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Strategic Patent Pledging:
The Role of Patent Centrality
in Innovation Collateralization

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Résumé

Cette thèse examine l’utilisation stratégique des brevets en tant que collatéraux dans le financement par dette des entreprises innovantes, en se concentrant sur la capacité des entreprises à engager des brevets non essentiels à leur technologie de base. En utilisant la centralité des brevets – définie comme la proximité technologique d'un brevet par rapport à la technologie de base de l’entreprise – comme indicateur principal des brevets de base, j'examine la relation entre le degré de proximité technologique et la probabilité que les brevets soient utilisés en tant que collatéraux, afin de tirer des conclusions sur l'indépendance stratégique des entreprises dans le processus de mise en gage des brevets. De plus, j'essaie de comprendre l'impact de l'utilisation stratégique des brevets sur les frais de financement et de savoir si un changement dans l’environnement réglementaire influence la trajectoire du comportement de mise en gage.

En analysant un ensemble de données de plus de 3 millions de brevets de 9 382 entreprises publiques américaines accordés entre 1950 et 2022, je constate que, malgré la prudence affichée par les entreprises au niveau de la mise en gage des brevets, elles sont souvent amenées à engager leurs brevets de base sous la pression des créanciers. La mise en gage de brevets de base tend à aboutir à de meilleures conditions de financement, tandis que la mise en gage de brevets non essentiels est souvent associée à des frais plus élevés. L'étude souligne également comment des facteurs externes, tels que la concurrence industrielle et les changements réglementaires, influencent les décisions des entreprises en matière de mise en gage des brevets, mettant en évidence les complexités de la collatéralisation de l'innovation dans le financement par dette.

Mots clés: *Utilisation Stratégique des Brevets, Collatéralisation des Brevets, Centralité des Brevets, Brevets de Base, Financement par Dette, Financement de l’Innovation, Finance d’Entreprise*

Abstract

This thesis examines the strategic use of patents as collaterals in debt financing by innovative firms, focusing on firms' ability to pledge patents non-essential to their core technology. Using patent centrality – defined as a patent's technology closeness to firms' core technology – as a key indicator of core patent, I investigate the relationship between the level of technology's closeness and the likelihood of patents being pledged as collaterals to draw conclusions on the firms' strategic independence in the patent pledging process. Additionally, I attempt to understand the impact of strategic patent pledging on financing expenses and whether a shift in regulatory environment influences the trajectory of pledging behavior.

Analyzing a dataset of over 3 million patents from 9,382 public US firms granted between 1950 and 2022, I find that despite firms exhibiting caution in patent pledging at the firm level, they often pledge core patents under creditor pressure. Pledging core patents tends to result in better financing terms, while non-core pledging is often associated with higher expenses. The study also highlights how external factors, such as industry competition and regulatory shifts, affect firms' pledging decisions, emphasizing the intricacies of innovation collateralization in debt financing.

Keywords: *Strategic Patent Pledging, Patent Collateralization, Patent Centrality, Core Patents, Debt Financing, Financing Innovation, Corporate Finance.*

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Table of contents

Résumé .... **i**

Abstract .... **ii**

Acknowledgements .... **iii**

Table of contents .... **iv**

List of Tables .... **vi**

List of Figures .... **vii**

1. Introduction **1**

2. Literature Review **5**

2.1. Financing Innovation 5

2.2. Patents as Collaterals 7

3. Hypotheses **9**

3.1. Hypothesis 1: Strategic Pledging 9

3.2. Hypothesis 2: Impact on Loan Terms 10

3.3. Hypothesis 3: AIPA 10

4. Data **13**

4.1. Data Sources 13

4.2. Identifying Key Variables: 14

4.2.1. Patent Centrality: *14*

4.2.2. Strategic Pledge: *15*

4.2.3. Industry Concentration *16*

4.3. Summary Statistics 17

5. Methodology **20**

5.1. Model to assess Strategic Pledging 20

5.2. Model to assess Impact on Loan Terms 21
5.3. Natural Experiment: AIPA 22
6. Results 24
6.1. Regression Result on Strategic Pledging 24
6.1.1. Baseline Regression Results on Strategic Pledging 24
6.1.2. Baseline Regression Results at Firm and Firm-Year Levels 28
6.1.3. Alternative "Patent Centrality" Definition 31
6.1.3. Baseline Regression Results for Different Technological Sectors 33
6.2. Regression Results of Strategic Pledging on Financing Expenses 38
6.2.1. Regression Results on Financing Expenses 38
6.2.2. Regression Results on Financing Expenses at Different Patent Centrality Thresholds 43
6.2.3. Regression Results on Financing Expenses for Non-Strategic Pledging 45
6.3. Natural Experiment: AIPA 47
6.3.1. DiD Regression Results on Pledged Patents 47
6.3.2. Natural Experiment at Different Patent Centrality Thresholds 49
6.3.3. Alternative Treatment Windows around AIPA reform 51
7. Conclusion 54
References 56
Appendix 62

List of Tables

Table 1: Patenting Firms with Pledged Patents. 7

Table 2: Different thresholds of "Patent Centrality" 15

Table 3: Summary Statistics of Key Variables. 17

Table 4: Summary Statistics of Core and Non-core Patents 18

Table 5: Summary Statistics of Pledged and Non-pledged Patents. 18

Table 6: Logistic Regression Results on Strategic Pledging 25

Table 7: Strategic Pledging, Firm and Firm-Year Levels 29

Table 8: Strategic Pledging, Alternative Patent Centrality Definition 33

Table 9: Firm Count by Technological Sector 34

Table 10: Logistic Regression Results on Strategic Pledging, by Technological Sector 36

Table 11: Strategic Pledging and Financing Terms 39

Table 12: Strategic Pledging and Financing Terms, Industry Concentration 42

Table 13: Strategic Pledging and Financing Terms, Alternative "Patent Centrality" Thresholds44

Table 14: Impact of Non-Strategic Pledging on Financing Terms 46

Table 15: AIPA-Reform and Strategic Pledging. 48

Table 16: AIPA-Reform and Strategic Pledging, Alternative "Patent Centrality" Thresholds ... 50

Table 17: AIPA-Reform and Strategic Pledging, Alternative Treatment Windows 52

List of Figures

Figure 1: Impact of AIPA Reform on Patent Pledging by Publication Lag 12
Figure 2: Number of Overall and Pledged Patents by Technological Sector 35

1. Introduction

The financing landscape for innovation has evolved significantly over the past few decades, with innovative firms increasingly gaining access to debt financing through the use of patents as collaterals. Loans backed by patents perform no less than those backed by traditional tangible assets (Loumioti, 2012), and firms with high patenting activity usually receive better financing terms (Chava et al., 2017). However, pledging valuable patents carries substantial risks. In the event of default, core patents may be acquired by entities exploiting high-value patents for litigation purposes, potentially obstructing future innovation (Ma et al., 2022; Duan, 2023). Such risks call into question whether innovative firms are inclined to pledge their most valuable patents as collateral.

Most studies on patents as collaterals have focused on understanding the creditor's assessment of patent pledgeability. By shifting the focus from how creditors evaluate patents to how firms make strategic choices about which patents to pledge, I seek to understand whether firms place any caution when securing debt with patents and whether this process is approached strategically. In particular, I address one key question: Do firms in the innovative space strategically utilize their patents as collaterals in debt financing? Specifically, I investigate whether innovative firms are more likely to pledge patents less central to their core technology to secure favourable financing terms while protecting their most valuable patents. The impact of such strategic action determines the second research question: Do firms benefit from strategic patent pledging? More precisely, does pledging non-core patents result in better financing terms? Finally, I examine the role of unprecedented regulatory event in patent pledging. My third research question is: Did a regulatory policy that weakened firms' competitive standing in innovation influence their tendency in pledging core or non-core patents for debt financing?

The baseline analysis relies on previous studies about the characteristics of patents pledged as collaterals, most prominently by Mann (2018). In my models, I incorporate the collateralized patent characteristics defined by Mann (2018) as control variables. My focus is on examining patent centrality – a patent's proximity to the firm's most central technology – as a key explanatory variable of patent pledging behavior. Patent centrality helps distinguish core versus non-core patents to determine if incidents of strategic patent pledging exist. Adapting a strategy outlined by Cappelli et al. (2023), I measure patent centrality by assessing how closely a patent's technology classes align with the firm's core technology class. To test the robustness and generalizability of my findings, I apply the models to multiple contexts and environments to explore the economic significance of the relationship between patent centrality and the likelihood of patent being pledged. In doing so, my study contributes to the growing body of literature on patent collateralization by shedding lights on the strategic decisions, or the lack thereof, that firms make when selecting patents for debt financing. The findings provide insights into whether firms are strategically safeguarding their most valuable patents, or if external factors, such as industry competition or regulatory shifts, influence their patent pledging behavior.

The results of my study suggest that, when data is analyzed at the patent level, there are limited strategic decisions made by firms in pledging patents. However, there is significant caution found at the firm and firm-year levels, where firms with higher technologically centric patent portfolio are more hesitant to pledge patents overall. Using the Herfindahl-Hirschman Index (HHI) to proxy for industry concentration, I also assess whether strategic pledging exists when firms are in highly competitive environments. At the patent level, increased industry competitiveness correlates with higher patent pledging activities, though higher reluctance to pledge core patent is also observed. At firm and firm-year levels, industry competition plays a less significant and more inconsistent roles, likely due to firm-specific and time-varying factors uncovered in this study. When applying the model to particular technology sectors, I also discover the same patterns as when the baseline regression is applied across the whole dataset. Core patents are more likely to be pledged regardless of the varying sizes and patenting activities of these sectors. As a robustness check, the definition of core patents is redefined based on Wu, Chen, and Lee (2010), which leads to the same observation as when Cappelli et al. (2023)'s patent centrality version is used.

My findings indicate that whether a patent is core or non-core plays a role in determining its pledgeability in debt financing. They also suggest a broader interpretation of the interplay between creditors' preferences and firms' strategies: Creditors' demands appear to be more dominant in the patent pledging process, often overriding firms' desire to protect their core patents. When firms seek debt financing, they may be less willing but more compelled to pledge their most valuable patents. Creditors, in turn, demonstrate a clear preference for core patents, likely due to their higher quality attributes – such as greater citation counts, longer time to expiration, and higher commercial value. It could also be that central patents represent the opportunities to exert more control over the firm's innovation process, or that they are more easily resold in the event of bankruptcy, as suggested by Ma et al. (2022).

To answer the second research question, I analyze the impact of different pledging choices on financing terms. My study finds that pledging non-core patents generally correlates with higher interest expenses for firms, while the opposite is true for core patents. This result is sensitive when controlling for fixed effects, as adding these controls could diminish the significance of observed relationships. Additionally, the results are sensitive to other determinants, such as industry competitiveness, suggesting that both observable and unobservable heterogeneity may influence the findings. In particular, higher industry competition in combination with strategically pledging non-core patents is related to lower interest expenses. This could likely be due to firms in highly competitive markets relying less on debt financing. The analysis is also conducted based on different thresholds that confine core patents, where the same result can be observed: pledging non-core patents go side by side with higher loan expenses. While pledging core patent typically results in better financing terms, the case for non-core patents is more complex. Although pledging non-core patents generally leads to higher interest expenses, the relationship between patent pledging and financing terms is influenced by other factors unobserved in this study, suggesting that firms' selection of patents as collaterals may be influenced by both strategic considerations and market conditions, rather than a straightforward preference for protecting technology.

Finally, I leverage a natural experiment to help better understand the causal impact of a policy enactment on the previously observed pledging behaviour. Using a generalized Difference-in-Differences (DiD) approach, I focus on the five-year periods before and after the enactment of the American Inventors' Protection Act (AIPA) in 2001. The results show that firms negatively affected by shorter patent publication timelines increased their use of core patents while reducing the pledging of non-core ones for debt financing. These findings hold across varying core patent thresholds and time periods surrounding the policy change, further emphasizing the significance of technology centrality in determining which patents are pledged as collaterals. This natural experiment illustrates the tangible effects of external regulatory pressures on firms' patent pledging decisions, with technology centrality emerging as a crucial factor. When a regulatory change weakened firms' competitive standing, their strategic independence in selecting which patents to pledge seemed to diminish, pushing them to align more with creditors' preferences for core patent collateral to meet debt financing commitments.

The remainder of this paper is structured as follows: Chapter 2 reviews the relevant literature in financing innovation and patent pledging, Chapter 3 discusses the main hypotheses developed based on the literature review and research questions, Chapter 4 describes the dataset and key variables of the study, Chapter 5 structures the methodology framework that tests the hypotheses in Chapter 3 using the dataset and variables in Chapter 4, Chapter 6 explores the results from the tests conducted based on the methodology of Chapter 5 and their robustness checks, and Chapter 7 concludes this paper.

2. Literature Review

Financing of innovative firms goes against the traditional theoretical concepts of corporate capital structure. Traditional corporate capital structure theories, starting with Modigliani-Miller's (MM I, 1958) capital structure irrelevance theorem and its subsequent adjustments (MM II, 1963), suggest that the choice of capital does not affect a firm's value, and that higher leverage generates both lower costs of capital and higher values from the present value of interest tax shield. However, elevated level of debt may raise interest rates on debt (Baxter, 1967), and the probability of default on debt payments, leading to bankruptcy and offsetting its tax shield benefits (Baxter, 1967; Pandey, 2015). Furthermore, if earnings are sufficiently low or negative, interest tax shields may be non-existent (Van Horne, 2009). Such earnings constraints are nothing less than common in innovative firms.

