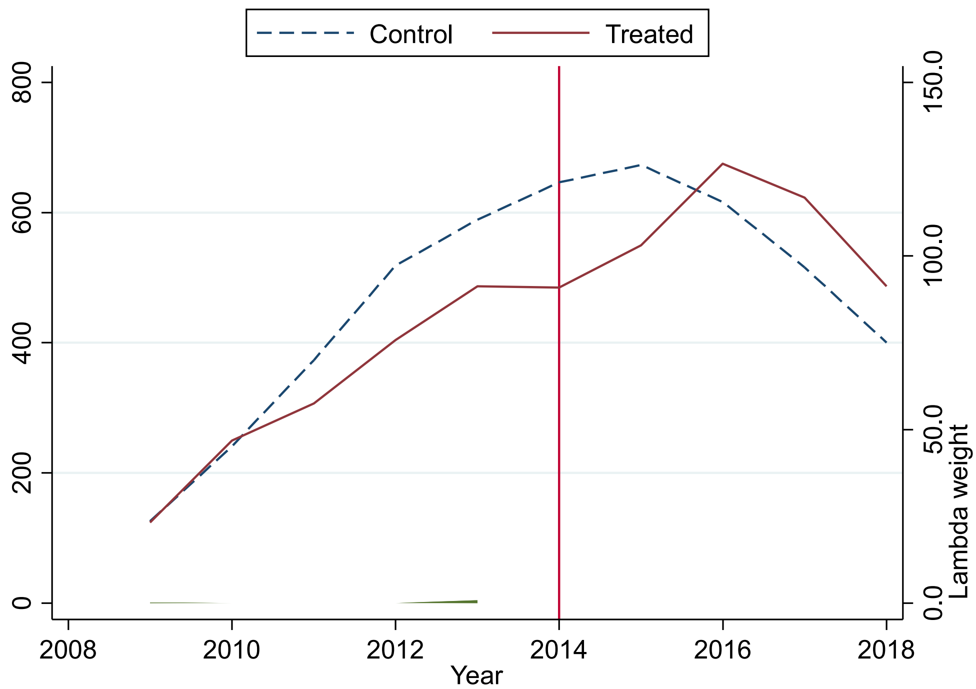
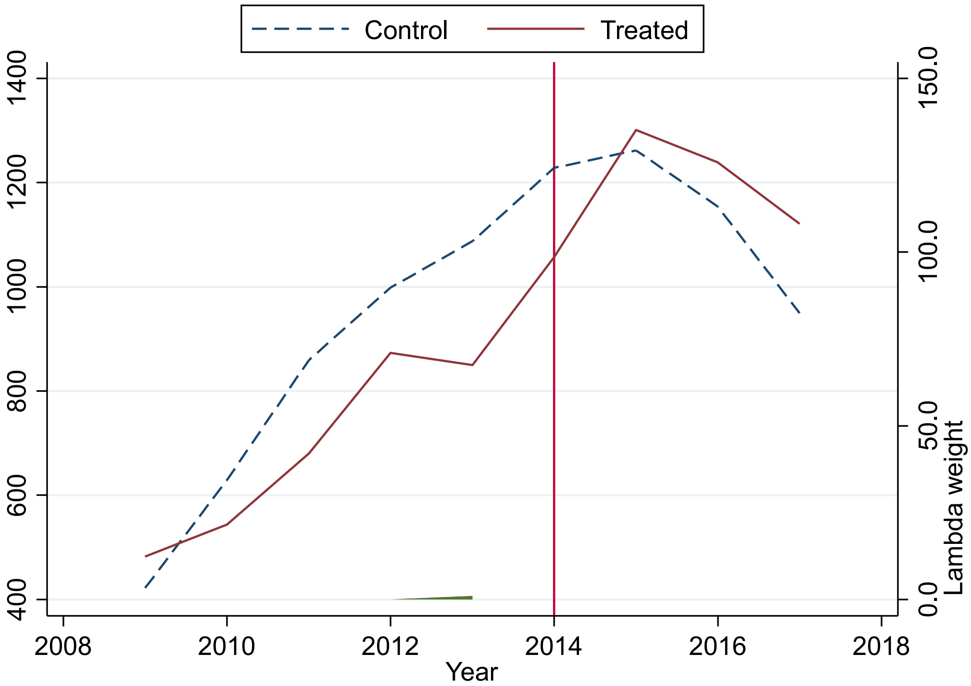
50.0
0.0
Lambda weight
2008
2010
2012
2014
2016
2018
Year

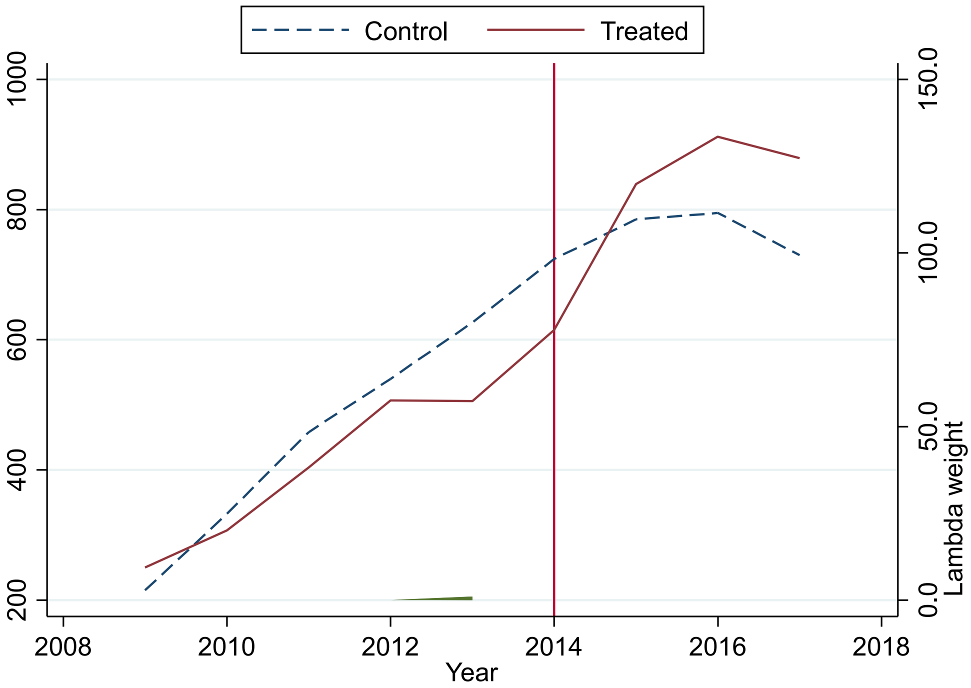

Control
Treated
800
600
400
200
0
150.0
100.0
50.0
0.0
Lambda weight
2008
2010
2012
2014
2016
2018
Year

