The Asian Journal of Technology Management Vol. 15 No. 1 (2022): 21-39

Patent Signals of IPO Performance: Evidence from High- and Low-Tech Industries in Japan

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Abstract: *Prior studies pointed to evidence that startups and venture capital (VC) companies tended to use different measures to provide signals to outsiders. This study adds to those previous insights by focusing on established firms' patenting behaviors and their effect on the amount of money raised at the initial public offering (IPO). Since technology intensity may differ considerably between high and low-tech companies, our main interest in this paper lies on whether the significance of pre-IPO patenting activities as a predictor of IPO performance also varies between these two industry categories. Using cross-sectional data representing 308 Japanese industrial firms' IPO commitments between 2000 and 2015, we find a robust positive correlation between patent applications and IPO performance. Contrary to the conventional wisdom proposing that high-tech firms with more patenting activities achieve better IPO performance, we show that the signaling power of patenting is stronger for the low-tech companies in our sample: While the high-tech firms do not seem to have significantly benefited from a patent signal, the low-tech firms seem to have attracted external investors more easily due to patenting at the IPO.*

Keywords: *Patent, signal, initial public offering (IPO), high-tech industries, low-tech industries*

1. Introduction

An initial public offering (IPO) is an important event. In it, companies can raise capital from public investors and gain greater ability to grow. It is impossible for outside investors to predict the long-term potential of an IPO company when objective financial information is unavailable. Indeed, convincing investors of its worth is a major challenge for any company going public. Firms usually use signals for quality, such as increased transparency and share listing credibility, to help attract outside investments.

Previous studies focused on various measures to signal the quality of IPO companies toward reducing uncertainty around IPO performance. Research has suggested that trustworthy third-party affiliates such as venture capitalists (Gomulya et al. 2019), corporate partners (Johan 2010), and auditors (Chan et al. 2021) could represent an effective signal for the IPO. Entrepreneurial lineage, founder backgrounds (Bruton et al. 2009),(Cohen and Dean 2005), and underwriter prestige (Arora and Singh 2019) could also affect investment decisions. In addition, Al-Shammari et al. (2013) identified firms' internationalization, alongside inter-organizational networks (Ozmel et al. 2013), as key factors reducing information asymmetry.

However, due to these signals' dynamic, evolving nature, modern investors have tended to no longer trust them at face value (Useche 2014), and instead look for concrete evidence of firms' innovation, such as patents, to gauge their potential. Patents could become a crucial signal, able to reduce information asymmetries and maximize attraction for investments. Czarnitzki et al. (2014) evaluated patents' properties as an ideal proxy to assess firms' quality; in short, they are expensive to operate and observable by

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Received: March 3rd, 2022; Revised: March 3rd, 2022; Accepted: March 3rd, 2022
Doi: http://dx.doi.org/10.12695/ajtm.2022.15.1.2
Print ISSN: 1978-6956; Online ISSN: 2089-791X.

outsiders. Firms may apply for a patent to leverage their performance enhancements under conditions of uncertainty. For example, as firms near a critical financing event such as the IPO, they are likely to increase their patenting activity to attract potential investors.

The degree of information asymmetry between a firm's insiders and outsiders tends to vary depending on how technologically intensive the firm is. A company's patenting motives and the technology underlying its innovations tend to influence information transparency. Complexity and a large number of patentable components have been known to characterize the high-tech sector (Leone et al.). Therefore, it may be difficult for high-tech firms to clarify patenting information for outsiders to use in assessing their validity: High-tech firms' innovation portfolios could be too sophisticated for outsiders to understand and interpret, hindering the provision of sufficiently coherent guidance on assessing their commercial prospects (Cohen et al. 2000).

Hence, informational asymmetry tends to be more severe the more high-tech a firm is, raising investor uncertainty. It follows that high-tech companies' patenting activities tend to be less reliable than traditional firms' as a signal of potential growth.

The purpose of this paper is twofold. First, we explore whether firms' patenting practices prior to an IPO could impact investors' perceptions of their potential IPO performance. Second, we investigate whether patenting activities in high- and low-tech industries drive different behaviors in terms of investments in IPO companies.

Empirical results from a sample of 308 IPOs Japanese manufacturing firms issued during the years 2000–15 strongly support our hypotheses (detailed in the next section). We find a significant and positive relationship between the number of patents filed in the five-year period immediately preceding an IPO and the amount of capital raised at the IPO. These results indicate that firms modified their patenting strategies by increasing the number of patent applications as the IPO neared. They likely did so to signal their innovative rigor toward improving IPO performance. This study also demonstrates the significance of pre-IPO patenting activities as a predictor of IPO performance, and how it could differ considerably between high- and low-tech industries. While the high-tech firms do not seem to have benefited significantly from a patent quality signal, the low-tech firms seem to have attracted external financing more easily during the IPO due to such a feature.