2.1. Financing Innovation

Characterized by limited or negative earnings and high-risk high-uncertainty investments, innovative firms often lack the cushion of internal funds and are shunned by traditional creditors for their lack of tangible assets to secure loans and unstable source of cash flows to service debt (Kerr & Nanda, 2015). Thus, these firms tend to carry lower debt proportion, as suggested by the trade-off theory (TOT). The TOT proposes that firms balance debt benefits (from interest tax shields) and costs (from bankruptcy) (Kraus & Litzenberger, 1973; Baxter 1967; Barklay & Smith, 1999). Firms' capital structure is adjusted either statically whenever their structure deviates from its target in the absence of capitalization costs (Bradley et al., 1984), or dynamically only when the benefits outweigh the costs of readjustments (Fisher et al., 1989). This target capital structure differs among firms based on their internal and external characteristics. Firms with higher earnings, lower probability of default, substantial tangible assets may prefer higher debt level, while growth firms, small firms, and firms with mainly intangible assets tend to carry lower debt proportion due to their higher probability of distress and greater loss in values in the event of bankruptcy (Frank & Goyal, 2009).

In this context, external equity financing allows innovative firms to access capital while maintaining their focus on R&D financing (Hall & Lerner, 2010). Venture Capital (VC) supports and enables the growth of start-ups, evidenced by higher-quality patent filings of VC-backed firms (Lerner & Nanda, 2020). Firms have also been found to prefer equity over debt financing during its growth stage (Fulghieri et al., 2020). This is contrary to the preferential treatment given to debt financing by both investors in agency cost theory (ACT) and firms in pecking order theory (POT). ACT recognizes the costs arisen due to the misalignment of interest between the managers (agents) and the shareholders (principals). Managers may not always act in the best interests of shareholders, making debt a possible mechanism for discipline, as debt providers require managers to focus on generating cash flows for paybacks, aligning their actions more closely with the interests of their shareholders (Jensen & Meckling, 1976). On the other hand, there is an apparent agency cost between debt- and equity holders (Jensen & Meckling, 1976; Myers, 1977). Hence, the optimal capital structure is where debt could minimize the total agency costs (of both equity and debt) and maximize its disciplinary benefits. POT adds on to this theory by dealing with the market imperfection of information asymmetry, which occurs when managers possess more knowledge of the intrinsic value of the firm than the outside capital market investors. Managers do not issue new shares unless they are fairly or overly priced by the market. Therefore, new shares issuance is viewed by rational capital market investors as a negative signal that the new shares are overpriced (Myers, 1984). Consequentially, firms' ideal financing order should be: 1) internal financing, 2) debt, and 3) equity. Firms with high earnings could internally fund their investment opportunities, while firms with low earnings depend on external financing options, taking on debt first before issuing equity at dwindling prices (Myers, 2003).

The deviation from ACT and POT witnessed in innovative firms is reverted when debt becomes accessible. Firms still prefer to raise debt securities when they reach mature stage (Fulghieri et al., 2020). For firms during growth stage, venture-oriented bank lenders and specialized nonbank lenders have arisen as alternatives to traditional banks to provide loan to start-ups, supplying roughly $5 billion to start-ups annually (Ibrahim, 2010). Robb and Robinson (2014) reported that 25% of start-up capital for two hundred growth-oriented companies is comprised of debts. Furthermore, regarding the performance of early debt, firms using debt in the name of the firm at the initial year of operations are significantly more likely to survive and achieve higher revenue three years after initiation than firms financed by all-equity, potentially due to the initial credit record and reputation building, selection of high-quality firms by bank lenders, and/or monitoring by lenders (Cole & Sokolyk, 2018).

2.2. Patents as Collaterals

For innovative firms to access debt financing, patents have emerged as a valuable collateral tool in the last few decades. As of 2024, based on the data collected for this thesis, more than 50% of US patenting firms had pledged their patents as collateral at some point.

Table 1: Patenting Firms with Pledged Patents

Pledged Patent	Firm Count
Yes	5,196
No	4,186

Patents are evidenced to be quality signals to secure external financing (Milani & Neumann, 2022). Firms with significant patenting activity are charged lower loan spreads by lenders (Chava et al., 2017), especially for smaller innovative firms facing negative internal liquidity shock (Milani & Neumann, 2022). For larger innovative firms, as patents can also reduce the cost of equity capital (Dass et al., 2015), firms with substantial patent portfolios rely less on raising new loans and generally prefer lower leverage in their structure (Chava et al., 2017; Titman & Wessels 1988). But overall patents retain a quality signal for financing even for global leaders in innovation (Milani & Neumann, 2022), as they improve the expected profitability by strengthening the returns from innovation and the firms' residual value in the event of failure (Ayerbe et al., 2023). Loans secured by intangibles perform no worse than other secured loans (Loumioti, 2012).

In determining whether patents are inherently valuable for collateral usage, lenders consider several similar elements as with tangible assets. Patents tend to help lower loan spreads if **1)** they are re-deployable, such that possess qualities that make them more valuable to a general class of firms, evidenced by the subsequent patents that belong to a wide range of technology classes (Chava et al., 2017; Loumioti, 2012; Mann, 2018) and its salability in the secondary markets (Hochberg, Serrano & Ziedonis, 2018), and if **2)** they carry longer remaining lifetime, during which the firm can exclusively capture the associated cash flows and not face the high risk of patents becoming obsolete (Chava et al., 2017; Zhang, Chen, & Wang, 2021; Caviggioli et al., 2019; Kim, 2016). The third factor is if **3)** they have strong technological quality (Fischer & Ringler, 2014; Yang, Gu, & Yang, 2021), as measured by the number of forward citations (Bessen, 2008; Burke & Reitzig, 2007; Trajtenberg, 1990). Other factors are related to the firm, if **4)** the firm has strong reputation, evidenced by sufficient time existed (Yang, Gu, & Yang, 2021) or larger size (Loumioti, 2012), and if **5)** the firm is backed by third parties, such as VC backing and government certification (Hochberg, Serrano, & Ziedonis, 2018; Yang, Zhang & Hu et al., 2022). The reputation of the equity investors significantly leverages the ability of firms to receive debts, so much so that the absence of which would make the economic effects of policies that aim at simulating innovation through debt channels muted (Yang, Zhang, & Hu et al., 2022). The higher the quality and quantity of patents pledged, the higher the chance of landing generous debt capital. Bracht & Czarnitzki (2022) estimated that Dutch (Swedish) firms that pledge complete patent portfolios, rather than separate patents or parts of the patent portfolios, could raise more than €7 (€10) billion additional debt capital, all else constant.

While access to debt financing supports innovation growth, it also influences the strategic direction of innovative firms. Though patent pledgeability can induce firms to switch from secrecy-based innovation to patent-based one (Dai et al., 2024), loans secured by patents (LSPs) evidently redirect technological firms' attention from long-term innovative strategies to short-term ones to monetize and litigate their patents (Ayerbe et al., 2023). The addition of patent collateral increases applications of exploitative patents and its proportion in total patent applications but shows no significant impact on exploratory innovation (Luo, Wang & Hu, 2024). This dynamic highlights a challenge for innovative firms: to capitalize on debt financing without compromising their strategic focus due to creditor pressures.

The choice of which patents to pledge can play a deterministic role in the subsequent control of creditors on the innovation trajectories of these firms. Innovative firms with a more diverse asset base and less reliance on one source of financing might prefer to retain their independence in strategic decisions and avoid compromising their most valuable patents.

3. Hypotheses

Based on past literature, I attempt to address a gap by examining how innovative firms approach patent selection during the debt securitization process. Specifically, I explore whether patenting firms strategically pledge less critical patents as collateral to optimize financing terms while safeguarding their core technology and maintaining independence in their innovative process. This overarching question guides the development of the hypotheses, which explore the strategic choices and outcomes of this decision-making process.

3.1. Hypothesis 1: Strategic Pledging

As previously discussed, the trade-off theory (TOT) implies that, to optimize their capital structure, innovative firms must weigh the benefits and costs of debt financing, particularly when collateralizing their loans with patents. For firms in general, the most relevant benefits of debt include reduced cost of capital and dilution for shareholders, while the costs mainly come from the risk of bankruptcy (Kraus & Litzenberger, 1973; Baxter, 1967l; Barklay & Smith, 1999). However, innovative firms face the additional risk of losing pledged patents, and with them, critical competitive technology, in the event of default (Ma et al., 2022). Firms facing litigation from patent trolls have been found to innovate at less efficient level and depend less on leverage (Duan, 2023). Hence, firms largely reliant on intangible assets tend to be more cautious with debt financing (Arundel, 2001; Frank & Goyal, 2009). Regardless, agency cost theory (ACT), pecking order theory (POT), and current findings on innovation financing suggest that debt is still a much-preferred financing option for these firms (Jensen & Meckling, 1976; Myers, 2003; Ibrahim, 2010; Robb & Robinson, 2014).

This dilemma gives rise to the hypothesis that firms would only pledge patents less integral to their core operations. However, such strategic decisions are likely feasible only to larger firms with more extensive patent portfolios. In contrast, smaller R&D-intensive firms, though benefiting more from external financing (Czarnitzki, Hall, & Hottenrott, 2014), are more likely to risk their most tradeable patents, or even their entire patent portfolio, to meet lenders' pledgeability thresholds (Hochberg, Serrano, & Ziedonis, 2018; Chava et al., 2017, Loumioti, 2012).

Hypothesis 1: Innovative firms can strategically pledge patents less central to their core technology and business operations, reserving core patents for strategic market expansion and innovation activities.

3.2. Hypothesis 2: Impact on Loan Terms

If innovative firms indeed prioritize non-central patents for collateral, as proposed in Hypothesis 1, this selective strategy may influence financing outcomes. Grounded in information asymmetry theory (Myers, 1984) and signalling theory (Spence, 1973), the utilization of loans secured by patents (LSPs) by innovative firms can serve as a positive signal to lenders about the firm's confidence in the prospects of their technology and overall financial stability. Extensive patenting activity, whether collateralized or not, has been found to be quality signals for debt providers (Milani & Neumann, 2022; Chava et al., 2017). However, firms using LSPs are evidently more inclined to redirect their focus on short-term strategies (Ayerbe et al., 2023; Luo, Wang & Hu, 2024), possibly to demonstrate short-term viability to align with lender expectations (Diamond, 1989; Stiglitz & Weiss, 1981). By pledging patents that are not essential to their core operations, innovative firms may mitigate this short-term pressure and retain their long-term growth strategies.

While the potential of improved loan terms through pledging non-central patents is underexplored, previous studies suggest that firms with effective collateral management are better positioned to negotiate favorable loans terms, due to perceived higher financial stability and lower risk (Berger & Udell, 1998; Black & Gilson, 1998). Strategic pledging allows firms to signal both their confidence in their technologies and their overall financial health. Lenders positively interpret these signals as indicators of lower risk and higher returns. These findings support the hypothesis that innovative firms employing a strategic approach to patent pledging may be viewed more favorably by lenders than those that do not.

Hypothesis 2: Innovative firms that strategically pledge non-central patents as part of their financing strategy are more likely to receive favorable financing terms compared to those that do not.

3.3. Hypothesis 3: AIPA

Previous hypotheses posit that innovative firms exercise strategic control over their patent portfolios, especially when utilizing patents as collateral for financing. This strategic behavior enables them to preserve their core technologies for long-term growth while securing favorable financing terms by signaling confidence to lenders. However, regulatory changes may directly influence this strategic behavior by affecting how firms choose which patents to pledge. Using a regulatory shift as a natural experiment, this empirical analysis aims to examine how technological centrality influences collateralization decisions, particularly in response to external stress.

One such pivotal change was the enactment of the American Inventors' Protection Act (AIPA) in 1999, which introduced several significant reforms to the U.S. patent system, promoting early dissemination of knowledge and reducing the uncertainty surrounding patent rights. A key provision, and the focus of this natural experiment, was the pre-grant publication requiring patent applications to be published within 18 months after filing, rather than being kept private until granted. This shift exposed firms' patents to the public –and consequentially to competitors–at an earlier stage, significantly increasing the risk of knowledge spillovers and reducing the secrecy surrounding ongoing innovations (Kim & Valentine, 2021). As a result of early disclosure requirement, firms might have had to adjust their patenting strategies, particularly their selection of patents for collateralization. To avoid exposing their core patents prematurely and risking competitive threats, firms might have been more likely to file and pledge peripheral patents as collateral to safeguard their core technologies from early competition.

Hypothesis 3: Post-AIPA, innovative firms are more likely to pledge non-core patents as collateral to protect their core technologies from early disclosure, leveraging this strategy to maintain competitive advantage and secure favorable financing terms.

Prior to the AIPA enactment, firms exhibited similar patent pledging behaviors as the uncertainty surrounding the policy's passage made it difficult for them to anticipate and pre-emptively adjust their patenting strategies (Kim & Valentine, 2021). The unanticipated nature of the AIPA's enactment allows for the assumption that, absent the AIPA, these firms would have continued to behave in parallel, making AIPA's imposition an exogenous shock. This supports the validity of the natural experiment for analyzing the causal impact of AIPA on pledging patents behaviors.