Effects on Tesla's Patent Citation (Forward Two Years)

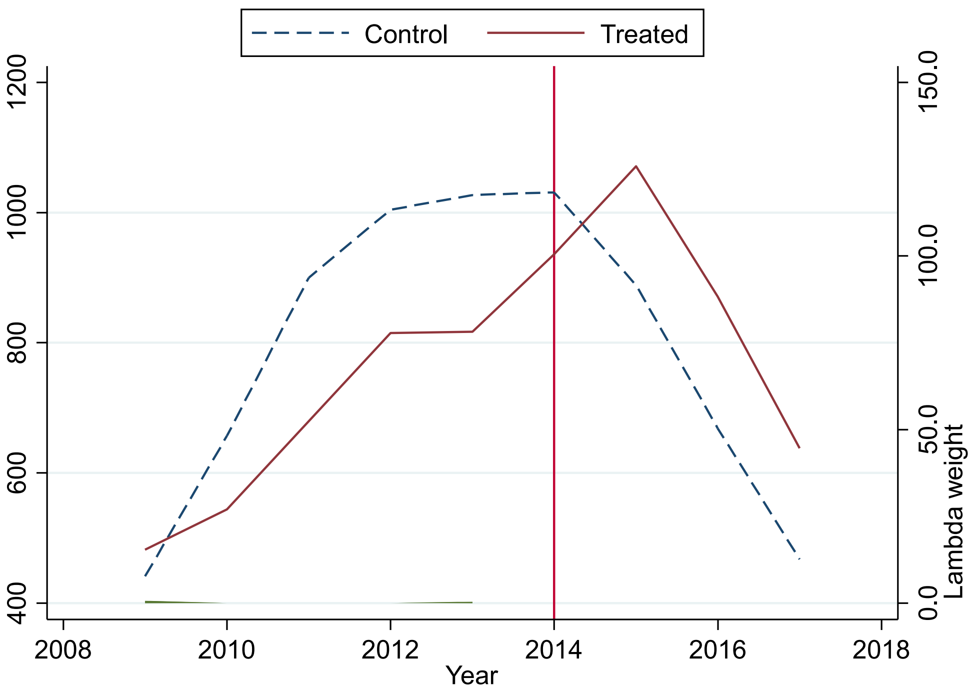
	(1) Total		(2) Distinct		(3) Total (For Granted Patents Applied Before Tesla's Announcement)		(4) Distinct (For Granted Patents Applied Before Tesla's Announcement)	
Patent Pledge	259.9678	(999.1205)	173.4816	(598.7586)	168.3895	(1.1e+03)	139.1444	(503.7241)
Fixed Effects	Yes		Yes		Yes		Yes	
N	639		639		639		639	

Note: Standard errors in parentheses
Source: PATSTAT
* $p < .10$, ** $p < .05$, *** $p < .01$

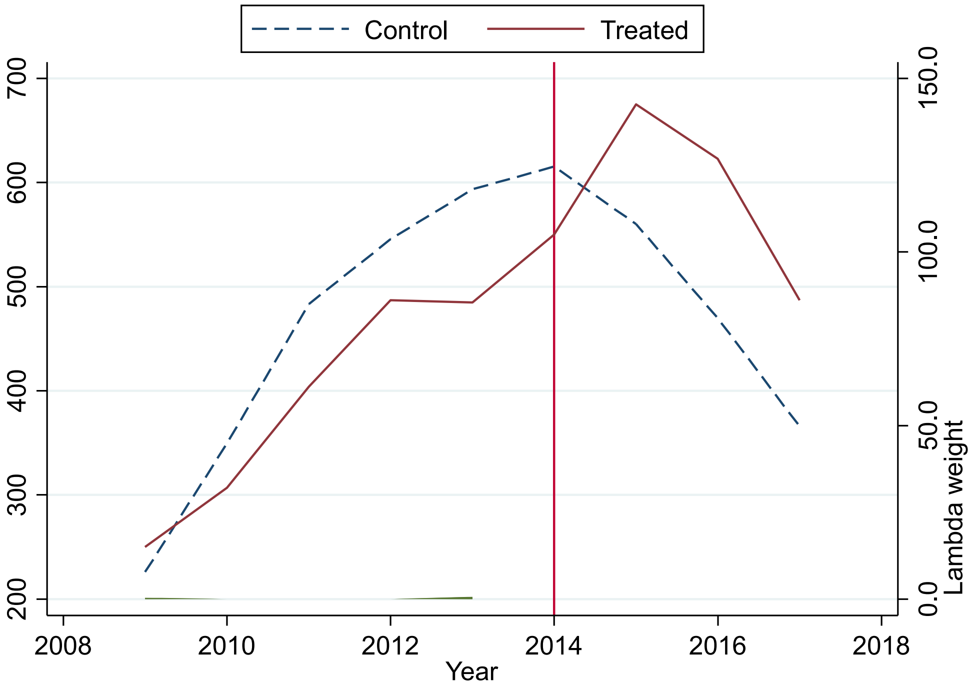




Control
Treated
1000
800
600
400
200
150.0
100.0
50.0
0.0
Lambda weight
2008
2010
2012
2014
2016
2018
Year



Control
Treated
1200
1000
800
600
400
150.0
100.0
50.0
0.0
Lambda weight
2008
2010
2012
2014
2016
2018
Year



B.3. Alternations in Tesla's Innovation Activities

B.3.1. Patenting Intensity

In contrast to the main results, the results for patenting intensity utilizing synthetic DID indicate that no statistically significant effects are observed. Nonetheless, the absence of well-defined counterfactual parallel control groups, as indicated by the corresponding figure for each outcome, diminishes the trustworthiness of results derived from synthetic DID analysis. The absence of smooth pre-treatment parallel control groups is due to the incorporation of control variables, which are omitted in the analysis for technology similarity and follow-on innovations alongside the main analysis.