2. Literature Review and Hypothesis Development

2.1. Patent as a Signal for IPO Performance

Feldman and Frondorf (2015) defined the IPO as a momentous occasion for any business, since it could provide an opportunity to gain capital from public investors and boost publicity, as well as potentially representing a liquidity event for present shareholders. At the same time, IPO firms could face many disadvantages attempting to raise capital, since they have tended to be young companies with low liquidation value and unstable business operations (Useche 2014). Information asymmetry, as an inevitable issue associated with privately-held companies, could additionally hinder potential investors from confidently predicting those companies' financial performance. Therefore, it would be important for any company going public to be able to convince stakeholders, particularly investors, of its potential for long-term growth, and hence its shares' attractiveness for investments (Cohen et al. 2000).

As mentioned earlier, studies have found IPO firms to have employed a range of signals—including affiliation with third parties such as venture capitalists (Megginson and Weiss 1991), corporate partners (Baum 2000), and auditors (Beatty 1989)—to mitigate the uncertainty surrounding the IPO process and compensate for perceived risks to investments. Investors could also evaluate the following factors to decide whether to invest in an IPO firm: entrepreneurial lineage and founder backgrounds (Eisenhardt and Schoonhoven 1990), (Higgins and Gulati 2006); board size and composition(Certo et al. 2001); underwriter prestige (Lange et al. 2001); and other key signals reducing information asymmetry. If uncertainty and information asymmetry can be minimized, patenting activities, as evidence of innovation and competency, may serve to signal quality for IPO performance.

Before discussing the role of patents as a signal for quality, we need to consider the motives for patenting as related to property rights. Graham and Sichelman (2008) argued that companies filed for patent protection most commonly to prevent infringement and secure exclusive rights to profit from their distinct product offerings. Another key set of motives has been to preempt competitors from acquiring patents on the same inventions, and to block patents to prevent rivals from benefiting from them (Cohen et al. 2000; Motohashi 2008).

Researchers previously posited that patents could generate revenue through licenses or develop an arsenal for cross-licensing negotiations over rights to the technology (Hall and Ziedonis 2001; Ziedonis 2004). They have also focused on the role of patents as shields against infringement cases; measures of the internal performance of a firm's technologists (Coursey 2009); substitutes for non-disclosure agreements (Artz et al. 2010); reputation boosters for companies (Basir 2020); and (Heeley et al. 2007). These motivations for filing patents can all be said to aim at either generating revenue or reducing costs.

Another way to generate revenue is to attract capital through financial events such as IPOs, where patents could serve as important signals for quality and reduce information asymmetries between firms and outside investors. A patenting firm's choice to disclose, rather than withhold, invention information in the face of technology-expropriation patents could be a credible proxy for transferring information about the underlying innovation (Hsu and Ziedonis 2008). From outsiders' perspective, a company with a patent portfolio may appear capable of maintaining profits or even outperforming those without one. Hence, especially before an IPO, some firms may attempt to secure patents to appear more valuable to outsiders estimating their quality or worth.

As mentioned, patents represent valid signals for quality due to their being expensive to operate and easily observable and verifiable by outsiders. Lemley identified patents as costly signals since administrative and attorneys' fees had been estimated to be usually about $25,000 per patent, in addition to the research and development (R&D) expenditures often needed to generate a patentable invention. As far as accessibility, information on patents is publicly available, which enables outsiders to investigate them via databases. Patents must include verifiable details as patent offices require candidates' ideas to be new, industrially applicable, and involve an inventive step to be eligible (Long 2002). Moreover, Useche (2014) claimed patent offices could help patenting companies strengthen credibility and add clarity to their inventions, since such authorities had come to be viewed as reliable intermediaries.

While some patents may not serve as direct evidence of a firms' invention capabilities, they may still be effective signals. A company's patent portfolio could reveal its target market (mass market or niche market) as well as intellectual property and marketing strategies (Lemley 2000). The number of a company's patent applications could serve as a proxy for internal company resources, revealing several key qualities which would otherwise be difficult to measure. For example, patents could demonstrate to investors a company's innovative capabilities and technical expertise, codify tacit knowledge, and hence signal its R&D competencies (Stuart et al. 1999; Graham and Sichelman 2008).

Patents can communicate a company's growth potential to investors at the time of the IPO. In light of patents' signaling mechanism, we predict the following:

H1: All other conditions being equal, patent activities near an IPO signal IPO performance.

2.2. Patent Signals: High-Tech Versus Low-Tech

High- and low-tech firms have tended to differ in various aspects.

First, high-tech companies have generally been found to have fewer tangible assets but invest more in intangible assets such as R&D, human resources, information technology, and patents and other intellectual property (Leone et al.;

Pukthuanthong-Le and Walker). Compared to low-tech companies, high-tech ones have more often faced cash shortages and constraints on tangible assets—shortfalls which investors could perceive as a sign of manufacturing unavailability.

Second, innovation projects could take years to be implemented; in the pharmaceutical industry, for example, chemical innovation projects could take decades to materialize. Since companies must typically allocate massive resources for such projects, high-tech firms' net income is often in the red, and even more so in the early years. This has tended to make company valuation quite conservative, with investors largely depending on their expectations of future growth to evaluate such companies, rather than on objective assessments based on the firms' present values.