<u>**Figure 1: Impact of AIPA Reform on Patent Pledging by Publication Lag**</u>

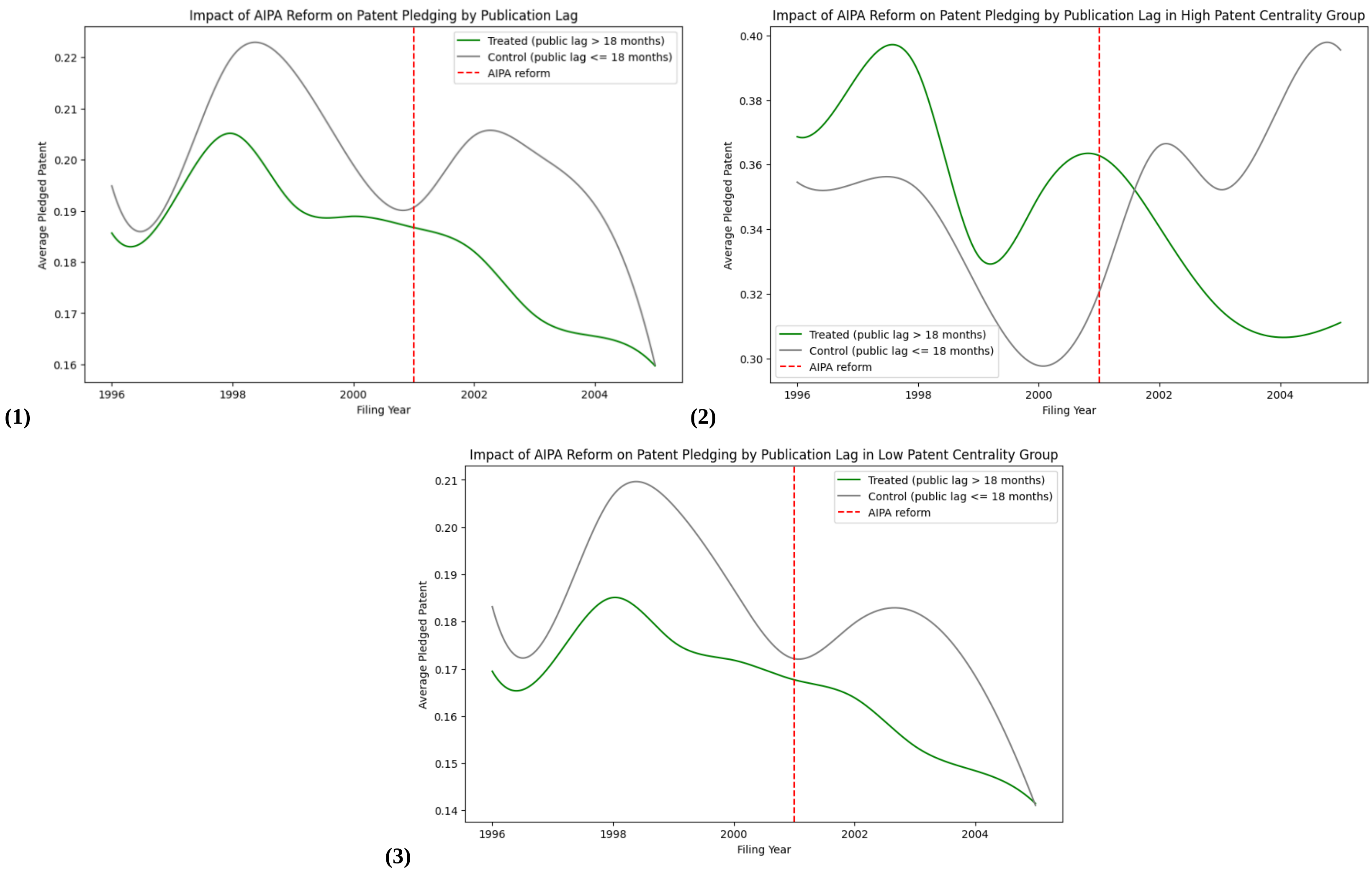

Figure 1. This figure shows the average proportion of pledged patents during 1996-2005, separated by the AIPA reform in 2001 (red dashed line). The green line represents patents from firms with an average publication lag greater than 18 months (treated group), while the grey line represents patents belonging to firms with an average publication lag of 18 months or less (control group). Graph (1) shows the pledging behaviors across the dataset. Graph (2) focuses on patents with high centrality to their firms' core technology, while Graph (3) examines patents with low centrality to firms' technology portfolios.

4. Data

4.1. Data Sources

The datasets used are collected from the United States Patent and Trademark Office (USPTO), CRSP, Compustat, and Capital IQ, unless otherwise specified.

The first dataset is the granted patent dataset collected from USPTO[1], which includes nearly 8.9 million entries of granted patents and 142 million entries of citations made to US granted patents by US patents from August 1868-April 2024. An insignificant amount of the dataset contains incorrect filing dates, which is removed during the data conversion.

The scope of the study requires patent data to be assessed on a firm-level basis, hence, the KPSS_2023 extended dataset[2] that matches the patent number with public US firms' identifiers (PERMCO/PERMNO) from CRSP during 1926-2023, is used. KPSS_2023 extended dataset provides 3.3 million unique patent numbers matched with 10,012 PERMNOs of public US firms, exclusive of patents that are assigned to multiple PERMNOs. Patents' information includes their Cooperative Patent Classification (CPC) classes, number of forward citations, and its innovation value in millions of (nominal and real) dollars. 3,308 patents with missing CPC class are excluded from the study.

Since all the relevant financial variables are collected from Compustat, tables linking PERMNOs/PERMCOs, CUSIP, and GVKEYs identifiers are collected from CRSP and Capital IQ to match PERMNOs available in KPSS_2023 dataset with the relevant Compustat's GVKEYs. One GVKEY could be matched with more than one PERMCOs/PERMNOs. Compustat's financial data available on WRDS has different time limits compared to the patent dataset KPSS_2023. The eventual firm-patent dataset includes data from 1950-2023 of 9,382 unique GVKEYs and nearly 3.29 million unique patent numbers. Missing financial data is back filled and front filled by GKVEY.

[1] Link to the USTPO granted patent dataset
[2] Link to the KPSS_2023 extended dataset

The combined dataset is then matched with patent assignment dataset collected from USPTO[3], containing 10.5 million patent transfers by parties between January 1980 - January 2024, involving roughly 18.8 million patents and patents applications. Based on the dataset description in "Patent transactions in the marketplace: Lessons from the USPTO Patent Assignment Dataset" by Graham, Marco & Myers (2018), 97,661 transactions typed as "security interest" agreements connected to around 1 million patents and patent applications are determined to be transactions involving patents used as collaterals. Pledged patents include design patents that are not available in the patent dataset. Patent assigned as collaterals involve patents filed as early as 1949, hence it is assumed that all patents available from 1950-2022 could still have been pledged during 1970-2024 (Sample patents filed in 1960 were found to be pledged as collaterals in 1980).

4.2. Identifying Key Variables:

4.2.1. Patent Centrality:

"Patent Centrality" is a continuous variable ranging from 0 to 1 based on the patent's proximity to the firm's core technology. The variable is determined in a similar manner to how "Core Technology" is calculated in Cappelli et al. (2023).

For each firm, a core CPC class is first identified based on the patent density within each CPC 4-digit class in the firm's entire patent portfolio, such that the CPC 4-digit class (e.g., A01B: Soil Working in Agriculture or Forestry; Parts, Details, or Accessories of Agricultural Machines or Implements) where the firm has the highest level of patent concentration represents its core technology. The formula for patent density as the share of patents s_i in CPC class i is:

$$s_i = \frac{Number\ of\ patents\ in\ CPC\ class\ i}{Total\ number\ of\ patents\ held\ by\ the\ firm}$$

Then, for each focal patent, the proportion of firm's patents within the same CPC 4-digit class determines the "Patent Centrality" variable, where the higher value indicates greater closeness to the firm's primary technological expertise. A patent could belong to multiple CPC classes. In such cases, the 4-digit CPC class that is most frequently reported in the patent document

[3] Link to USPTO Patent Assignment dataset

is considered the main technology of the patent. If more than one CPC 4-digit classes have the same frequency, the main class is assigned randomly. Choosing 4-digit level aligns with frequent practice in innovation studies (e.g., Somaya, 2003; Ganco, 2013), as it provides a balanced level of detail without over-specifying the technology focus.

4.2.2. Strategic Pledge:

Developed from Hypothesis 1 in section 3.1, the concept of strategic pledging is defined as the choice of innovative firms to select patents less central to their core technology while preserving the patents most closely related to their core technology. “Strategic Pledge” is a binary variable that indicates whether a collateralized patents is a non-core patent.

The approach used to define core patents is an extension of the “Patent Centrality” variable described in section 4.2.1. Three different thresholds 50th, 75th, and 90th percentile of “Patent Centrality” are used as indicators of “core” designation, with 75th percentile being the baseline threshold.

Table 2: Different thresholds of “Patent Centrality”

Threshold	Patent Centrality	Number of Core Patents
50th percentile	0.082	1,656,717
75th percentile	0.236	824,667
90th percentile	0.406	333,896

Any patent with “Patent Centrality” below the threshold(s) is considered a relatively non-core patent. This strategy allows for distinguishing patents most aligned with the firm’s core technological domain across industries and timeframes and is superior in terms of simplicity and consistency in comparison to alternative methods that utilize citation counts.

A notable example of defining core patents based on co-citations, Wu, Chen, and Lee (2010) use a Core Technology Analysis (CTA) strategy to identify a firm’s core Technological Capabilities (TCs). They identify core patents based on the number of co-citations for a specific patent application year equating or surpassing the threshold value of value of $H_t = \max(3, \mu_t + k\sigma_t)$, where k is a constant representing the probability that the candidate patent belonging to one of the company's core TCs. The number 3 indicates correlation coefficient of the focal cited patent with other citing patents. For this study, implementing CTA poses a few limitations. First, as noted by the authors, the threshold for citations, which typically accumulate over time, within a year constraint, is rather high, especially for patents representing radical innovations or new technologies, which usually only have few citation counts. Second, there are significant missing values in the citation category (e.g. cited by applicant, cited by examiner) of the available dataset, which should help understand whether the focal patent is of strategic importance. Furthermore, the USPTO's backward and forward citations dataset has also been reported to have significant noise (Cotropia et al. (2013); Sun and Wright (2022)), which can potentially complicate the identification of core patents.

To negate the impact of year-specific constraints, missing data, and citation noise, the measure of centrality based on patent density in CPC classes, which captures the firm's core technology by focusing on patent clustering within specific technological domains rather than historical citation patterns alone, is preferred. The multi-threshold method also accommodates for differences across industries and technological maturity levels.

4.2.3. Industry Concentration

"Industry Concentration" is a moderating variable used to examine whether firms in concentrated versus competitive industries behave differently in terms of patent pledging and loan terms. The competition level of an industry is usually measured through quantitative proxies that reflect the market dynamics, concentration, and competitive intensity within an industry. Common proxies include Herfindahl-Hirschman Index (HHI), Market share of Largest Firms (e.g. CR4 or CR8), Number of Firms within an Industry, and Lerner Index (Price-Cost Margin).

Here, HHI is used as proxy for the concentration level of a firm's industry. HHI is a common measure of the size of firms in relation to the industry they are in and is an indicator of the industry's level of competition. Firm's industry is determined based on the CPC 3-digit code (e.g. A01: Agriculture). Since one firm could file patents related to multiple CPC classes, the CPC 3-digit class with the most patents filed is determined as the main industry the firm operates in. The sample used includes 9,382 firms categorized into 121 distinctive industries.

Industry HHI is calculated as follows:

$$Industry\ HHI_t = \sum_{i=1}^{n} S_{i,t}^2$$

Where n is the total number of firms belong to the industry that are present in the dataset and $S_{i,t}^2$ is the square of the market share of a firm, based on the firm-level annual revenue collected from Compustat. Lower $Industry\ HHI_t$ indicates more industry competitiveness, while higher values indicate concentration.

4.3. Summary Statistics

Table 3: Summary Statistics of Key Variables

Variable	Count	Mean	Median	Std.	Min	Max
Patent Centrality	3,292,112	0.16	0.08	0.19	0.00	1.0
Log Market Cap	3,292,109	4.91	4.48	1.11	3.93	11.90
CPC classes per Patent	3,292,112	1.82	1.0	1.13	1.0	38.0
Citations per Patent	3,292,112	11.77	4.0	23.52	0.0	155.0
Patent Age	3,292,112	28.45	22.0	21.94	1.0	190.0
Strategic Pledge	3,292,112	0.07	0.0	0.26	0.0	1.0
Industry Concentration	3,292,112	0.07	0.002	0.19	0.0	1.0
Pledged Patents	3,292,112	0.11	0.0	0.32	0.0	1.0
Log Total Debt	3,292,112	3.74	4.25	2.72	0.44	10.05
Log Interest Expense	3,292,109	1.47	0.39	1.66	0.27	8.79
Note: *Winsorized at 1% and 99% level.*						

Table 3. This table summarizes the statistics of key variables used in regression analyses covering US public firms' patents filed between 1950 and 2023. "Log Market Cap" is the log transformation of Market Capitalization, which is the closing shares price multiplied by the number of shares outstanding, in a fiscal year. "CPC classes per Patent" is the number of CPC classes assigned to each patent, higher value indicates that the patent has a wider technological application. "Citations per Patent" is the number of forward citations of a patent, which determines the patent's technological value. "Patent Age" is calculated based on the difference between the latest year a patent could have been collateralized (2024) and the filing year of the patent. "Pledged Patent" is a binary variable equaling 1 when a patent is pledged as collateral, and 0 otherwise. "Strategic Pledge" is a binary indicator that takes 1 if the entity strategically used non-core patent as collateral based on the baseline threshold 75th percentile of "Patent Centrality", which is 0.2363. "Log Total Debt" and "Log Interest Expense" are log transformation of firm-level total debt and interest expense collected from Compustat.