Effects on Tesla's Patenting Activity (Current)		
	No Forward	
Patent Pledge	0.0094	(12.8983)
Control Variables	Yes	
Fixed Effects	Yes	
N	759	

Note: Standard errors in parentheses
Source: PATSTAT Compustat SDC_Platinum
$^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$

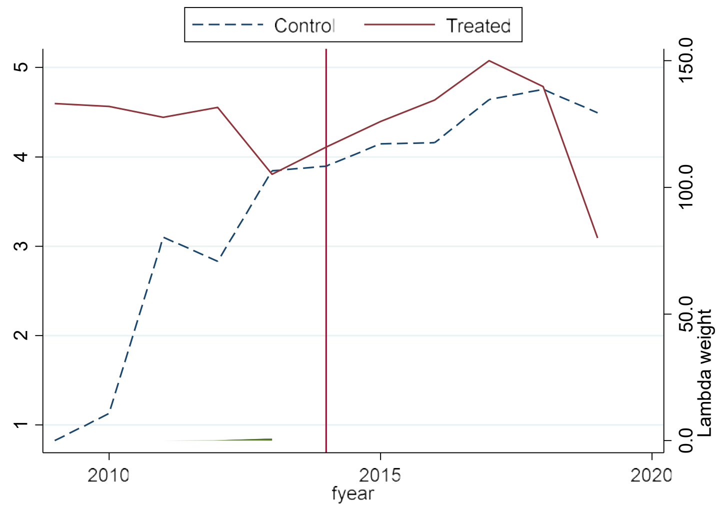


Figure: Synthetic DID Result for Patenting Intensity of Tesla – Granted Patent Applications

Effects on Tesla's Patenting Activity (Forward One Year)		
	Forward One Year	
Patent Pledge	0.6287	(2.4651)
Control Variables	Yes	
Fixed Effects	Yes	
N	690	

Note: Standard errors in parentheses
Source: PATSTAT Compustat SDC_Platinum
$^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$

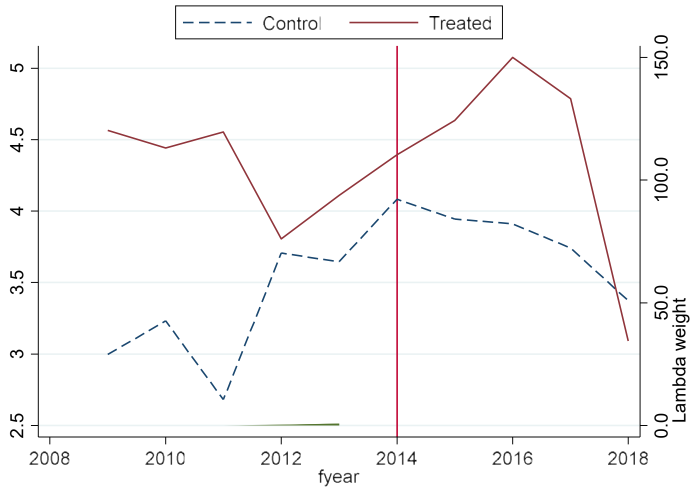


Figure: Synthetic DID Result for Patenting Intensity of Tesla – Granted Patent Applications (Forward 1-Year)

Effects on Tesla's Patenting Activity (Forward Two Years)

	Forward Two Years	
Patent Pledge	0.1606	(9.3989)
Control Variables	Yes	
Fixed Effects	Yes	
N	621	

Note: Standard errors in parentheses
Source: PATSTAT Compustat SDC_Platinum
* $p < .10$, ** $p < .05$, *** $p < .01$

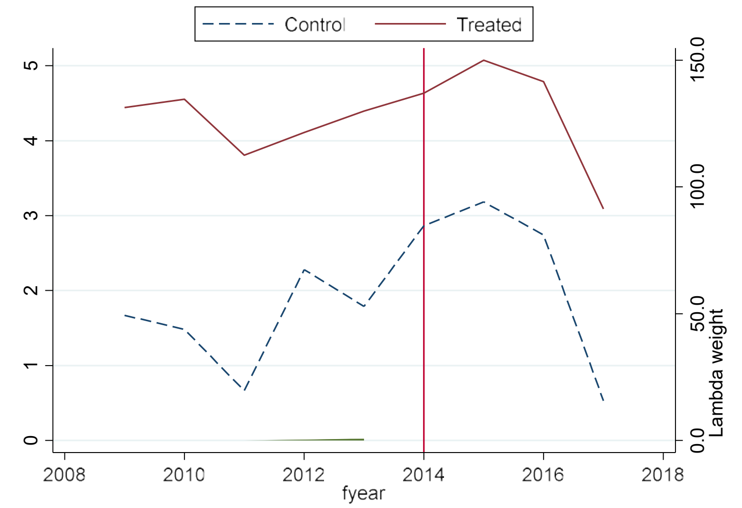


Figure: Synthetic DID Result for Patenting Intensity of Tesla – Granted Patent Applications (Forward 2-Years)

B.3.2. Innovation Intensity

Consistent with the main results, the subsequent robustness checks demonstrate no statistically significant results, demonstrating an absence of a discernable effect on Tesla's innovation intensity. Although the created control groups are not flawless, it is visually apparent that the pre-treatment parallel trends of the control groups are justifiable for both the no forward case and the forward two years case, hence enhancing the confidence of the results for these scenarios.