The degree of information friction between a firm's insiders and outsiders has typically varied according to the firm's technological intensity (Guiso 1998). The technologies characteristic of high-tech firms are primarily complex in nature, comprised of a large number of patentable components (Levin et al. 1987). In this case, firms may face difficulties clarifying patenting information that outsiders can use to assess their validity (Levin et al. 1987). Innovative portfolios of high-tech companies can be too sophisticated for outsiders to interpret and understand to the point where coherent guidance on assessing their commercial prospects cannot realistically be provided (Guiso 1998). The informational asymmetry is more severe with regard to high-tech firms and thus increases investor uncertainty. Therefore, patent activities in high-tech companies are less reliable as signals of potential growth compared to those of traditional firms.

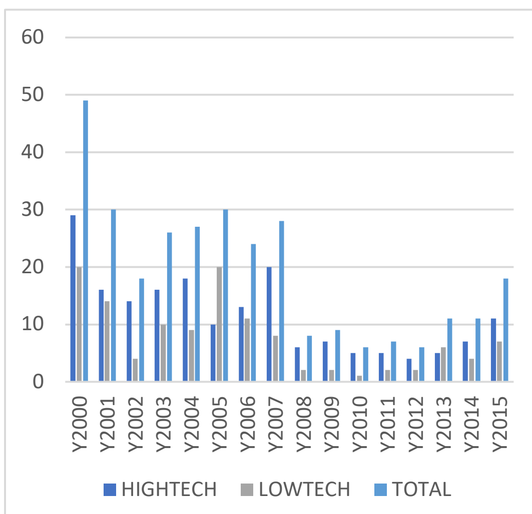

Figure. 1.
Number of High- and Low-Tech Firms in Each IPO Year

High-tech firms tend to have little incentive to disclose details on their inventions to outsiders, since doing could reveal information competitors could use to gain an advantage in technology. Hence, low-tech firms have a relatively higher incentive to obtain a patent, being more eager to file for them as a signal to outsiders due to their limited alternatives for achieving credibility. We have developed the corresponding hypotheses as follows:

H2a: All other conditions being equal, there will be a negative relationship between the patent activities of high-tech companies near an IPO and their IPO performance.

H2b: All other conditions being equal, there will be a positive relationship between the patent activities of low-tech companies near an IPO and their IPO performance.

3. Methodology and Research Model

3.1. Methodology

a. IPO Sample and Data

Our study draws upon data from various sources: financial- and corporate-attribute data from

Nikkei FinancialQUEST; patent information from the Japan Platform for Patent Information (J-PlatPat); IPO-related data from prospectuses and the Japan Exchange Group (JPX) database; and manufacturing industry classifications from the Organization for Economic Cooperation and Development (OECD). We obtained data on total proceeds from prospectuses filed by all Japanese firms that undertook IPOs between the years 2000 and 2015.

We selected the sampling period based on the stability of market conditions and regulatory settings in terms of signaling and disclosure. Until the year 2000, the IPO market had been overhyped due to the dot-com bubble and bio bubble; and after the year 2016, Japanese IPO companies became subject to stricter codes of conduct due to repetitive scandals involving disclosure and governance, which may have come to force IPO companies to reconsider signaling strategies including disclosure. For patenting data, we manually counted the number of patent applications filed by each IPO firm during the five-year periods leading up to the IPO date.

Our study also addresses the effect of patents on IPO performance for firms in different industrial categories. For this purpose, we referred to the "TSE New Industry" codes from Financial QUEST to limit our selection to firms operating in manufacturing (see Appendix 1 for the "TSE New Industry" classification). We divided the information into two sub-samples—high-tech companies and low-tech companies—using the OECD classification for the manufacturing sector (Table 1). The resulting sample comprises 308 manufacturing IPOs listed in the Japanese Stock Market Exchange between January 2000 and December 2015. Finally, we set apart for analysis two sub-samples, containing 186 high-tech firms and 122 low-tech firms, respectively.

Table 1.
OECD Classification of High- and Low-Tech Industries

High-Tech Industries	Low-Tech Industries
Aerospace	Rubber and plastic products
Computer and office machinery	Shipbuilding
Electronics and communications	Other manufacturing
Pharmaceuticals	Non-ferrous metals
Scientific instruments	Non-metallic mineral products
Motor vehicles	Fabricated metal products
Electrical machinery	Petroleum refining
Chemicals	Ferrous metals
Other transport equipment	Paper printing
Non-electrical equipment	Textile and clothing
	Food, beverage, and tobacco
	Wood products

Figure 1 illustrates the number of IPO high- and low-tech companies each year from 2000 to 2015. After a steady climb from 2000 to 2007, in 2008, the number of IPO firms began to dramatically decline in Japan due to the global financial crisis. The growth in the number of IPO firms began to show signs of recovery in 2013, when Japan appeared to overcome the global recession.

b. Variable Definitions
Independent Variable

- *Patenting Activities: Number of Patent Applications*

"Patent performance" in this study is defined as the total number of patents a particular company filed in the five-year period immediately before an IPO. We place an emphasis on this period as patents offer a relatively short term of protection (20 years from the date of filling); therefore, those filed long ago might not reflect a firm's present innovation performance (Megginson and Weiss 1991). We use a log-transformed variable of the number of patent applications (Log(Patent +1)) to address the valuation data skew and reduce its heterogeneity.