Table 4: Summary Statistics of Core and Non-core Patents

	Num. of Patents	Patent Centrality	Log Market Cap	CPC classes per Patent	Citations per Patent	Patent Age	Industry Concentration	% Pledged Patent	Pledged Patent Frequency
Core Patent									
False	2,467,309	0.068	4.915	1.825	10.900	31.803	0.068	0.097	0.220
True	824,803	0.431	4.912	1.810	14.363	18.435	0.083	0.173	0.409
Paired t-test result: t-statistic = 1.000, p-value = 0.338.									

Table 4. "Core Patent" is determined by the "Patent Centrality" 75th percentile baseline threshold of 0.2363. "Pledged Patent Frequency" is the number of times a patent has been used as collateral. Other variables are as described above.

Table 5: Summary Statistics of Pledged and Non-pledged Patents

	Num. of Patents	% Core Patents	Patent Centrality	Log Market Cap	CPC classes per Patent	Citations per Patent	Patent Age	Industry Concentration	Pledged Patent Frequency
Pledged Patent									
False	2,909,452	0.234	0.150	4.913	1.822	11.128	29.275	0.071	0.0
True	382,660	0.374	0.229	4.926	1.817	16.625	22.204	0.080	2.3
Paired t-test result: t-statistic = 1.000, p-value = 0.334.									

Table 5. "Core Patents" is determined by the "Patent Centrality" 75th percentile baseline threshold of 0.2363. Other variables are as described above.

There are a few notable observations from the summary statistics. In Table 4, core patents are more likely to be pledged (17.3% of core patents having been pledged as collateral compared to 9.7% of non-core patents). They are also more likely to be cited, based on "Citations per Patent", nearly twice as likely to be re-pledged, based on "Pledged Patent Frequency", and a lot newer than non-core patents, based on "Patent Age". Meanwhile, Table 5 shows that, among pledged patents, 37.4% are core patents, translating to a higher average patent centrality among pledged patents. Pledged patents are also newer, on average. Additionally, a pledged patent would likely be re-pledged at least once, based on "Pledged Patent Frequency" in both Tables. However, the paired t-test results in both tables indicate that there is no significant difference in the chosen characteristics of core versus non-core patents and of pledged versus non-pledged patents.

5. Methodology

This chapter outlines the models used to examine the factors influencing patent pledging and the impact of strategic pledging on loan terms. The analysis consists of two main models aligned with Hypotheses 1 and 2, with additional variants incorporating industry competitiveness. The last model testing Hypothesis 3 is a natural experiment using generalized difference-in-differences (DiD) design.

5.1. Model to assess Strategic Pledging

This model evaluates the likelihood of strategic pledging in innovative firms, using the level of patent centrality within the firm's patent portfolio as a predictor. A logistic regression model in equation (1) is established based on Hypothesis 1. The dependent variable, "Pledged Patent" ($pledged\_patent$), is binary, taking value of 1 if the patent has been pledged as collateral and 0 otherwise.

$$logit\big(P(pledged\_patent = 1)\big) = \beta_0 + \beta_1(patent\_centrality) + \beta_2 \ln(mcap) + \beta_3(cpc\_count) + \beta_4(cites\_count) + \beta_5(patent\_age) + \varepsilon \quad (1)$$

Where: β_0 is a constant and ε is an error term.

As previously described in section 4.2.1., the key explanatory variable is "Patent Centrality" ($patent\_centrality$). Control variables serve as proxies for the qualities found to be indicative of whether a patent is accepted as collateral by debt providers, as discussed in section 2.2. These qualities include:

1) Re-deployability: proxied by "CPC Classes per Patent" (cpc_count),

2) Remaining lifetime: proxied by "Patent Age" ($patent\_age$),

3) Technological quality: proxied by "Citations per Patents" ($cites\_count$),

4) Firm size: proxied by "Log Market Cap" ($\ln(mcap)$), and

5) Backing by third parties such as VCs or governments.

The last quality is not controlled in this model, due to the assumption that public firms have sufficient access to equity investments. Public firms have also been observed to less likely pledge patents than private firms, potentially due to this relatively easier capital access (Mann, 2018). Coefficients in the model are interpreted in terms of log-odds. A baseline patent-level result, as well as firm level and firm-year level results based on the same model aggregated at various levels, are reported.

To explore the potential effect of industry competitiveness, a variant model incorporates "Industry Concentration" ($industry\_hhi$) as defined in section 4.2.2. This addition allows for better examination of whether firms in competitive versus concentrated industries differ in their approach to patent pledging. The model is as follows:

$$logit\big(P(pledged\_patent = 1)\big) = \beta_0 + \beta_1(patent\_centrality) + \beta_2(industry\_hhi) + \beta_3(patent\_centrality \times industry\_hhi) + \beta_4 \ln(mcap) + \beta_5(cpc\_count) + \beta_6(cites\_count) + \beta_7(patent\_age) + \varepsilon \quad (2)$$

Where: β_0 is a constant and ε is an error term.

This expanded model includes an interaction term between "Patent Centrality" and "Industry Concentration" ($patent\_centrality \times industry\_hhi$) to capture any differential effects of patent centrality on pledging across varying industry competitiveness levels.

5.2. Model to assess Impact on Loan Terms

To evaluate Hypothesis 2, which examines the impact of strategic pledging on loan terms, model (3) is employed. The dependent variable is the "Log Interest Expense" ($\ln(interest\_expense)$), which captures the cost of debt financing for each firm. The key independent variable is "Strategic Pledge" ($strategic\_pledge$) derived from model 1, indicating whether the firm strategically pledged non-central patents. Control variables include the baseline control variables from Hypothesis 1, acting as proxies for the qualities assessed by creditors in accepting patents as collaterals. A new control variable "Log Total Debt" is added to control for the size of debt, as larger debt amounts may influence the interest burden the firms face.

$$\ln(interest\_expense) = \beta_0 + \beta_1 (strategic\_pledge) + \beta_2 \ln(mcap) + \beta_3 (cpc\_count) + \beta_4 (cites\_count) + \beta_5 (patent\_age) + \beta_6 \ln(total\_debt) + \mu + \vartheta + \varepsilon \quad (3)$$

Where: β_0 is a constant, μ is the firm fixed effects, ϑ is the time fixed effects, ε is an error term.

The model is evaluated on different "Strategic Pledge" variables, which are assigned different "Patent Centrality" thresholds of 50th, 75th, and 90th percentile for comprehensive comparison.

Similar to the regression conducted for Hypothesis 1, this model is also extended to include industry's competitiveness indicator "Industry Concentration" ($industry\_hhi$) to gauge whether firms in concentrated industries have different lending outcomes when using strategic pledging. This variant model is as follows:

$$\ln(interest\_expense) = \beta\_0 + \beta\_1 \ (strategic\_pledge) + \beta\_2 \ (industry\_hhi) + \beta\_3 \ (strategic\_pledge \times industry\_hhi) + \beta\_4 \ \ln(mcap) + \beta\_5 \ \log(cpc\_count) + \beta\_6 \ (cites\_count) + \beta\_7 \ (patent\_age) + \beta\_8 \ \ln(total\_debt) + \mu + \vartheta + \varepsilon \quad (4)$$

Where: β_0 is a constant, μ is the firm fixed effects, ϑ is the time fixed effects, ε is an error term.

The interaction term between "Strategic Pledge" and "Industry Concentration" ($strategic\_pledge \times industry\_hhi$) assesses whether the effect of strategic pledging on loan terms varies dependent on the competitive dynamics of the industry. This extension provides deeper insights into how external market structures might influence the relationship between patent pledging and loan terms.

5.3. Natural Experiment: AIPA

A natural experiment is conducted to assess the causal effects of "Patent Centrality" on "Pledged Patent", using the American Inventor's Protection Act (AIPA) as a setting. AIPA reform serves as an external shock –a key feature of natural experiments that helps isolate causal relationships. Since AIPA led to changes in the disclosure of patents, it introduced a random event that allows for observation of how firms treat patents of different technological importance differently before and after the event. This natural experiment helps validate the results from the models above, reinforcing that "Patent Centrality" influences patent pledging decisions.

To assess the immediate effects of AIPA, only patents filed between 1996-2005 are included in the sample. This sample is then split into two groups of High and Low "Patent Centrality" based on the 75th percentile used to determine the "Strategic Pledge" variable in section 4.2.1. A generalized difference-in-differences (DiD) model is applied for each "Patent Centrality" level to assess how firms adjusted their patent pledging behavior after AIPA. The treatment group includes patents from firms with average publication lag longer than 18 months, while the control group represent patents from firms with average publication lag shorter than 18 months before AIPA's enactment. The generalized DiD estimator is as bellows:

$$P(pledged\_patent = 1) = \beta_0 + \beta_3(post\_AIPA \times treatment\_group) + \mu + \vartheta + \varepsilon \quad (5)$$

Where: β_0 is a constant, μ is the firm fixed effects, ϑ is the time fixed effects, ε is an error term.

The firm fixed effects μ controls for time-invariant firm characteristics, while time fixed effects ϑ accounts for any changes across time that affect all firms. The coefficient β_3 of the interaction term between "AIPA" and "Treatment Group" ($post\_AIPA \times treatment\_group$) would reveal whether treated patents, whether in core or non-core patent group, behaved differently post-reform. This allows for the interpretation of a causal link between "Patent Centrality" and "Pledged Patents" and helps confirm of whether firms could strategically pledge their patents.

6. Results

This chapter discusses the results of the baseline regression model on the likelihood of strategic pledging in innovative firms, the regression model on the effects of strategic pledging on financing expenses, and the difference-in-difference (DiD) natural experiment. Variants of each model and their implications are also analyzed in respective sections. Relevant robustness checks are also presented in respective sections.

6.1. Regression Result on Strategic Pledging

6.1.1. Baseline Regression Results on Strategic Pledging

Table 6 summarizes the baseline logistic regression and extended regression result when industry competitiveness is factored in. Contrary to the argument made in Hypothesis 1, Table 6 indicates that patents more connected to the core technology of a firm are significantly more likely to be pledged as collaterals, possibly implying that pledged patents are more dependent on creditors' preferences than on firms' strategic pledging decisions.

Table 6: Logistic Regression Results on Strategic Pledging

	Dependent variable: Pledged Patent	
	(1)	**(2)**
Patent Centrality	1.3441***	1.2914***
	(0.008)	(0.009)
Log Market Cap	0.0014	0.0017
	(0.002)	(0.002)
CPC classes per Patent	-0.0311***	-0.0312***
	(0.002)	(0.002)
Citations per Patent	0.0078***	0.0078***
	(0.000)	(0.000)
Patent Age	-0.0156***	-0.0157***
	(0.000)	(0.000)
Industry Concentration		-0.1230***
		(0.013)
Patent Centrality x Industry Concentration		0.5794***
		(0.038)
Observations	3,292,112	3,292,112
Pseudo R^2	0.03697	0.03707

Note:

*Significance level denoted as * for p<0.1, ** for p<0.05, and *** for p<0.01.*

Standard errors indicated in brackets are robust to firm-level cluster correlation.

Table 6. Column (1) represents the baseline regression result of model (1). Column (2) includes "Industry Concentration" and "Patent Centrality x Industry Concentration" as per model (2).

In Column (1), "Patents Centrality" has a coefficient of 1.3441, significant at 1% level, indicating that a 1-unit change in "Patent Centrality" increases the log-odds of a patent being pledged by 1.3441, holding all other factors constant. In odds, for a 1-unit increase in "Patent Centrality", the odds of a patent being pledged are multiplied by approximately $e^{1.3441} \approx 3.835$, a 1-unit increase in patent centrality nearly quadruples the odds of the patent being pledged. In probability, based on the formula $odds = \frac{p(x)}{1-p(x)}$, where $p(x)$ represents the probability, the coefficient estimates correspond to a probability of about 79%. This value is substantially higher compared to other variables' coefficients, suggesting a much stronger effect of patent centrality on the likelihood of a patent being pledged compared to other factors.