Effects on Tesla's Innovation Activity (Current)

	No Forward	
Patent Pledge	-3.0669	(3.5300)
Control Variables	Yes	
Fixed Effects	Yes	
N	759	

Note: Standard errors in parentheses
Source: PATSTAT Compustat SDC_Platinum
$^{*} p < .10$, $^{**} p < .05$, $^{***} p < .01$

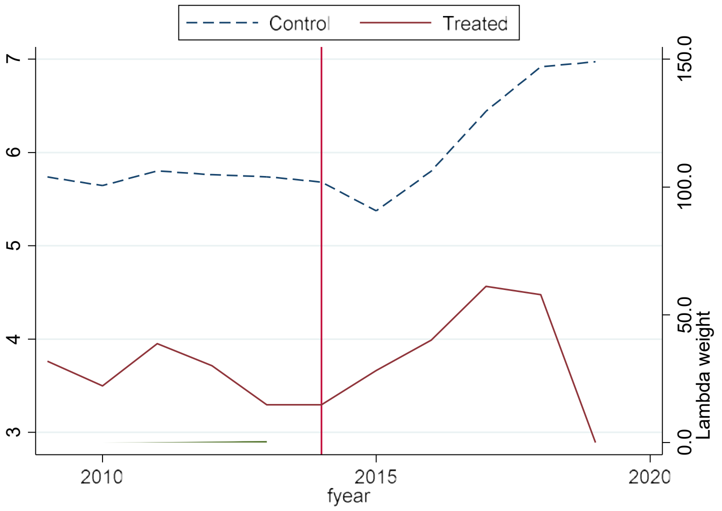


Figure: Synthetic DID Result for Innovation Intensity of Tesla – Patent Families with at least One Granted Patent Applications

Effects on Tesla's Innovation Activity (Forward One Year)

	Forward One Year	
Patent Pledge	0.8665	(12.1296)
Control Variables	Yes	
Fixed Effects	Yes	
N	690	

Note: Standard errors in parentheses
Source: PATSTAT Compustat SDC_Platinum
* $p < .10$, ** $p < .05$, *** $p < .01$

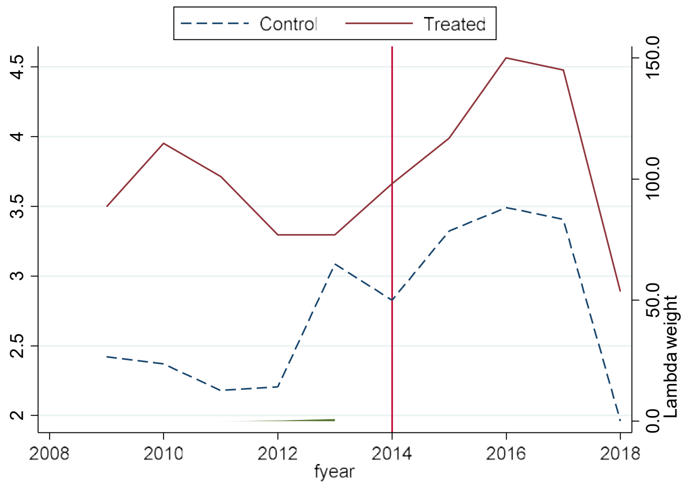


Figure: Synthetic DID Result for Innovation Intensity of Tesla – Patent Families with at least One Granted Patent Applications (Forward 1-Year)

Effects on Tesla's Innovation Activity (Forward Two Years)

	Forward Two Years	
Patent Pledge	2.7714	(2.3708)
Control Variables	Yes	
Fixed Effects	Yes	
N	621	

Note: Standard errors in parentheses
Source: PATSTAT Compustat SDC_Platinum
* $p < .10$, ** $p < .05$, *** $p < .01$

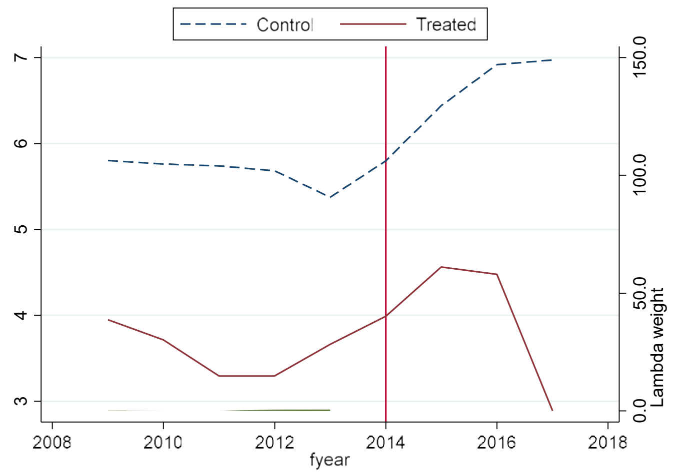


Figure: Synthetic DID Result for Innovation Intensity of Tesla – Patent Families with at least One Granted Patent Applications (Forward 2-Years)

B.3.3. Innovation Quality

In accordance with the main analysis, the average number of claims per patent (scope) and the number of forward citations are used to gauge the quality of innovation. The conclusion yielded from robustness checks is consistent with the main results.

B.3.3.a. Forward Citation

Analogous to robustness checks for forward citations without control factors in evaluating effect on follow-on innovations, the subsequent results indicate no statistically significant findings on forward citations (both total and distinct) when control variables are incorporated, aligning with the main results.