Dependent Variable

- *IPO Performance: Total Proceeds*

Our dependent variable, "total proceed," pertains to the amount of capital raised by firm i at the IPO date (t). We calculate total proceed by multiplying the number of the total issue of firm i at the IPO date (t) by the issue price of firm i at the IPO date (t). Such measure of IPO performance is appropriate for firms that tend to be cash-constrained and have a long, expensive development process (as in Higgins et al. 2011). Furthermore, this method of evaluation avoids potential problems of over-allocation in pre-money valuation (Ritter and Welch 2002). To account for skewness in the data, we use log transformation for total proceed.

Control Variables

- *Firm Size: Total Assets*
  Previous research suggested that larger firms were expected to have less information asymmetry (Barth and Kasznik 1999) and more patents in general. Therefore, we calculate the logarithm of total assets one year before the IPO to control for the size effect.
- *Firm Age: Age at IPO*
  We calculate a firm's age by taking the natural logarithm of the difference between the date of its IPO and the date of its establishment. We expect the companies with a long history of operations to have had a better IPO performance than younger firms.
- *Underpricing: First-Day Opening Price*
  Previous literature indicated that underpricing was negatively related to IPO performance (Zhou and Sadeghi 2019). We define underpricing as the first-day opening price less the offer price divided by the offer price. Offer and opening prices data was obtained from the JPX database.
- *Financial Ratio: Debt Ratio*
  "Debt ratio" is defined here as a company's total debt in proportion to its total assets in the year before the IPO. As a measure of firms' solvency, it is expected to influence the amount of capital they aim to raise from IPOs.
- *Prestigious Underwriter Backing: UW Dummy*
  Firms with more prestigious underwriters have tended to display better IPO performance (Higgins and Gulati 2001). We include a dummy variable we call "UW" to measure the effect of underwriter reputation on the total proceed. UW is code 1 if the underwriter is one of the top three most famous underwriters in Japan (i.e., Daiwa Securities, Nomura Securities, or SMBC Nikko Securities), and 0 otherwise.
- *Stock Market Effect: STOCK Dummy*
  We also introduce a dummy variable we call "STOCK Dummy," coded 1 if the companies were quoted in "first section" and "second section" Japanese stock exchanges, and 0 otherwise. The first and second sections are collectively referred to as the "main markets," where first- and second-tier companies are listed (Chan et al. 2021). Since most prominent companies are listed in the first and second sections, a positive relationship between main market and IPO performance is expected.
- *High-Tech and Low-Tech: Technological Intensity Dummies*
  To estimate the differential effects of patenting on IPO performance for companies in the different industry categories, we include dummy variables indicating the level of technological intensity between high- and low-tech. As already mentioned, we employed the OECD's manufacturing classification based on technological intensity (Table 1) to split our sample into high- and low-tech companies. We use 1 for companies belonging to the high-tech sector and 0 otherwise. Likewise, we use 1 for companies belonging to the low-tech sector and 0 otherwise.
- *Year-Related Dummies*
  A set of yearly time dummies is coded as "Year2000" to "Year2015," with "year companies go public" being included to account for overall business cycle effects.

Appendix 2 presents a summary of all variables, their definitions, and expected outcomes, expressed in plus and minus signs.

3.2. Research Model

To test the hypothesized relationship H1, we use the following ordinary least square regression:

$$LN(Total\ Proceed\_i) = \beta 0 + \beta 1 * LN(Patent\_i+1) + \beta 2 * CVs + \varepsilon i \ (1)$$

Where:

- Total Procceed_i is the capital a firm i is able to gain at the IPO date (t);
- Patent_i is the total of patent applications filed by firm i in the five years preceding the IPO date (t);
- CV is a vector of Control Variable.

Positive and significant β-1 is expected to support H1.

To estimate a differential effect of patenting on firm performance at the IPO for the different industry categories, we include dummy variables indicating technological intensity between high- and low-tech industries. We employ the following OLS regression, with the interaction term between Patenting and Technology Advantage, for testing hypotheses H2a and H2b:

$$LN(Total\ Proceed\_i) = \beta 0 + \beta 11 * High\_tech\_i * LN(Patent\_i+1) + \beta 12 * Low\_tech\_i * (Patent\_i+1) + \beta 2 * CVs + \varepsilon i \ (2)$$

Where:

- Total Proceed_i is the amount raised by firm i at the IPO date (t);
- Patent is the total of patent applications filed by firm i in the five years preceding the IPO date (t), with (Log(Patent +1)) being used to address the valuation data skew and reduce its heterogeneity;
- High-tech: Dummy variable assigned a value of 1 if IPO company is high-tech company and 0 otherwise;
- Low-tech: Dummy variable assigned a value of 1 if IPO company is low-tech company and 0 otherwise;
- CV is a vector of Control Variable.