The result indicates that central patents – those likely more crucial to a firm's technology focus – are being pledged at a much higher rates than initially hypothesized. This could be due to creditors' preference for highly central patents, either as a means of exerting better control on the firms' innovative activities, or because non-core patents might not meet the quality requirements set out by creditors in general. To ensure that debtors' investment policies align with their interests, creditors may favor assets that provide more reliable control over the firm's innovation pipeline. This is evident in the tendency of firms financed by patent-back loans to shift their innovation efforts toward short-term, revenue-generating projects and litigating their patents (Ayerbe et al., 2023; Luo, Wang & Hu, 2024). This dynamic becomes more pronounced during bankruptcy, where creditors can influence the sales of core patents, affecting the diffusion of innovation and the firm's technological assets (Ma et al., 2022). The other explanation lies in the inherent values of the patents themselves. Regardless of whether a patent is core or non-core, creditors are likely to place high emphasis on the intrinsic quality and re-salability of collaterals (Mann, 2018). These qualities are likely to be more prominent in core patents, compared to non-core ones. In either cases, the result points to a potential misalignment between firms' strategic goals (i.e. reserving core patents for innovation) and creditors' demands (i.e. securing valuable patents), where creditors' preferences override firms' strategic discretion.

For control variables: "Log Market Cap" has a positive but statistically insignificant coefficient (0.0014), suggesting that the log of market cap has an almost negligible impact on the log-odds of a patent being pledged. It could be inferred that creditors place less emphasis on the firm's overall size when lending to innovative firms than on the actual value and quality of the collaterals, unlike the consensus gentium that large firm size – usually closely related to stronger reputation – enables flexibility in debt financing (Diamond, 1991; Hooks, 2003), likely due to the nature of the intellectual property assets. "CPC classes per Patent" has negative and significant coefficient (-0.311), implying that patents belonging to more CPC classes are less likely to be pledged. This contradicts the previous academic results on the broad application of technology classes being a good indicator of re-deployability (Chava et al., 2017; Loumioti, 2012; Mann, 2018). A potential explanation for this is that firms that are in the public sphere may still have some level of strategic choice in retaining patents with high versatility. "Citations per Patent" positive (0.0078) and "Patent Age" negative (-0.0156) coefficients align with previous studies on lenders' preferences for highly cited and newer patents.

The baseline regression results show that the proximity of patents to core technology plays a significant role in determining the likelihood of the patents being pledged. Other factors, higher citations, less diverse technologies, and younger patent age also play a role in collateral selection, though at much lower intensity. The economic significance of patent centrality highlights an important inference that innovative firms lean more towards meeting the creditor's requirements to secure financing than protecting their core patents in cases of defaults.

To assess the choices of pledged patents in different market environment, Column (2) includes additional variables indicating the impact of industry concentration and the interaction between "Patent Centrality" and "Industry Concentration".

Higher "Industry Concentration" (lower competition) is associated with a decreased likelihood of pledging patents (-0.1230), suggesting that firms in more concentrated industries with lower competition are less inclined to pledge patents. The interaction term "Patent Centrality x Industry Concentration" (0.5794) is positive and significant at 1% level, indicating that the effect of patent centrality on the likelihood of patent pledging is stronger in more concentrated industries. This suggests that firms in concentrated industries are more willing to pledge their central, valuable patents, possibly because they face less competitive risk. The risk of losing a strategic advantage by pledging central patents may be mitigated by this lack of competition, allowing firms to use critical assets as collaterals, minimizing financing costs without fear of losing market leadership. The coefficients of other variables remain similar to the baseline model results, both in magnitude and significance, indicating that these relationships hold even when accounting for industry concentration and its interactions with patent centrality.

Findings from Column (2) can be summarized as follows: Firms in concentrated industries appear less reliant on patent pledging. However, when they do pledge, the pledged patents are more likely to be central patents. Concurrently, firms in more competitive industries (low HHI) may be more inclined to use patents as collaterals, but, due to higher competitive risks, are more likely to pledge non-central ones. This result supports previous findings on industry competitiveness and its relation to innovation and financing.

Competition triggers firms to innovate, which generates an "escape the competition" effect (Aghion, Harris, Howitt, and Vickers, 2001), thus firms in such industries are more likely to have patents to pledge when financing with debts. However, competitive industries tend to be less reliant on debt (Mackay & Phillips, 2005), especially R&D-intensive ones (Thakor & Lo, 2021). This is likely due to creditors' concerns over profitability and uncertainty, which negatively affect asset pledgeability (Valta & Frésard, 2012; Hou & Robinson, 2006; Valta, 2011). Given the higher chance of pledged assets being undervalued and thus not generating the most favourable financing terms, innovative firms in heightened competition might be less willing to pledge core patents. Moreover, there is also high risk of losing technologically centric patents and the ability to innovate post-default, especially when patent trolls – those attempt to capitalize on litigation of patents than exploiting the technologies – are strong participants during the reselling process (Ma et al., 2022). Core patents with high litigation risk are of particularly high interest to patent trolls (Ma et al., 2022). In turn, creditors basing collateral selection on past successful resale might prefer core patents as pledges. As such, the effect of patent centrality on patent pledging is nuanced in the presence of industry competition.

6.1.2. Baseline Regression Results at Firm and Firm-Year Levels

Built on the same baseline regression model and extended model in section 6.1.1., this section presents the results from the baseline regression where data is aggregated at firm level and firm-year level. Given that the majority of pledged patents in the sample dataset are not core patents, the analysis seeks to offer insights into the overall strategic tendencies of firms regarding patent pledging in the long-term (firm-level) and short-term (firm-year level).

The results of Table 7 paint a contrasting picture to the patent-level analysis shown in Table 6. When data is aggregated at firm or firm-year level, firms appear to be less likely to pledge patents if their patent portfolio is more closely related to their core technology, implying that, in a broader context, firms tend to reserve their core patents, partially aligning with Hypothesis 1.

Table 7: Strategic Pledging, Firm and Firm-Year Levels

	Dependent variable: Pledged Patent			
	(1)	**(2)**	**(3)**	**(4)**
	Firm Level	**Firm Level**	**Firm-Year Level**	**Firm-Year Level**
Average Patent Centrality	-2.6619***	-2.6976***	-0.7179***	-0.6979***
	(0.095)	(0.105)	(0.084)	(0.086)
Average Log Market Cap	-0.1251***	-0.1293***	0.1829***	0.1837***
	(0.029)	(0.030)	(0.015)	(0.015)
Average CPC classes per Patent	-0.4727***	-0.4712***	-0.0945***	-0.0944***
	(0.034)	(0.000)	(0.015)	(0.015)
Average Citations per Patent	0.0101***	0.0102***	0.0099***	0.0099***
	(0.001)	(0.001)	(0.001)	(0.001)
Average Patent Age	-0.0285***	-0.0293***	-0.0341***	-0.0340***
	(0.002)	(0.002)	(0.001)	(0.001)
Industry Concentration		-0.5796*		0.1025
		(0.309)		(0.086)
Patent Centrality x Industry Concentration		0.4529		-0.1970
		(0.038)		(0.205)
Observations	9,382	9,382	95,413	95,413
Pseudo R^2	0.08448	0.08496	0.07814	0.07843

Note:

*Significance level denoted as * for p<0.1, ** for p<0.05, and *** for p<0.01.*

Standard errors indicated in brackets are robust to firm-level cluster correlation.

Table 7. Column (1) includes "Patent Centrality" and all control variables presented in model (1), aggregated at firm level. Column (2) includes "Industry Concentration" and "Patent Centrality x Industry Concentration" interaction term as per model (2), also at firm level. Columns (3) and (4) are aggregated at firm-year levels. All independent variables are averaged across the firm's patent portfolio in Columns (1) and (2) and across patents held in a specific year in Columns (3) and (4).

At firm level, “Average Patent Centrality” has negative and highly significant coefficients (-2.6619 in Column (1) and -2.6976 in Column (2) significant at 1% level). This suggests that, on average, firms with more central patents are less likely to pledge technologically centric patents as collateral. In terms of odds, $e^{-2.6619} \approx 0.07$, meaning a 1-unit increase in average patent centrality of a firm’s portfolio reduces the odds of pledging a patent by approximately 93%, much stronger than the economical significance of patent centrality at patent level. In Column (2), coefficients for “Industry Concentration” (-0.5796) are negative and marginally significant at 10% level, which aligns with the result presented at patent-level in Table 5. However, the interaction term between “Patent Centrality x Industry Concentration”, while positive, is statistically insignificant, indicating that industry competitiveness does not have a moderating effect on patent centrality and pledging behavior at the firm level.

At firm-year level, the key explanatory variable “Patent Centrality” shows a similar pattern as at firm level, though with less severity. The absolute values of the coefficient of “Average Patent Centrality” are smaller (-0.7179 in Column (3) and -0.6979 in Column (4)), though still negative and significant at 1% level. This indicates that the choice of whether to pledge central patents may be influenced by factors that vary over time. One potential explanation is that short-term factors (such as liquidity needs or debt obligations in a given year) may pressure firms to occasionally pledge central patents despite their long-term value. “Industry Concentration” becomes positive in the firm-year model but indicates no significant impact. Furthermore, the interaction term “Patent Centrality x Industry Concentration” (-0.1970) remains statistically insignificant, suggesting a minute influence of industry concentration on the relationship between patent centrality and pledging at firm-year level, but this is not consistent or strong enough to generate a statistically significant coefficient.

Other variables exhibit consistent coefficient results with those at patent level, except for “Average Log Market Cap”, whose coefficients become negative and significant at firm level, indicating that firms with larger market capitalizations are less likely to pledge patents, likely due to better access to diverse types of financing (the diversity of financing usage apparent in large firms has been discussed in Hooks (2003)) and may not need to use patents as collateral as often as smaller firms. However, at firm-year level, the coefficient of “Average Log Market Cap” turns positive, indicating that in specific years, larger firms may be more likely to pledge patents, possibly at pressure of higher year-specific financing needs. This contradicts with the insignificance relationship of market cap and pledged patent on an individual patent level, indicating that market cap is primarily relevant at the aggregate firm or firm-year level, not at the patent level.

To summarize, at patent level, there is weak evidence of firms' strategic abilities in choosing patents for collateralization. Instead, they suggest that creditors' preferences may dominate those of firms in security selection. This also implies that firms are more willing to risk the patents of their core technologies to meet creditor demands. However, at the firm and firm-year level, firms generally appear to be less likely to pledge central patents. In certain years, though, short-term factors (e.g. liquidity needs) can override the longer-term preference to protect core patents. This discrepancy between levels of analysis suggest that firms may still exhibit strategic patent pledging behavior, as firms with more non-core patents seem more likely to pledge patents. Firms with a broader patent pools could strategically package their non-core patents into larger collateral portfolio to enhance their pledgeability (Bracht & Czarnitzki, 2022).

6.1.3. Alternative "Patent Centrality" Definition

To verify the appropriateness of the key explanatory variable, "Patent Centrality" is redefined based on Wu, Chen, and Lee (2010), mentioned in section 4.2.2. The explanatory variable, denoted as "Wu Patent Centrality", is a binary variable that takes value of 1 if it is a core patent under the Core Technology Analysis (CTA) and 0 otherwise (Wu, Chen, & Lee, 2010). No other adjustments are made. The adjusted models from models (1) and (2) are as follows:

$$\begin{aligned} logit\big(P(pledged\_patent = 1)\big) \\ = \beta_0 + \beta_1(wu\_patent\_centrality) + \beta_2 \ln(mcap) + \beta_3(cpc\_count) \\ + \beta_4(cites\_count) + \beta_5(patent\_age) + \varepsilon \end{aligned}$$

Where: β_0 is a constant and ε is an error term.

and

$$logit\big(P(pledged\_patent = 1)\big) = \beta_0 + \beta_1(wu\_patent\_centrality) + \beta_2(industry\_hhi) + \beta_3(wu\_patent\_centrality \times industry\_hhi) + \beta_4 \ln(mcap) + \beta_5(cpc\_count) + \beta_6(cites\_count) + \beta_7(patent\_age) + \varepsilon \quad (2)$$

Where: β_0 is a constant and ε is an error term.

The revised regression results are presented in Table 8, which shows a fairly consistent outcomes to the ones presented in Table 6 for baseline regression. “Wu Patent Centrality” is positively associated with “Pledged Patent”, though in much lesser magnitude compared to “Patent Centrality”. “Wu Patent Centrality” also alters how other variables behave, supposedly due to this variable no longer explains the same portion of the variation in pledged patents. “CPC classes per Patent” coefficient increases in absolute value but reduces its significance level from 1% to 10%.

More notably, in Column (2), “Industry Concentration” and “Wu Patent Centrality x Industry Concentration” coefficients reverse signs and became insignificant, implying that industry competitiveness has no significant impact on how firms pledge patents or how creditors accept them as collaterals, heavily contradicting the regression results presented in Table 6. This points to the possibility of 1) multicollinearity, or 2) “Wu Patent Centrality” better explaining the relationship between patents and pledging in a way that reduces the need for the interaction term. However, based on the results of Variance Inflation Factor (VIF) values of independent variables, there is only a low level of multicollinearity, such that VIFs are more than 1 but less than 2[4]. Moreover, Pseudo R^2 is slightly reduced from 0.03707 in Column (2) Table 6 to 0.02740 in Column (2) Table 8, indicating that Wu, Chen, and Lee (2010)’s core patent definition does not capture the same underlying factors driving patent pledging decisions as effectively as the Cappelli et al. (2023)’s version does.

[4] Refer to Appendix 1, Table 1 for the complete Variance Inflation Factor (VIF) test results.