Effects on Tesla's Patent Citation (Current)

	(1) Total		(2) Distinct	
Patent Pledge	-0.3247	(3.4911)	-0.5818	(13.6628)
Control Variables	Yes		Yes	
Fixed Effects	Yes		Yes	
N	759		759	

Note: Standard errors in parentheses
Source: PATSTAT
$^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$

Effects on Tesla's Patent Citation (Forward One Year)

	(1) Total		(2) Distinct	
Patent Pledge	0.8477	(2.4057)	-0.5338	(2.8891)
Control Variables	Yes		Yes	
Fixed Effects	Yes		Yes	
N	690		690	

Note: Standard errors in parentheses
Source: PATSTAT
$^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$

Effects on Tesla's Patent Citation (Forward Two Years)

	(1) Total		(2) Distinct	
Patent Pledge	-0.5085	(4.9425)	0.1064	(3.3487)
Control Variables	Yes		Yes	
Fixed Effects	Yes		Yes	
N	621		621	

Note: Standard errors in parentheses
Source: PATSTAT
$^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$

B.3.3.b. Claims per Patent

The robustness checks for average claims per patent, consistent with the main research results, do not reveal statistically significant findings, suggesting no notable impact from Tesla's patent pledge.

Effects on Tesla's Patents' (granted) Quality/Scope (Current)

	No Forward	
Patent Pledge	-4.4415	(9.4422)
Control Variables	Yes	
Fixed Effects	Yes	
N	759	

Note: Standard errors in parentheses
Source: PATSTAT Compustat SDC_Platinum
* $p < .10$, ** $p < .05$, *** $p < .01$

Effects on Tesla's Patents' (granted) Quality/Scope (Forward One Year)

	Forward One Year	
Patent Pledge	-0.9902	(76.0021)
Control Variables	Yes	
Fixed Effects	Yes	
N	690	

Note: Standard errors in parentheses
Source: PATSTAT Compustat SDC_Platinum
* $p < .10$, ** $p < .05$, *** $p < .01$

Effects on Tesla's Patents' (granted) Quality/Scope (Forward Two Years)

	Forward Two Years	
Patent Pledge	20.1154	(24.0192)
Control Variables	Yes	
Fixed Effects	Yes	
N	621	

Note: Standard errors in parentheses
Source: PATSTAT Compustat SDC_Platinum
* $p < .10$, ** $p < .05$, *** $p < .01$

C. Robustness Checks on Tesla's Innovation Activities Based on US Patents

The main analysis indicates that the adoption of patent pledge has varying impacts on Tesla's global patenting efforts and its innovation activities. The main analysis concludes that Tesla did not substantially enhance its invention operations; nonetheless, the company became more proactive in patenting its innovations across many patent offices. Considering Tesla's status as a US company and the significance of the US economy, it is prudent to examine firms' patenting behavior in the US as a robustness check, as firms are likely to secure protection for their ideas within the country. Robustness checks on patenting in the United States are conducted for both regular Two-Way Fixed Effects (TWFE) and synthetic Difference-in-Differences (DID) methodologies. This section's study concludes that no definitive causal relationship is established between Tesla's patent pledge and its patenting activities in the United States. Consequently, the result further substantiates the findings derived from the main analysis about Tesla's innovation intensity.

C.1. Standard DID (TWFE)

The findings obtained from TWFE regarding the number of granted patent applications filed in the US indicate that Tesla significantly augmented its patenting activity in the US by around 135.85% (one year forward) and 132.55% (two years forward). The event study for these two outcomes demonstrates no breach of the parallel trend assumption. Nonetheless, the honest DID analysis for linear pre-trend indicates the potential existence of a linear pre-trend, implying an endogenous factor influencing Tesla's patenting activities in the US. Therefore, the evidence that the patent pledge promotes Tesla's patenting in the US is insufficient.

Effects on Tesla's Patent Application in the US (granted)

	(1) Current		(2) Forward 1Y		(3) Forward 2Y	
Patent Pledge	0.8987*	(0.5309)	1.3585**	(0.5922)	1.3255**	(0.5551)
Constant	5.2812**	(2.6353)	8.3875***	(2.9080)	7.6610***	(2.4517)
Control Variables	Yes		Yes		Yes	
Fixed Effects	Yes		Yes		Yes	
N	560		502		443	
r2_a	0.0930		0.1405		0.1654	

Note: Standard errors in parentheses
Source: PATSTAT Compustat SDC_Platinum
* $p < .10$, ** $p < .05$, *** $p < .01$

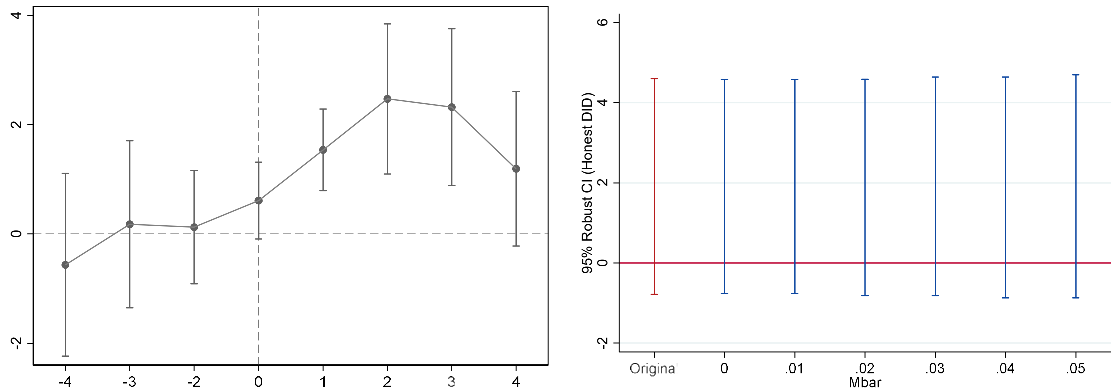


Figure: Event Study and Honest DID result for patenting Intensity of Tesla in the US – Granted Patent Applications (Forward 1-Year)