We expect β11 to receive a negative value, supporting H2a: All other conditions being equal, there will be a negative relationship between the patent activities of high-tech companies near an IPO and their IPO performance. Conversely, we expect β12 to receive a positive value, supporting H2b: All other conditions being equal, there will be a positive relationship between the patent activities of high-tech companies near an IPO and their IPO performance.

4. Findings and Result

4.1. Preliminary Analysis

Table 2 presents the descriptive statistics for the 308 IPO firms in our sample. The average total proceeds of an IPO for these companies were about 10568.64 million yen.

Table 2:
Summary Statistics

Variable	Mean	Min	Med	Max
Dependent Variable				
1.Total Proceed	10568.6	56.00	1572.8	1210500
2.Ln (Total Proceed)	21.40	17.84	21.17	27.82
Independent Variable				
3.Firm has Patent (%)	0.76	0.00	1.00	1.00
4.Number of Patent	97.35	0.00	6.00	18893.0
5.Ln (Patent +1)	2.06	0.00	1.94	9.84
Control Variable				
6.Total Asset (mil. Yen)	34846.1	2.80	7208.2	222857
7. Ln (Total Asset)	22.70	17.12	22.69	4.00
8. Debt Ratio (%)	0.56	0.02	0.56	28.430
9. Age at time of IPO	32.69	1.00	32.00	5.14
10.Ln (Age at IPO)	3.22	0.00	3.46	110.0

Table 2 (Continued)
Summary Statistics

Variable	Mean	Min	Med	Max
Control Variable				
11.Underpricing (%)	**33.40**	**-93.74**	**12.44**	**4.70**
12.UW Dummy (%)	0.62	0.00	1.00	566.6
13.STOCKDummy(%)	0.13	0.00	0.00	1.00
14.High-tech Dummy (%)	0.61	0.00	1.00	1.00
15.Low-tech Dummy (%)	0.39	0.00	0.00	1.00

The minimum proceeds a company could gain were found to be 56 million yen, and the maximum to be 1210500 million yen. This wide total proceed value range was to be expected, since our sample includes firms from different manufacturing sectors.

In terms of innovation capital, 76% of the Japanese manufacturing companies filed at least one patent prior to their IPOs. Overall, the firms filed on average 97.35 patents prior to their IPOs.

Table 2 shows that the number of patents firms filed could vary from zero to 18893 in the five years prior to their IPOs. The average age of a firm filing for an IPO was 32.69 years, and the average firm size was 34846.11 million yen. Firms' sizes varied widely, from 2.8 million yen to 2228574 million yen. Table 2 also provides descriptive statistics for the average debt ratio. The mean debt-to-total-asset ratio is found to be 0.56, with the median being the same (0.56). Moreover, of the 308 firms observed, 62% were vouched for by prestigious underwriters, and 13% were listed in first- and second-section stock exchanges.

Table 3 displays the correlation among variables. Correlation analysis was used to test any multicollinearity issues in variables and scrutinize the presence of more than an extract linear correlation between independent variables. Severe multicollinearity between independent variables will offer unnecessary bias in the regression results. Thus, a vigilant check should be made to verify its inexistence.

Table 3.
Correlation Table

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
(1)	1.0									
(2)	.25	1.0								
(3)	.44	.39	1.0							
(4)	(-) .22	.27	.37	1.0						
(5)	.05	(-) .01	(-) .04	(-) .08	1.0					
(6)	(-) .18	(-) .05	(-) .25	(-) .17	(-) .06	1.0				

Table 3. (Continued)
Correlation Table

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(7)	.22	.14	.23	.09	.10	(-) .05	1.0			
(8)	.27	.27	.38	.23	.00	(-) .03	.22	1.0		
(9)	.23	.22	(-) .77	(-) .11	.22	.00	.10	.08	1.0	
(10)	(-) .23	(-) .22	.07	.11	(-) .02	.00	(-) .10	(-) .08	(-) 1.0	1.0

Note: (1): Ln(Total Proceed); (2): Ln(Patent +1); (3):Ln(Total Asset); (4): Ln(Age at IPO); (5): Debt Ratio; (6): Underpricing; (7): UW Dummy; (8): STOCK Dummy; (9):High-Tech Dummy; (10): Low-Tech Dummy.

Some of the control variables show a negative correlation, such as that between underpricing and Ln(Total Asset); underpricing and Ln(Age at IPO); and high-tech industries and Ln(Age at IPO). Meanwhile, other control variables display a positive relationship, such as that between Ln (Total_Asset) and Ln (Age at IPO); high-tech industries and debt ratio; and underpricing and debt ratio.