Table 8: Strategic Pledging, Alternative Patent Centrality Definition

	Dependent variable: Pledged Patent	
	(1)	**(2)**
Wu Patent Centrality	0.3531***	0.3574***
	(0.059)	(0.058)
Log Market Cap	-0.0010	-0.0010
	(0.024)	(0.024)
CPC classes per Patent	-0.0491*	-0.0491*
	(0.027)	(0.027)
Citations per Patent	0.0084***	0.0084***
	(0.001)	(0.001)
Patent Age	-0.0197***	-0.0197***
	(0.003)	(0.003)
Industry Concentration		0.0104
		(0.177)
Wu Patent Centrality x Industry Concentration		-0.0483
		(0.209)
Observations	3,292,112	3,292,112
Pseudo R^2	0.02740	0.02740

Note:

*Significance level denoted as * for p<0.1, ** for p<0.05, and *** for p<0.01.*

Standard errors indicated in brackets are robust to firm-level cluster correlation.

Table 8. Column (1) includes "Patent Centrality" and all control variables presented in model (1). Column (2) includes "Industry Concentration" and "Patent Centrality x Industry Concentration" interaction term as per model (2).

6.1.3. Baseline Regression Results for Different Technological Sectors

To evaluate whether firms in different industries exhibit different behaviours when it comes to pledging patents, the baseline regression model is analyzed for the top ten technological sectors that have utilized pledged patents. The top ten patent-pledging technological industries, defined previously in section 4.2.3, are selected based on the highest number of pledged patents.

The number of firms belonged to each sector is presented in Table 9. Figure 2 presents the total number of patents and patents pledged belonging to each sector.

The results of the regression by technological sector are presented in Table 10, showing a moderate consistency with the original baseline regression results. In several subgroups, "Patent Centrality" has a strong and significant association with "Pledged Patents", while in others, the interaction is more muted. With the exception of "Citations per Patent", control variables' coefficients and their p-values also vary between sectors.

Table 9: Firm Count by Technological Sector

CPC 3-digit	USPTO Assigned Name	Firm Count
H04	Electricity/Electric Communication Technique	822
G06	Physics/Instruments/Computing; Calculating or Counting	1,169
H01	Electricity/Electric Elements	385
Y10	Technical Subjects Covered by Former USPC	361
A61	Health/Medical or Veterinary Science; Hygiene	1,422
B60	Transporting /Vehicles in General	169
C08	Chemistry/Organic Macromolecular Compounds	140
G01	Physics/Instruments/Measuring; Testing	514
G03	Physics/Instruments/Photography; Cinematography...	77
G11	Physics/Instruments/Information Storage	117

Note: *Y10 is a special tag for patents assigned to technical subjects based on the former US patent classification (USPC), which might include patents of firms from multiple industries.*

Figure 2: Number of Overall and Pledged Patents by Technological Sector

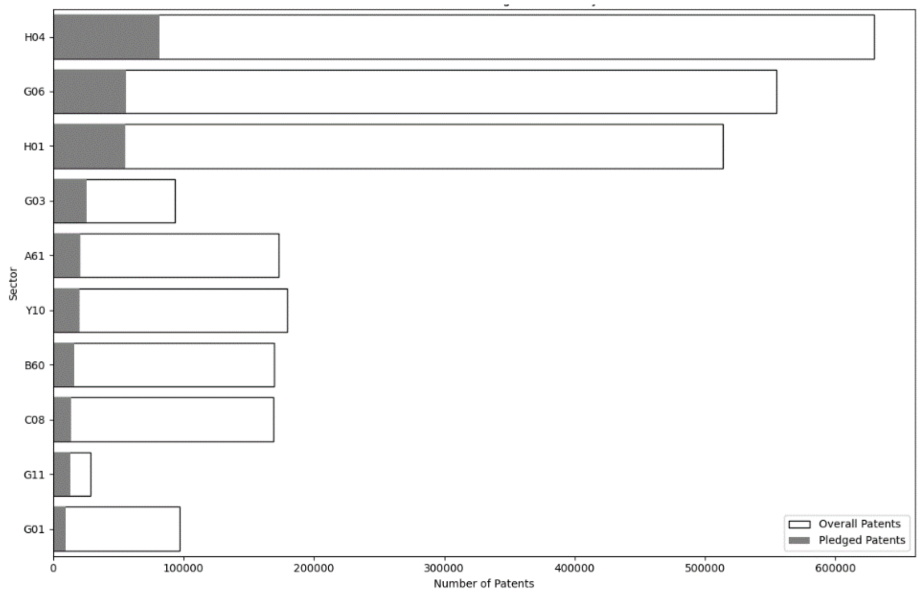

Figure 2. This figure shows the total number of patents filed and pledged by all firms in each technological sector in Table 9. Greyed area represents the proportion of total patents per sector that have been pledged at least once.

Figure 2 offers several interesting insights: 1) the firms in top three sectors – H04, G06, and H01 – own more than 50% of granted patents available in the sample. They also have roughly the same share of pledged patents in their total patent portfolios. 2) Among the focused sectors, G03 has the lowest number of firms, produces less patents than seven other sectors, but generates the fourth largest pool of pledged patents. 3) A61, B60, Y10 and C08 have roughly the same patenting and pledging behaviors. 4) Nearly half of the patents granted to G11 firms has been pledged. Despite a relatively small patent portfolio, G11 firms are among the most frequent users of patents as collaterals.

Table 10: Logistic Regression Results on Strategic Pledging, by Technological Sector

	Dependent variable: Pledged Patent									
CPC 3-digit	**H04**	**G06**	**H01**	**Y10**	**A61**	**B60**	**C08**	**G01**	**G03**	**G11**
Patent Centrality	2.40**	2.13***	1.04	2.69**	2.67***	1.78	0.53	2.19***	-3.11	1.54**
	(0.96)	(0.74)	(0.80)	(1.11)	(0.43)	(1.75)	(1.48)	(0.54)	(2.15)	(0.76)
Log Market Cap	-0.09*	-0.08	-0.08	0.22*	0.09***	-0.1***	0.29**	0.16**	-0.01	-0.03
	(0.05)	(0.06)	(0.05)	(0.12)	(0.03)	(0.04)	(0.13)	(0.08)	(0.06)	(0.15)
CPC classes per Patent	-0.05	-0.9**	-0.09*	-0.13*	0.07**	-0.08	-0.03	0.01	0.00	-0.01
	(0.05)	(0.04)	(0.05)	(0.08)	(0.03)	(0.06)	(0.04)	(0.05)	(0.02)	(0.04)
Citations per Patent	0.01***	0.01***	0.01***	0.01	-0.00	0.01*	0.01***	0.01***	0.02***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.000)
Patent Age	-0.0***	0.02	-0.0***	-0.0***	0.01	-0.01	-0.0***	-0.0***	-0.1***	-0.04
	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.04)
Observations	629,483	554,818	513,860	179,375	173,102	169,762	168,746	91,195	93,546	28,367
Pseudo R^2	0.04043	0.03833	0.06653	0.09487	0.06311	0.01479	0.09011	0.07320	0.2163	0.06766

Note:

*Significance level denoted as * for p<0.1, ** for p<0.05, and *** for p<0.01.*

Standard errors indicated in brackets are robust to firm-level cluster correlation.

Table 10. Each column represents the result of the baseline regression model (1) on patents belonging to a specific technological sector. The sector is denoted based on the CPC 3-digit code.

In Table 10, the relationships between “Patent Centrality” and “Pledged Patent” are positive and significant at 1% level in three out of ten sectors, and positive and significant at 5% level in three others. The rest of the subgroups shows this relation to be positive but insignificant, with the exception of G03, where “Patent Centrality” has a negative but insignificant coefficient (-3.11).

Comparing firms with fairly similar patenting and patent pledging behaviors in details show some contradicting outcomes. For example, with H04, G06, and H01, the “Patent Centrality” coefficients, though all positive, are significant at varying levels. This indicates somewhat consistent but less pronounced tendency for firms in these sectors to pledge central patents, suggesting an uncovered variety of sector-specific characteristics that might influence patent pledging.

The second group with similar patenting density A61, Y10, B60, and C08 also have varying “Patent Centrality” coefficients. “Patent Centrality” is highly positive and strongly significant in A61, fairly significant in Y10, and non-significant in B60 and C08, further pointing to alternative mechanisms driving patent pledging decisions.

G03 and G11 are both extensive users of patents for pledging. However, only G11 seems to pledge patents based on their centrality to technology. G03 deviates from the broader trend of central patents being used as collateral. Given the Pseudo R^2 for G03 is disproportionately high (0.2163) compared to others’, this sector may have unique factors influencing patent pledging that are not visible based on the dataset.

The results suggest that patent centrality is generally a powerful predictor of patent pledging, especially in sectors with strong patenting and patent-pledging activities, further confirming the baseline regression results. However, the varying statistical significance and economical strength of this relationship across different industries suggest that sector-specific factors – such as the nature of the technology, market conditions, or firm-specific financing strategies – can significantly influence patent pledging behavior. These findings highlight the complex role of patent centrality in the pledging process. The lack of consistency between sectors highlights the need to consider the broader industry context when analyzing firms’ patent collateralization strategies.

6.2. Regression Results of Strategic Pledging on Financing Expenses

6.2.1. Regression Results on Financing Expenses

Table 11 evaluates the impact of strategic patent pledging on firms' financing terms. Contrasting Hypothesis 2, strategically pledging, or pledging non-central patents, correlate with higher interest expenses in certain models, suggesting either that non-central patents are deemed inadequate for creditors to provide lower interest rates, or that other factors (e.g. firm size or debt levels) are more influential in determining financing terms.

Table 11: Strategic Pledging and Financing Terms

	Dependent variable: Log Interest Expense			
	(1)	**(2)**	**(3)**	**(4)**
Strategic Pledge	0.2172***	0.1726***	-0.0047	-0.0000
	(0.049)	(0.0496)	(0.0153)	(0.0105)
Log Market Cap	0.7949***	0.7756***	0.4625***	0.4697***
	(0.089)	(0.0824)	(0.0538)	(0.0534)
CPC classes per Patent	-0.0085	-0.0117***	-0.0153***	-0.0075***
	(0.007)	(0.0040)	(0.0051)	(0.0029)
Citations per Patent	0.0060***	0.0053***	0.0003**	0.0003**
	(0.001)	(0.0008)	(0.0002)	(0.0001)
Patent Age	0.0045	0.0016		
	(0.003)	(0.0034)		
Log Total Debt	0.0858***	0.0797***	0.0196***	0.0087***
	(0.0858)	(0.0151)	(0.0046)	(0.0026)
Entity FE	No	Yes	No	Yes
Time FE	No	No	Yes	Yes
Observations	3,292,112	3,292,112	3,292,112	3,292,112
R^2	0.337	0.3136	0.1359	0.1383

Note:

*Significance level denoted as * for p<0.1, ** for p<0.05, and *** for p<0.01.*

Standard errors indicated in brackets are robust to cluster correlation by firm and year.

"Patent Age" is fully absorbed by Time FE and is removed from the model for this reason.

"Strategic Pledge" is determined based on pledged patents' proximity to core technology "Patent Centrality" at 75^{th} percentile level of 0.2363.

Table 11. Column (1) is the OLS Regression Results based on model (3). Columns (2), (3), and (4) are Panel OLS Regression Results that include either or both Entity and Time Fixed Effects. Due to "Patent Age" being fully absorbed while conducting Panel OLS regression with Time Fixed Effects, regression in Columns (3) and (4) used the same variables in (1), (2), and (3) except for "Patent Age".

In Table 11 Column (1) (OLS Regression), “Strategic Pledge” has a positive and significant coefficient (0.2172 at 1% level), such that when a firm strategically pledge (when “Strategic Pledge” = 1) compared to not pledging (“Strategic Pledge” = 0), the “Log Interest Expense” increases by approximately 21.72%. This indicates that firms employing strategic pledging tend to incur higher interest expenses, in contrary to Hypothesis 2, which expects a negative relationship between the two variables. The result in Column (2) (with entity fixed effects), the coefficient is positive (0.1726) and significant at 1% level, reinforcing the result from Column (1), which implies that even after controlling for firm-specific factors, firms with strategic pledging behavior incur higher interest expenses. Column (3) and (4) are where the coefficients for “Strategic Pledge” become statistically insignificant and negative, though remarkably close to zero. This suggests that the relationship between strategic pledging and financing terms is time-dependent, or firm-specific factors (e.g. perceived riskiness, firm size, debt levels) heavily influence the outcome, making it harder to generalize the relationship.

These results suggest that, for creditors, non-central patents in general are less valuable or harder to monetize in the event of default, aligning with the idea established based on the baseline regression results in section 6.1.1. While non-core patents might meet the basic criteria for collateral, they might still not be valued as highly as core patents. Creditors place considerable importance on the quality of collaterals (Bracht & Czarnitzki, 2022), indicating that even the substantial size, and likely the reputation, of public innovative firms do not compensate for the uncertainty surrounding pledged non-core patents. Additionally, given the lack of control over firm’s core innovation, creditors utilize higher interests as disciplinary tools for loans secured by non-core patents, further reflecting the perceived risk. This suggests that, despite the strategic rationale in pledging non-core patents, firms face a trade-off of incurring higher financing costs to protect their core innovations. The analysis in section 6.2.3., where the impact of pledging core patents on interest expenses is assessed, will further explore whether such phenomenon holds true when core patents are used as collateral, to further clarify the role of collaterals’ core technology proximity in determining financing terms.