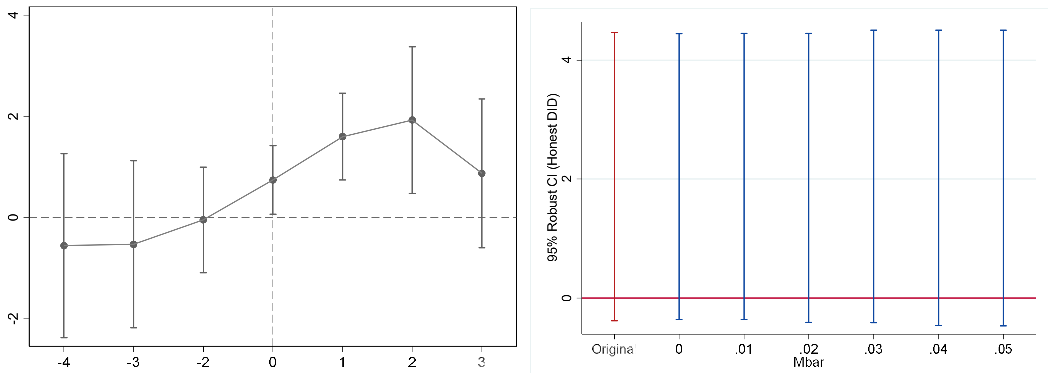


Figure: Event Study and Honest DID result for patenting Intensity of Tesla in the US – Granted Patent Applications (Forward 2-Years)

C.2. Synthetic DID

No statistically significant effects are achieved using synthetic DID, with the parallel control group adequately created for both no forward and forward one-year cases.

Effects on Tesla's Patenting Activity in the US (Current)

	No Forward	
Patent Pledge	-2.9460	(16.1083)
Control Variables	Yes	
Fixed Effects	Yes	
N	759	

Note: Standard errors in parentheses
Source: PATSTAT Compustat SDC_Platinum
$^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$

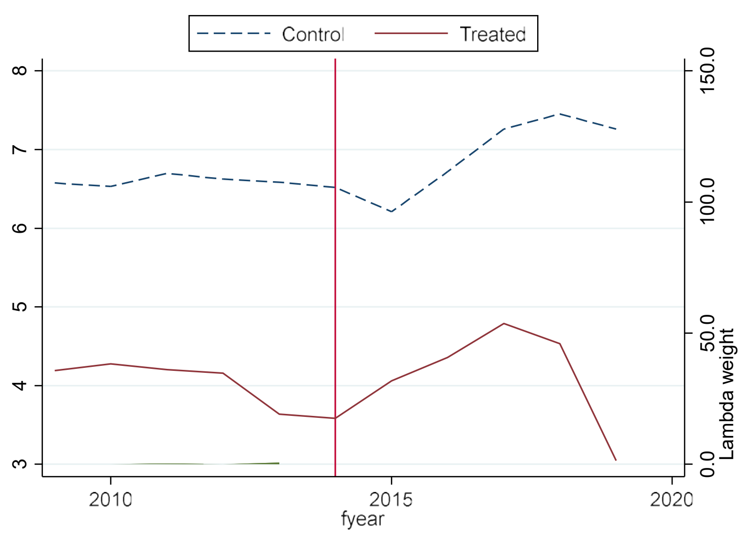


Figure: Synthetic DID Result for Tesla's Patenting Intensity in the US – Granted Patent Applications Filed in the US

Effects on Tesla's Patenting Activity in the US (Forward One Year)

	Forward One Year	
Patent Pledge	1.9168	(11.3860)
Control Variables	Yes	
Fixed Effects	Yes	
N	690	

Note: Standard errors in parentheses
Source: PATSTAT Compustat SDC_Platinum
* $p < .10$, ** $p < .05$, *** $p < .01$

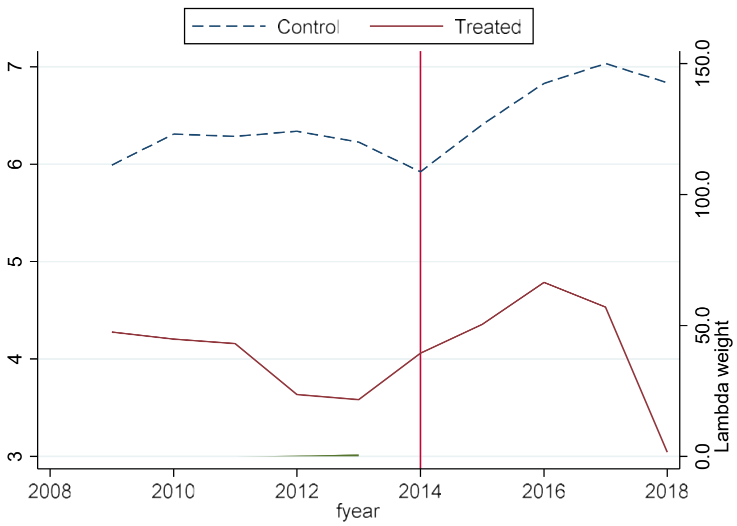


Figure: Synthetic DID Result for Tesla’s Patenting Intensity in the US – Granted Patent Applications Filed in the US (Forward 1-Year)

Effects on Tesla's Patenting Activity in the US (Forward Two Years)

	Forward Two Years	
Patent Pledge	0.3673	(9.0045)
Control Variables	Yes	
Fixed Effects	Yes	
N	621	

Note: Standard errors in parentheses
Source: PATSTAT Compustat SDC_Platinum
* $p < .10$, ** $p < .05$, *** $p < .01$

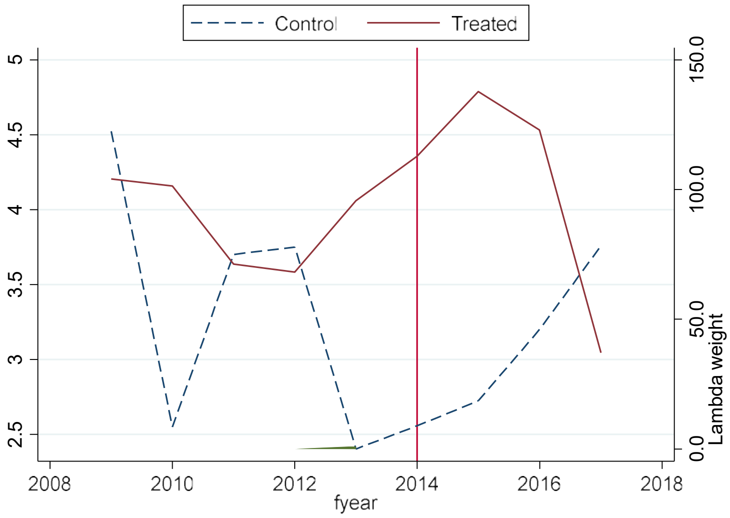


Figure: Synthetic DID Result for Tesla's Patenting Intensity in the US – Granted Patent Applications Filed in the US (Forward 2-Years)

D. Placebo Test

To further ensure the robustness of this research, I have also conducted placebo tests for all the statistically significant main results that pass the test for parallel trend and linear pre-trend. The results from placebo tests further corroborate that the robust results yielded from the main analysis is unique to Tesla in 2014.