The sign of correlation indicates whether variables will have similar or different types of changes in their paired variable: The highest correlation among control variables is between dummy-variable IPO companies listed in first- and second-section stock market exchanges (STOCK Dummy) and Ln(Total Asset), with a value of 0.38—far lower than the cut-off point of 0.9 (Gujarati and Porter 1999). Therefore, the coefficient value in Table 3 suggests no severe multicollinearity issues, implying that all variables in this study display an independent characteristic justifying their inclusion in the regression model.

4.2. Main Analysis

Table 4 summarizes the test results for the hypotheses built in this study. Model 1 presents the general impact of patents' signaling effect on IPO performance, while Model 2 illustrates the patents' signaling effect on each of the groups in the sample, with degrees of impact differing between high- and low-tech industries in terms of IPO performance. All our hypotheses here are supported with significant effects.

For Hypothesis 1, we expected patent activities near an IPO to signal IPO performance. Consistently with our prediction, the results from Model 1 demonstrate that Ln(Patent+1) receives a positive coefficient (0.0548) and is highly significant (P-value <0.05); we thereby find qualified support for Hypothesis 1. This indicates that the greater the patent activities near the IPO were, as measured by the number of total patent applications in the five years preceding the IPO, the better the IPO performance turned out to be. We can infer that the estimated return of each additional log patent application increased total proceeds by 5.48%, other factors remaining fixed.

Previous literature suggested that patents might serve as a signal to lenders and investors, facilitating access to external financing in addition to their original function of protecting an invention from imitation. The present study was motivated by a gap in the literature regarding the role of patents as a signal for quality for manufacturing firms. Our findings add to the knowledge that patents tend to play a particularly valuable signaling role in startup and venture capital firms, by demonstrating patents' centrality in attracting external financing for all the manufacturing firms, even those long in business.

Table 4.
Hypothesis Testing Results

Variable	**Model 1 (H 1)**	**Model 2 (H2a&H2b)**
Intercept	8.1871***	8.0856***
	(0.826)	(0.814)
Ln(Patent+1)	0.0548**	
	(0.041)	
High_tech*Ln(Patent+1)		-0.0585**
		(0.037)
Low_tech*Ln(Patent+1)		0.1313**
		(0.042)
Ln(Total Asset)	0.4804***	0.4861**
	(0.058)	(0.057)
Ln(Age at IPO)	-0.6793***	-0.6643***
	(0.089)	(0.088)
Debt Ratio	0.1077	0.1000
	(0.640)	(0.603)
Underpricing	-0.0019**	-0.0018**
	(0.001)	(0.001)
UW Dummy	0.2512*	0.1980
	(0.140)	(0.139)
STOCK Dummy	0.5298***	0.5495***
	(0.203)	(0.200)
High_tech Dummy	4.3290***	4.4879***
	(0.410)	(0.408)
Low_Tech Dummy	3.8581***	3.5976***
	(0.426)	(0.430)
Year Dummies	Yes	Yes
F-Value	24.43***	23.27***
Observation	308	308
Adjust R^2	0.446	0.462

*Note: Values are regression coefficients with standard errors in parentheses; *p<0.1, **p<0.05, ***p<0.01.*

In our next model (Model 2), we allow the patent signal to vary according to the industry category to which the firm belongs (high- or low-tech). The results provide strong support for our main hypotheses, suggesting that the effect of patents in our sample varied according to how tech-intensive the firms were. The null hypothesis that the effect of patents is the same for both groups (- 0.0585 - 0.1313 = -0.1898) can be rejected at the p<0.01 level. The negative (-0.0585) and significant coefficient estimates (p<0.05) for the interaction term (Log (Patents+1) * High-tech) indicate that, for the high-tech firms, an increase in the patenting activities near the IPO reduced the money they collected from the IPO. By contrast, the positive (0.1313) and significant (p<0.05) interaction term (Log (Patents+1) * Low-tech) indicates that, for the low-tech firms, increasing the patenting activities near the IPO increased the money they collected at the IPO. Thus, we find strong support for Hypothesis 2a as well as Hypothesis 2b.

The results of control variables for both models are mostly consistent with the previous literature on IPOs. The size of the firm (total asset) has a positive influence on total proceed in both models at the 1% significance level. This implies that larger companies have higher IPO valuations in terms of assets, presumably because they are less risky than smaller companies. Surprisingly, the impact of the firm's age ("age at IPO") on IPO performance showed a reverse impact to our expectation that firms with more experience before going public would perform better at the IPO than younger firms. The results for the effect of firm age size were negative for both Model 1 (-0.6793) and Model 2 (-0.6643) at the 1% significance level. Our explanation for this is that younger firms tend to invest more in innovation and patenting activities compared to older firms, which helps reduce uncertainty about their quality to outsider investors, ultimately leading to better overall IPO performance.

The effect of the financial indicator measured by debt ratio is positive but not significant, providing no support for the relationship between a company's solvency and its IPO performance. Underpricing shows a negative and statistically significant sign consistent with our expectations. This implies that IPO companies probably reduce the price to maximize the shares they sell, which facilitates their total proceed gains.