The most notable factor associated with reduced interest expense in Table 11 is “CPC classes per patent”, which has a negative and statistically significant coefficient in Columns (2) to (4). This suggests that patents with more diverse technological classifications are associated with lower interest expenses, aligned with findings from Chava et al. (2017) that a strong patent portfolio helps lower loan spreads. However, this result somewhat contrasts with the baseline regression, where patents assigned to more CPC classes are less likely to be pledged. This discrepancy highlights firms' potential reluctance to pledge versatile patents, despite such assets being more highly valued by creditors and more effective in reducing financing costs to firms. Additionally, higher citation patents – typically viewed as a proxy of technology quality – are more likely to be pledged, as suggested by the positive and significant coefficients in the baseline model. However, higher "Citations per Patent" is associated with higher "Log interest expenses", which possibly reflects the perceived risk or uncertainty that accompanies firms with influential, cutting-edge technologies. These pattern suggest that the inherent riskiness of intangible assets might offset the potential financing cost reductions these highly valuable assets bring.

It would also be valuable to consider external factors in assessing firms' interest expenses. Firms facing higher competition might face higher expenses due to the perceived risk of defaulting and exiting the markets. Table 12 investigates the role of industry concentration in the relationship between strategic patent pledging and firms financing terms. Specifically, it assesses whether firms operating in more concentrated industries experience different financing outcomes when pledging non-central patents.

Table 12: Strategic Pledging and Financing Terms, Industry Concentration

	Dependent variable: Log Interest Expense			
	(1)	**(2)**	**(3)**	**(4)**
Strategic Pledge	0.2325***	0.1838***	-0.0024	-0.0006
	(0.160)	(0.0466)	(0.0077)	(0.0104)
Log Market Cap	0.7946***	0.7747***	-0.0029	0.4697***
	(0.036)	(0.0346)	(0.0311)	(0.0534)
CPC classes per Patent	-0.0085*	-0.0118***	-0.0153***	-0.0075***
	(0.004)	(0.0027)	(0.0045)	(0.0028)
Citations per Patent	0.0060***	0.0054***	0.0003***	0.0003***
	(0.000)	(0.000)	(0.0001)	(0.0001)
Patent Age	0.0045***	0.0016		
	(0.000)	(0.0025)		
Log Total Debt	0.0855***	0.0783***	0.0196***	0.0085***
	(0.000)	(0.0085)	(0.000)	(0.0026)
Industry Concentration	-0.0219	-0.1559**	-0.0029	-0.0254
	(0.055)	(0.0619)	(0.0311)	(0.0307)
Strategic Pledging x Industry	-0.2059**	-0.1245	-0.0322	0.0069
Concentration	(0.082)	(0.0890)	(0.0411)	(0.8405)
Entity FE	No	Yes	No	Yes
Time FE	No	No	Yes	Yes
Observations	3,292,112	3,292,112	3,292,112	3,292,112
R^2	0.338	0.314	0.1359	0.1383

Note:

*Significance level denoted as * for p<0.1, ** for p<0.05, and *** for p<0.01.*

Standard errors indicated in brackets are robust to cluster correlation by firm and year.

"Patent Age" is fully absorbed by Time FE and is removed from the model for this reason.

"Strategic Pledge" is determined based on pledged patents' proximity to core technology "Patent Centrality" at 75^{th} percentile level of 0.2363.

Table 12. Column (1) is the OLS Regression Results based on model (4). Columns (2), (3), and (4) are the Panel OLS Regression Results that include either or both Entity and Time Fixed Effects. Due to "Patent Age" being fully absorbed while conducting Panel OLS regression with Time Fixed Effects, regression in Columns (3) and (4) used the same variables in (1), (2), and (3) except for "Patent Age".

In Table 12 Column (2), the coefficient is negative (-0.1559) and significant, implying a 15.59% reduction in interest expense for each unit increase in industry concentration. This could be economically significant, supporting the idea that firms in concentrated industries secure better financing terms for their greater market power or stability. However, the lack of statistical significance in other columns suggests that this effect might be sensitive to the model specification. In Columns (1), (3), and (4), the coefficient is smaller or not significant, indicating that the effect of industry concentration on interest expense might be context-dependent or influenced by the inclusion of firm- and time-specific factors.

The results for the interaction term "Strategic Pledge x Industry Concentration" are conflicting. The interaction term is negative and significant (-0.2059) only when conducting an OLS Regression in Column (1). At 5% significance level, firms that engage in strategic pledging experience a 20.59% further reduction in interest expense compared to those that do not strategically pledge patents. This indicates that the combination of industry concentration and strategic pledging could provide a compounded benefit in terms of reducing financing costs, despite the positive coefficient in "Strategic Pledging". It implies that creditors view firms in concentrated industries much more favourably and thus offering better loan terms, despite firms in such industries usually carry higher leverage (Mackay & Phillips, 2005). However, Columns (2), (3), (4) all indicate that the interaction term, either positive or negative, is insignificant, such that once fixed effects are included, industry concentration does not significantly affect the relationship between strategic pledging and financial terms. This may suggest that the observed effect in Column (1) is driven by specific model conditions or that firm- and time-specific factors play a larger role in financing decisions than the interaction between strategic pledging and industry concentrations.

6.2.2. Regression Results on Financing Expenses at Different Patent Centrality Thresholds

Table 13 presents the OLS regression results on the impact of strategic pledging at different threshold definitions of "Patent Centrality". The results strengthen the notion that pledging patents non-centric to the core technology of innovative firms is associated with higher interest expenses. The coefficients, though diminishing as the thresholds get higher, remain positive and significant.

Table 13: Strategic Pledging and Financing Terms, Alternative “Patent Centrality” Thresholds

	Dependent variable: Log Interest Expense		
	(1)	**(2)**	**(3)**
Patent Centrality Threshold	**75th**	**50th**	**90th**
Strategic Pledge	0.2172***	0.2310***	0.1732***
	(0.049)	(0.035)	(0.037)
Log Market Cap	0.7949***	0.7950*	0.7952***
	(0.089)	(0.036)	(0.036)
CPC classes per Patent	-0.0085	-0.0080*	-0.0088**
	(0.007)	(0.004)	(0.004)
Citations per Patent	0.0060***	0.0060***	0.0059***
	(0.001)	(0.000)	(0.000)
Patent Age	0.0045	0.0044***	0.0045**
	(0.003)	(0.002)	(0.002)
Log Total Debt	0.0858***	0.0857***	0.0857***
	(0.0858)	(0.009)	(0.009)
Observations	3,292,112	3,292,112	3,292,112
R^2	0.337	0.337	0.337

Note:

*Significance level denoted as * for p<0.1, ** for p<0.05, and *** for p<0.01.*

Standard errors indicated in brackets are robust to cluster correlation.

Table 13. For comparability, column (1) reports the OLS Regression Results of model (3) at the baseline “Patent Centrality” threshold of 75th percentile. Column (2) reports the same regression for threshold of 50th percentile and column (3) for threshold of 90th percentile.

While the effect of “Strategic Pledge” diminishes from 50th percentile to 90th percentile threshold, coefficients remain positive and significant across all thresholds. This suggests that even patents closer to the core (90th percentile) still carry higher financing costs when pledged, though the impact is less severe than patents further from the core at 75th and 50th percentile. It further implies the high value creditors place on proximity to core technology, regardless of how the core patent is defined. “CPC Classes per Patent” and “Citations per Patent” remain consistent across thresholds, reinforcing the idea generated in 6.2.1. that more versatile patents lower financing costs while higher cited patents are associated with higher interest expenses. Creditors might be placing more scrutiny on patents less central to core operations when assessing loans.

The findings across Tables 11 to 13 indicate that strategic pledging generally correlates with higher financing costs. However, the relationship between strategic pledging and interest expenses is inconsistent across different model variations. Controlling for fixed effects diminishes the explanatory power of strategic pledging to insignificant. Firm-specific factors, market concentration, and debt levels are more significant in determining favorable financing terms than the act of strategic pledging alone.

6.2.3. Regression Results on Financing Expenses for Non-Strategic Pledging

For a holistic understanding of the relation of patent pledging and financing expense, model (3) is modified such that the key explanatory variable would be "Non-Strategic Pledge". "Non-Strategic Pledge" is a binary variable that takes value of 1 where "Pledge Patent" equals 1 and "Strategic Pledge" equates to 0, and 0 for all other cases. In other words, a non-strategic pledge is when a core patent is pledged. No other variables is adjusted. The model is presented below:

$$\begin{aligned}\ln(interest\_expense) &= \beta_0 + \beta_1 \,(non\_strategic\_pledge) + \beta_2 \ln(mcap) + \beta_3 \,(cpc\_count) \\ &+ \beta_4 \,(cites\_count) + \beta_5 \,(patent\_age) + \beta_6 \ln(total\_debt) + \mu + \vartheta + \varepsilon\end{aligned}$$

Where: β_0 is a constant, μ is the firm fixed effects, ϑ is the time fixed effects, ε is an error term.

The results of the regression are shown in Table 14. Across all variants of the model, control variables remain fairly consistent with the results presented in Table 11 where "Strategic Pledge" is the key explanatory variable. There are also minute differences between the explanatory power of each regression results between Table 11 and Table 14.

Table 14: Impact of Non-Strategic Pledging on Financing Terms

	Dependent variable: Log Interest Expense			
	(1)	**(2)**	**(4)**	**(5)**
Non-Strategic Pledge	-0.0083***	0.0439*	0.0332	0.0294***
	(0.042)	(0.0237)	(0.0228)	(0.0111)
Log Market Cap	0.7954***	0.7758***	0.4625***	0.4697***
	(0.036)	(0.0348)	(0.0193)	(0.0180)
CPC classes per Patent	-0.0090**	-0.0125***	-0.0152***	-0.0076***
	(0.004)	(0.0027)	(0.0027)	(0.0014)
Citations per Patent	0.0060***	0.0054***	0.0003***	0.0003***
	(0.000)	(0.0004)	(0.0001)	(0.0000)
Patent Age	0.004***	0.0013		
	(0.002)	(0.0025)		
Log Total Debt	0.0856***	0.0795***	0.0196***	0.0087***
	(0.009)	(0.0087)	(0.0036)	(0.0022)
Entity FE	No	Yes	No	Yes
Time FE	No	No	Yes	Yes
Observations	3,292,112	3,292,112	3,292,112	3,292,112
R^2	0.336	0.3131	0.1360	0.1383

Note:

*Significance level denoted as * for p<0.1, ** for p<0.05, and *** for p<0.01.*

Standard errors indicated in brackets are robust to cluster correlation (by firm in (2), by time in (3), and by firm and time in (4)).

"Patent Age" is fully absorbed by Time FE and is removed from the model for this reason.

"Strategic Pledge" is determined based on pledged patents' proximity to core technology "Patent Centrality" at 75^{th} percentile level of 0.2363.

Table 14. Column (1) is the OLS Regression Results based on model (3). Column (2) is the Panel OLS Regression without fixed effects of model (3). Columns (3), (4), and (5) include either or both Entity and Time Fixed Effects. Due to "Patent Age" being fully absorbed while conducting Panel OLS regression with Time Fixed Effects, regression in Columns (4) and (5) used the same variables in (1), (2), and (3) except for "Patent Age".

The most noticeable differences are in the coefficients of the key explanatory variables. Column (1) (OLS Regression) shows "Non-Strategic Pledge" coefficients to be negative and significant at 1% level, indicating that firms experience lower interest expenses when pledging core patents. This finding aligns with the notion that creditors view core patents, which are central to a firm's technology and business operations, as more valuable, thus offering more favorable financing terms.

This effect is reversed when fixed effects are introduced in (2), (3), (4), where "Non-Strategic Pledge" coefficients become positive. However, the relation is only highly significant in Column (4) where both entity and time fixed effects are included, suggesting that firms that pledge core patents bear higher interest expenses in specific cases, possibly due to firm-specific or time-varying factors like financial distress or market conditions. Such underlying firm-related issues might negate or even reverse the benefits from pledging core patents.

The overall results suggest that creditors value core patents more than non-core ones, as indicated by lower interest expenses in the OLS regression without fixed effects. However, the value creditors place on core patents might be context dependent. Firm- and time-specific factors captured by fixed effects may mitigate or even reverse this effect, potentially reflecting firms' underlying financial or operation risks.

6.3. Natural Experiment: AIPA

6.3.1. DiD Regression Results on Pledged Patents

As discussed in Hypothesis 3, firms facing external pressure might be more reluctant to pledge their core patents at the risk of heightened competition. Incorporating AIPA as the external shock, generalized DiD regression compliments earlier findings on strategic pledging behaviors in innovative firms.

Table 15 summarizes the results assessing how the AIPA reform affected pledging behavior for patents, particularly in terms of the technological centrality of the patents. The interaction term measures how treated firms (those with publication lags > 18 months) responded after AIPA when they pledge patents in high and low "Patent Centrality" groups. The results are varied, such that, in high centrality group, the reform increased the probability of pledging, while for low centrality patents, the probability decreased.