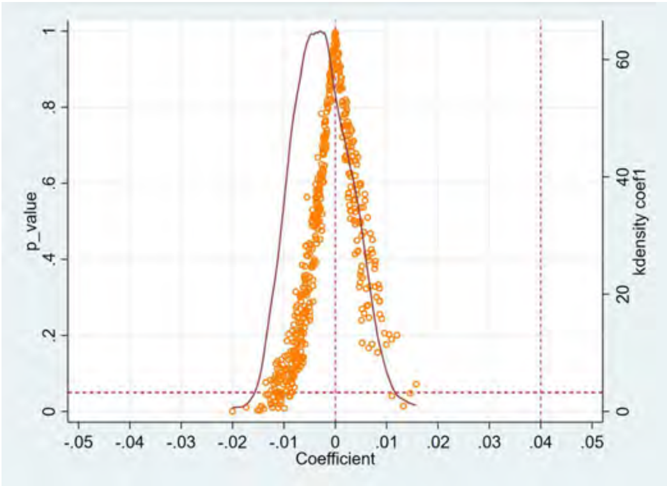


Figure: Placebo test result for Jaccard Similarity – No forward

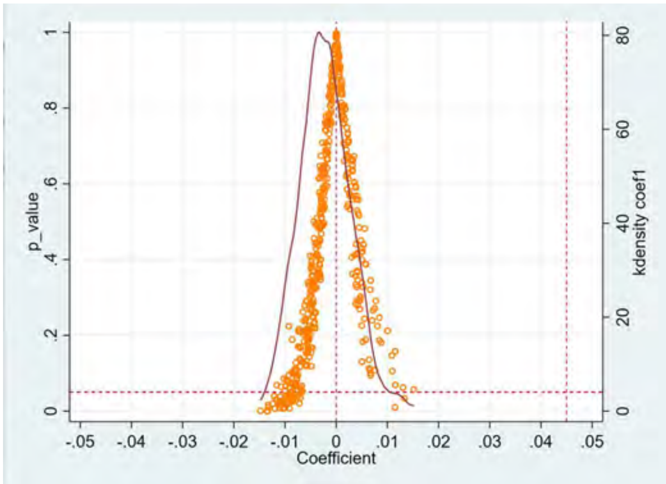


Figure: Placebo test result for Jaccard Similarity – Forward 1-year

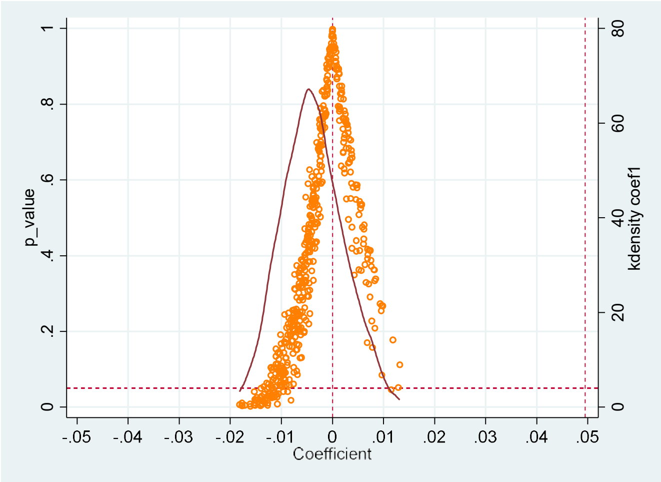


Figure: Placebo test result for Jaccard Similarity of granted patents applied before strategy