The companies in our sample paid attention to the reputation of the underwriter; this was demonstrated by the positive 0.2512 in Model 1 and statistically significant (P-value<0.1) of UW. Companies evaluated by prestigious underwriters are more likely to appear trustworthy in the eyes of investors and thus to achieve a successful IPO.

The next control variable, the stock market effect (STOCK Dummy), is significant at 0.01. STOCK Dummy produces a positive association to total proceed. The first and second sections offer a market for trade in which the most prominent companies are listed. These companies tend to receive large sums of money from investors, as they are expected to grow steadily in the future.

Robustness Test

For our initial analyses, we grouped companies into high- and low-tech based on the OECD classification, which has located information and communication technology (ICT) industries in the service rather than manufacturing sector. Meanwhile, sources such as Bertoni et al. (2011) and Loughran (2004) have classified ICT industries as high-tech manufacturing industries. Since ICT has been a key driver for productivity and economic growth in high-tech manufacturing industries over the last few decades, especially in countries like Japan, renowned for its advances in the sector, we expected many ICT companies to have been pursuing IPOs. These aspects and blurred sector lines prompted us to once again investigate the impact of patent signals on IPO performance, using an updated data sample including ICT companies. We apply the same research model to the new data set, to test the same hypotheses.

In this robustness check, we follow the new manufacturing classification method in the Bertoni et al. (2011) paper displayed in Table 5. Our new data set includes companies in ICT industries such as software, Internet, information technology, and telecommunications, all also defined as high-tech. With the addition of ICT to our sample, the total number of companies came to 387. ICT accounts for 20% of all companies in the sample and 27.90% of high-tech companies.

Table 5.
New Manufacturing Classification

High-tech Industries	Low-tech Industries
Aerospace	Rubber and Plastic Products
Computer and office machinery	Shipbuilding
Electronics & communications	Other Manufacturing
Pharmaceuticals	Non-ferrous Metal
Scientific instruments	Non-metallic mineral products
Motor Vehicles	Fabricated metal products
Electrical Machinery	Petroleum refining
Chemicals	Ferrous Metal
Other Transport Equipment	Paper Printing
Non-electrical Equipment	Textile and Clothing
Software	Food, Beverage, and Tobacco
Internet	Wood Product
Information Technology	
Telecommunication	

Table 6 summarizes the test results for our hypotheses under the new data set in the study. Model 3 illustrates the general impact of patents' signaling effect on IPO performance, and Model 4 its impact on IPO performance across both high- and low-tech industries. In short, we find that the regression results from the new data set also support each of our hypotheses.

We find qualified support for Hypothesis 1 in Model 3, where Ln(Patent +1) receives a positive (0.0668) and significant (P-value<0.1) coefficient. This indicates that the greater the patent activity was before an IPO, as measured by the total number of patent applications in the five years before going public, the better the resulting IPO performance was. We can estimate that each additional log patent application increases the total proceeds by 6.68%, other factors remaining fixed. In both data samples, the effect of the patent signal is the same: positive and significant. We conclude that, in general, the manufacturing companies leveraged patent applications to achieve better IPO performance.

Table 6.
Robustness Test Results

Variable	Model 3 (H1)	Model 4 (H 2a&H2b)
Intercept	10.0932***	9.7081***
	(0.689)	(0.678)
Ln(Patent+1)	0.0668*	
	(0.037)	
High_tech*Ln(Patent+1)		-0.0773**
		(0.033)
Low_tech*Ln(Patent+1)		0.1016**
		(0.042)
Ln(Total Asset)	0.3427***	0.3610**
	(0.048)	(0.048)
Ln(Age at IPO)	-0.6507***	-0.5810***
	(0.080)	(0.081)
Debt Ratio	0.0531	0.0757
	(0.167)	(0.167)
Underpricing	-0.0023***	-0.0022**
	(0.001)	(0.001)
UW Dummy	0.3906***	0.3985***
	(0.129)	(0.130)
STOCK Dummy	0.9309***	0.9205***
	(0.176)	(0.173)
High_tech Dummy	5.3055***	4.3980***
	(0.176)	(0.347)
Low_Tech Dummy	4.786***	4.3980***
	(0.357)	(0.360)
Year Dummies	Yes	Yes
F-Value	31.35***	28.82***
Observation	378	378
Adjust R^2	0.378	0.433

*Note: Value are regression coefficients with standard errors in parentheses; *p<0.1, **p<0.05, ***p<0.01.*

Model 4 shows how patent activities affected IPO performance differently between high- and low-tech industries. First, the negative (-0.0773) and significant coefficient estimates (p<0.05) for the interaction term (Ln(Patent+1)*High-tech) indicate that, for firms with advanced technology, increasing patent activity reduced the capital raised at the IPO. The result supports Hypothesis 2a: All other conditions being equal, for low-tech companies, there will be a positive relationship between the amount of patent activities before an IPO and the resulting IPO performance. Conversely, the positive (0.1016) and significant (P-value<0.05) coefficient of the interaction term (Ln(Patents+1)*Low-tech) suggests that, for low-tech firms, increasing patent activity before an IPO will increase the capital raised at the IPO.