Table 15: AIPA-Reform and Strategic Pledging

	Dependent variable: Pledged Patent			
	(1)	**(2)**	**(3)**	**(4)**
Patent Centrality Level	**High**	**Low**	**High**	**Low**
Post-AIPA x Treatment Group	0.0089***	-0.0052***	0.0095***	-0.0048***
	(0.0027)	(0.0015)	(0.0027)	(0.0003)
CPC classes per Patents			-0.0076***	-0.0027***
			(0.0006)	(0.0003)
Citations per Patents			0.0001***	0.0002***
			(0.0000)	(0.0000)
Entity FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	185,955	557,838	185,955	557,838
R^2	0.000	0.000	0.0012	0.0005

Note:

*Significance level denoted as * for p<0.1, ** for p<0.05, and *** for p<0.01.*

Standard errors indicated in brackets.

Table 15. Column (1) presents the result of the generalized DiD model (5) for high "Patent Centrality" group, while columns (2) present the results from same model for low "Patent Centrality" group. Control variables unaffected by entity and time fixed effects from model (1) are included in model (5) for both groups. Column (3) reflects the results of this addition for high "Patent Centrality" group, and column (4) present the extended model results for low "Patent Centrality" group.

In Column (1) (High Centrality), the coefficient for the interaction term "Post-AIPA x Treatment Group" is positive (0.0089) and significant at 1% level. This suggests that after AIPA, high-centrality patents were more likely to be pledged. Meanwhile, in Column (2) (Low Centrality), the coefficient is negative (-0.0052) and significant at 1% level, indicating that after AIPA, low-centrality patents were less likely to be pledged. The signs remain consistent when the relevant control variables ("CPC classes per Patents" and "Citations per Patents" were added).

The AIPA influenced firms' willingness to pledge patents in a manner contradicting Hypothesis 3, which expects firms under external pressure would be more reluctant to pledge core patents. Instead, the reform led to an increase in the likelihood of pledging high-centrality patents, whereas low-centrality patents saw a reduction in pledging likelihood. This suggests that the external shock did not discourage firms from using core patents as collateral. On the contrary, firms seemed more inclined to pledge core patents, possibly due to the benefits from securing financing that outweighed the potential loss of such patents.

These results support and extend the findings established in the baseline regression model. As shown in the previous sections, core patents are highly regarded by creditors and firms are more likely to pledge these core patents to creditors' preferences. The AIPA reform appears to have shifted firms' strategic decisions regarding patent pledging, altering the perceived risk or opportunity associated with using patents as collateral, prompting firms to adjust their pledging behaviour according to creditors. Specifically, creditors might have been more stringent post-AIPA, due to perceived higher competition risk related to earlier exposure of valuable patents. As a result, firms became unable to rely on non-core patents for pledging.

While firms in heightened competitive industries tend to rely less on debt financing (Mackay & Phillips, 2005), they might still pledge patents when needed. However, as seen in section 6.1.1, firms in competitive industries are more likely to pledge non-central patents. Regardless, creditors do not value non-core patents as favourably as core ones in general, as in sections 6.2.1. and 6.2.3. Creditors also undervalue pledged assets if firms are in competitive markets (Valta & Frésard, 2012; Hou & Robinson, 2006; Valta, 2011). Thus, firms that have to seek debts and are willing to pledge patents, under negative external shocks like AIPA, are likely to pledge core patents instead of non-core ones. This lack of strategic choice highlights that firms facing earlier disclosure of valuable patents and heightened competition would be willing to take on the increased risk associated with pledging core patents if it means securing more favorable financing terms.

6.3.2. Natural Experiment at Different Patent Centrality Thresholds

Table 16 presents the panel regression results showing the impact of AIPA on "Pledged Patent" under different "Patent Centrality" thresholds, namely 50^{th} and 90^{th} percentile. There is slight variation between different thresholds of "Patent Centrality". However, the general results reinforce the conclusions drawn from the previous analysis on how AIPA reform affected firms' strategic pledging behaviors in section 6.3.1.

Table 16: AIPA-Reform and Strategic Pledging,

Alternative "Patent Centrality" Thresholds

	Dependent variable: Pledged Patent			
	(1)	**(2)**	**(3)**	**(4)**
Patent Centrality Threshold	**50^{th}**	**50^{th}**	**90^{th}**	**90^{th}**
Patent Centrality Level	**High**	**Low**	**High**	**Low**
Post-AIPA x Treatment Group	-0.0028***	-0.0056***	0.0152***	-0.0044***
	(0.0019)	(0.0018)	(0.0044)	(0.0014)
Entity FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	372,719	371,074	74,398	669,395
R^2	0.0000	0.000	0.0002	0.0000

Note:

*Significance level denoted as * for p<0.1, ** for p<0.05, and *** for p<0.01.*

Standard errors indicated in brackets.

Table 16. Columns (1) and (2) use the 50^{th} percentile as the patent centrality threshold to distinguish between high and low patent centrality groups. Column (1) presents the result of the generalized DiD model (5) for high "Patent Centrality" group, while column (2) presents the results from same model for low "Patent Centrality" group. Columns (3) and (4) use the 90^{th} percentile as the threshold to differentiate high and low centrality groups. Column (3) shows the result of the generalized DiD model (5) for high "Patent Centrality" group, and (4) shows the model results on low "Patent Centrality" group.

For patents around the 50^{th} percentile, the AIPA reform led to a reduction in the likelihood of patent pledging for both high- and low-centrality groups, with the effect being stronger for the low centrality group. This is evidenced in the negative and significant coefficients of the interaction term (-0.0028 (1) and -0.0056 in Column (2)). The stronger effect for low-centrality patents suggest that these patents were deprioritized for collateralization after the reform. However, in Column (3), the coefficient 0.0152 is positive and significant, indicating that for patents in the top 10% centrality (i.e. very high centrality), treated firms increased their pledging after AIPA. The effect on high-centrality patent group in the 90^{th} percentile and above is also particularly higher than other centrality groups, showing a strong trend in core patent pledging post-AIPA. In Column (4) (Low Centrality), the coefficient remains negative (-0.0044) and significant at 1% level, suggesting that patents below the 90^{th} percentile centrality threshold are less likely pledged post-AIPA. The consistent reduction in pledging for low-centrality patents post-reform in Columns (2) and (4) implies that firms moved away from using non-core, lower- value patents for collateral after the AIPA reform, consistent with previous findings in section 6.3.1.

These results further solidify the causal link between patent centrality and pledging likelihood. Firms are more likely to pledge patents in higher centrality group, especially after the AIPA reform. Conversely, patents with low centrality are less likely to pledged, post-AIPA. The rationale here is that core patents, being integral to the firm's competitive advantage, provide more security and potential recovery value to lenders. Hence, innovative firms, under possible creditor pressure, shift away from pledging less-valuable patents during phases of regulatory changes that could negatively impact these firms.

6.3.3. Alternative Treatment Windows around AIPA reform

The post-treatment window is shifted to 3 years and 7 years after AIPA to check the sensitivity of the results to the timing of the actual treatment. Table 17 presents the results from such changes. Similar conclusions could be drawn from here that high-centrality patents are more likely to be pledged after AIPA, while low-centrality patents are less utilized for debt financing, though the impact varies over time.

Table 17: AIPA-Reform and Strategic Pledging, Alternative Treatment Windows

	Dependent variable: Pledged Patent			
	(1)	**(2)**	**(3)**	**(4)**
Post-treatment window	**3 years**	**3 years**	**7 years**	**7 years**
Patent Centrality Level	**High**	**Low**	**High**	**Low**
Post-AIPA x Treatment Group	0.0058*	-0.0069***	0.0089***	-0.0052***
	(0.0033)	(0.0018)	(0.0027)	(0.0015)
Entity FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	116,813	349,106	185,961	557,869
R^2	0.0000	0.000	0.0000	0.0000

Note:

*Significance level denoted as * for p<0.1, ** for p<0.05, and *** for p<0.01.*

Standard errors indicated in brackets.

Table 17. Columns (1) and (2) use a window of 3 years before (1998-2000) and after (2001-2003) AIPA reform (in 2001). Column (1) presents the result of the generalized DiD model (5) for high "Patent Centrality" group, while column (2) presents the results from same model for low "Patent Centrality" group. Columns (3) and (4) use a window of 7 years before (1994-2000) and after (2001-2007) AIPA reform (in 2001). Column (3) shows the result of the generalized DiD model (5) for high "Patent Centrality" group, and (4) shows the model results on low "Patent Centrality" group.

The coefficients in both high and low patent centrality groups at alternative treatment windows remain consistent with the original 5-year window. In the high patent centrality group, patents are more likely to be pledged post-AIPA. The impact of AIPA grows more pronounced over time as well, as the coefficient increases to 0.0089 and significant at 1% level from the 5-year mark, as shown in Table 15, from 0.0058 with 10% significance level in 3 years post-AIPA, suggesting that firms are more willing to pledge their core patents the longer they are exposed to the post-AIPA environment. The 5-year and 7-year windows show no difference, indicating a flatter impact over the longer timeframe. In the low patent centrality group, an opposite effect is noted. In 3 years post-AIPA, the coefficient is negative (-0.0069) and significant at 1% level, suggesting a reduction in pledging of low centrality patents. This impact is subdued in 5 to 7 years post-AIPA (-0.0052), though still significant at 1% level, indicating a persistent but lessening impact of AIPA on the low patent centrality group.

The alternative treatment windows introduce some variation in the coefficients, but such variance does not alter the previously established conclusion: AIPA influenced firms to pledge more central patents over less-central ones, with the effect becoming more pronounced as the post-reform period lengthens. This result is robust across different time frames, reinforcing that firms become more inclined to pledge core patents while reducing pledging of less central patents post-AIPA. The natural experiment indicates a significant causal relationship between patent centrality and patent pledging.

7. Conclusion

The key findings of my thesis suggest that core patents are more likely to be pledged, potentially due to creditors' preferences outweighing firms' ability to strategically pledge less-central patents. This finding holds even under an alternative definition of core patents. However, when assessed at firm and firm-year levels, firms with portfolios closely tied to core technologies tend to safeguard patents and only pledge core patents in specific time periods, revealing some degree of strategic considerations when pledging patents. Furthermore, when analyzing strategic pledging in relation to varying industry dynamics, I find that innovative firms in highly competitive industries, while more likely to collateralize patents, tend to be more reluctant to pledge core ones than those in concentrated industries. This is likely due to the lower leverage typically carried by firms in competitive markets, where creditors may view the heightened threats of competition negatively. In contrast, firms in concentrated industries show a higher willingness to pledge more technologically central patents, potentially because of the lower perceived risks. The baseline regression is also conducted for specific technological sectors. Among the top patent-pledging sectors, the relationship between patent centrality and pledged patents varies in significance but generally points to a similar idea that core patents are more likely to be chosen as collaterals. This holds regardless of the size and patenting activities of the sectors.

Examining how the choice of pledging core versus non-core patents affects interest expenses shows mixed results. Firms that pledge core patents tend to benefit from lower interest expenses, while non-core patent pledging is often associated with higher financing costs. These results revert in signs and become insignificant when time- and sometimes firm-fixed effects are included. This suggests that other time- or firm-specific factors might be more critical in determining interest expenses. Non-core patent pledging correlates with higher interest expenses under varying thresholds of patent centrality. The only exception to this relationship is when firms are in concentrated industries, where non-core pledging is linked to more favourable loan terms.

The natural experiment using the enactment of the American Inventors' Protection Act (AIPA) as an exogenous shock supports the causal relationship between patent centrality and pledging behaviour. Despite the increased risks posed by earlier patent publications under AIPA, core patents were more likely to be pledged, underscoring creditors' dominant role in collateral decisions. A significant decline in the number of non-core patents pledging also suggests that firms might have catered more to creditors' preferences than their strategic considerations in the wake of regulatory change. Firms might also have weighed the benefits in receiving favourable financing terms much higher than the costs from losing their most vulnerable patents.

These findings offer several directions for future research. One direction involves refining the definition of "Strategic Pledge" and "Core Patent" as different interpretations may provide deeper insights into firms' pledging behaviours. Additionally, due to data limitation, I only use interest expenses as a proxy for financing terms. However, assessing other more direct loan terms, such as loan spreads or interest rates of specific secured loans, may allow for a more precise and consistent assessment of the impact of pledging core versus non-core patents on financing outcomes. Another valuable area of exploration could be the long-term performance of firms that pledge core versus non-core patents. Such research would offer a more comprehensive understanding of how choosing patents for pledging affects innovation trajectories. Previous research has solidified that pledging patents redirect firms' attention to shorter-term monetizing innovative activities (Ayerbe et al., 2023; Luo, Wang, & Hu, 2024). However, the long-term impact on firms' performance has yet to be explored. The hypotheses raised in this study regarding creditors' apparent preference for core patents and their dominance in the patent pledging process also warrant further investigation. Given the studied firms are all listed firms with access to equity financing, strategic patent pledging could also be assessed in the broader context of strategic capital structuring or of asset allocation. Moreover, despite the seemingly important role of patent centrality in pledging patents through my regression analysis, the summary statistics indicate no significant difference in the selected characteristics of core versus non-core patents and pledged versus non-pledged patents, suggesting that there may still be other elements of patents and firms that play a more significant role. Lastly, the models from this study could be applied to different contexts and regulatory environments or to firms in the private markets to draw a more comprehensive view of patent collateralization behaviours.

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Appendix

Table 1: Multicollinearity Test Results

Independent Variable	VIF
Patent Centrality	1.1026
Log Market Cap	1.4723
CPC Classes per Patent	1.0210
Citations per Patent	1.0319
Patent Age	1.7335
Log Total Debt	1.6597
Industry Concentration	1.0291