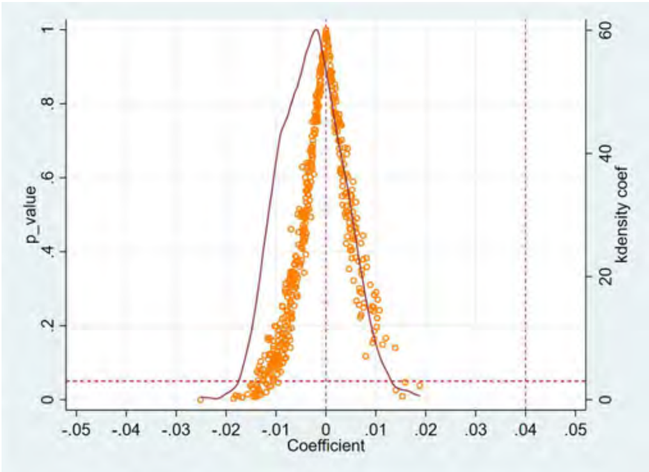


Figure: Placebo test result for Cosine Similarity

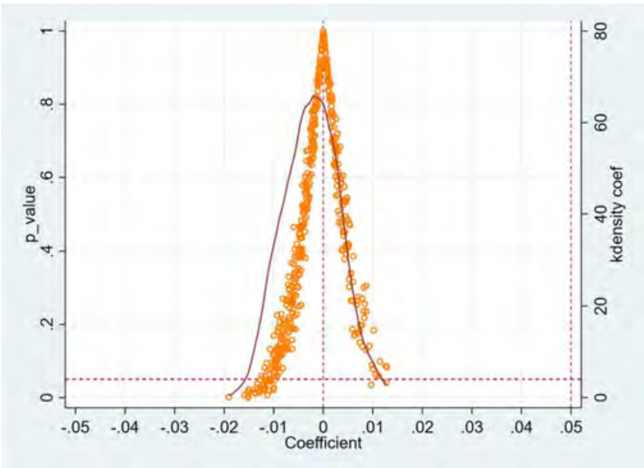


Figure: Placebo test result for Cosine Similarity – Forward 1-year

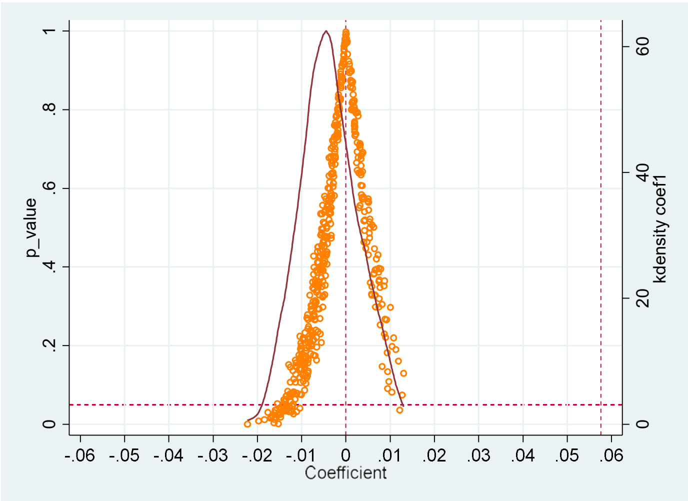


Figure: Placebo test result for Cosine Similarity of granted patents applied before patent pledge

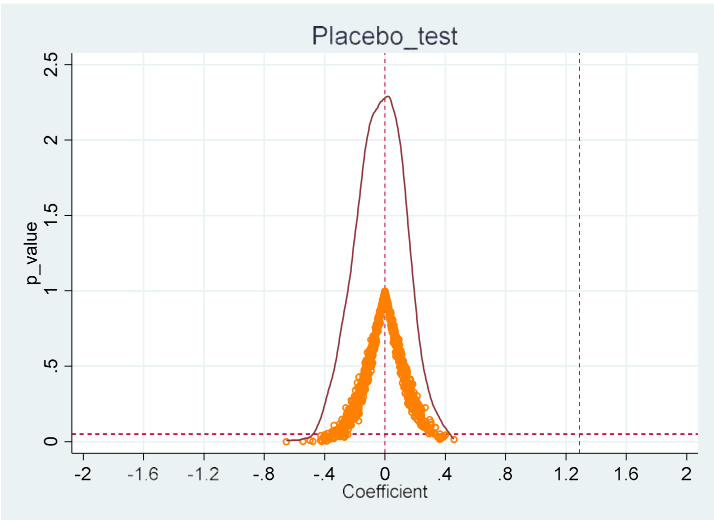


Figure: Placebo test result for Patenting Intensity of Tesla – Granted Patent Applications (Forward 2-Years)

E. Extract Each Firm's Patent Data in PATSTAT Online

Given that Compustat, SDC Platinum, and PATSTAT are not interlinked, it is essential to match the data from these sources. PATSTAT online does not explicitly provide firm-level data; therefore, users must extract data for each firm using specific SQL coding. A sample SQL code for identifying the names of a certain firm required for extracting the firm's patents is provided below, as per the instructions from the European Patent Office (EPO) technical guidance. For example, in the case of Tesla, the SQL is:

```
SELECT tls206_person.[psn_name], count(appln_id) total
FROM [patstat2023a].[dbo].[tls206_person]
  join tls207_pers_appln on tls206_person.person_id = tls207_pers_appln.person_id
where psn_name like '%tesla%'
group by tls206_person.[psn_name]
order by total desc
```

Based on the search result yielded from SQL coding above, reasonable names with enough number of patents are handpicked. Through this process, the names 'TESLA', 'TESLA MOTORS', 'Tesla, Inc.', 'TESLA MOTORS CANADA ULC' are reckoned as names used for extracting Tesla's patent in PATSTAT online. For some names with very limited number of patents (i.e. less than 10) compared to variations of other names of the same firm (i.e. more than 10000) are excluded. The same procedure is repeated for each firm included in the sample. The full list of the names used for data extraction through PATSTAT online can be provided upon request.

F. Coarsened Exact Matching

Given this paper's nature of quantitative case study, Coarsened Exact Matching (CEM) should be a good approach. However, the result below suggests that CEM is not suitable for this study as no groups can be matched with Tesla and the covariates are complete imbalance with Multivariate L1 distance equal to 1.

```
Matching Summary:
-----------------
Number of strata: 650
Number of matched strata: 0

             0     1
      All  748    11
  Matched    0     0
Unmatched  748    11


Multivariate L1 distance: 1

Univariate imbalance:

                L1       mean      min       25%       50%       75%       max
     rdint  .35829     .03524   .03561    .01687    .02493    .13504  -.24508
     lnage  .82754    -1.3107   1.7918   -1.0116   -1.1575   -1.7677  -2.3749
      lnat  .47059    -1.5228   1.0217   -1.9117   -1.1426    -.9004  -3.1262
       roa  .88636    -.24331   .57289   -.41426   -.13063     -.163        .
      ppea  .76738      .3412   .16961     .3646    .38407    .42791   .08199
  leverage  .43449      .0861   .00836    .14632    .15006    .05648        .
capexasset   .7393     .09772   .03791    .06157    .08152    .15429        .
    tobinq  .58021     1.6531   1.5354    1.2217    2.3097    2.2235        .
    lerner  .94652    -.53657   4.5601    -1.023   -.29263   -.28718  -.67897
  lernersq  .27005     .25267  1.1e-05   -.00527   -.01221    .83987  -32.266
   kzindex  .59358     15.638   485.37    18.452    9.3817    .44466        .
   instown  .86364    -.22388        0   -.05309    -.1907   -.26265  -.31743
```

7.