The result of the regression supports Hypothesis 2b: All other conditions being equal, for high-tech companies, there will be a negative relationship between the amount of patent activity before an IPO and the resulting IPO performance. Model 4 represents the impact patent signals had on the IPO performance of companies in the high-tech sector, including ICT. The coefficient in Model 4 (-0.0773) is more negative than that in Model 2 (-0.0585), other conditions being equal. This signifies that the patent signal in the new data set further reduced, severely, the capital raised at the IPO.

ICT industries have tended to be characterized by swift technological changes and a short effective lifespan for innovation (Useche 2015). As a result, patents may not effectively reward innovation, and outside investors may not seriously consider patents as a proxy for evaluating firms' quality and potential. Additionally, technology in ICT is complex by nature; many patents may be filed for each innovation project, often relating to other patents in a different innovation project. Since ICT companies may undertake many projects at once, grasping their patent portfolios may be a challenging task for many investors. Hence, signals can potentially negatively affect IPO performance for ICT companies in particular, and high-tech companies in general.

In low-tech industries, patents could help firms increase the amount of capital raised through an IPO. A one-unit increase in log patents raised the total proceeds in the sample by 10.16%. However, in industries characterized by advanced technology such as ICT, patents are associated with a reduction in the money raised from investors at the IPO. For high-tech companies, a one-unit increase in log patents correlated with a 7.73 % decrease in the total proceeds. While this figure seems small, it can translate to a significant amount of money in real life. Therefore, high-tech firms with complicated patent portfolios ought to exercise caution when using patents as signals. To fully benefit from the power of signals, they should adjust their patent strategies and combine it with other proxies investors could more easily interpret.

6. Discussion and Conclusion

Previous literature pointed to signaling as an important and effective mechanism to reduce information asymmetry between a company and outside stakeholders. Our study adds to these insights by studying the patent signal and its effect on one of the most significant events in a firm's life: the IPO. We assert that firms adjust their patent strategies and increase the number of patents they file as the IPO date draws near, to signal the quality of their enterprise. To maximize their IPO performance, companies usually seek an internal proxy that can signal their potential value to outsiders. Theoretically, patents are property rights that protect an invention and prevent infringement from rivals. Since patents are costly to obtain and observable and verifiable by outsiders, they are also clearly applicable as a signal for company performance.

High-tech companies' technologies tend to be complex by nature; one invention may comprise a large number of patentable elements. Their innovations are much less comprehensible to outside observers than to insiders, as historical patent data offers little guidance in assessing the prospects of their present patent activities. In attempting to interpret the value of an invention, outside investors should be knowledgeable about the underlying technology; all patents associated with the invention and their relationships; and how the patents relate to other similar inventions. In addition, investors should have a grasp on the company's innovation projects overall, to be able to discern which inventions are likely to generate profits in the future, and the potential timeframe for a return on their investment.

These considerations suggest that informational frictions are more severe with regard to high-tech firms, as IPO investors may not be able to fully interpret the rich information the patent system provides on the quality of firms' technologies. In this context, patents may not reduce information asymmetries associated with innovation activities. Investors are likely reluctant to lend their money to high-tech firms with a complicated patent portfolio, figuring they may be eager to allocate excessive resources to innovation projects which are risky and highly intangible.

By contrast, most companies in the low-tech sector tend to have simpler innovation portfolios, consisting of relatively few patentable elements, which makes the assessment of patent activities considerably easier for outsiders. Low-tech firms seem to allocate resources in a balanced manner between intangible assets for innovation projects and tangible assets such as plant and machinery equipment, which are essential for their daily operations. This balanced approach to resource allocation likely gives investors confidence in firms' long-term development and helps them view patents as a signal for company quality.

Consequently, low-tech firms may raise more investments via an IPO than high-tech firms that do not significantly benefit from patent signals.

As a final note, this study has limitations which may offer fruitful directions for future research.

First, our approach in measuring some of the control variables was less precise than desired, limiting the number of tests that could be performed to verify some of our hypotheses. However, the qualitative and intangible nature of many of the variables makes this limitation difficult to avoid.

Second, some degree of simultaneity bias might have occurred in our research. Future research should take into account endogeneity problems which may arise for self-selection bias, and simultaneity between the number of patent applications prior to IPO and IPO performance measured via proceed money.

Third, investors may consider both the quality and quantity of patents, rather than one or the other, in evaluating a company's patent activities. The absence of qualitative considerations may have affected our findings, as we used application counts as the only measurement of patent activity. Future research may benefit from a more detailed assessment of a variety of quality indicators—such as patent claim, patent citation, and patent family (IPC)—to propose a broader approach to patent signaling values.

Despite these limitations, our study contributes in several ways to the current understanding of signaling theory. To our knowledge, ours is the first study specifically investigating the signaling value of Japanese patent applications. Moreover, while previous works provided evidence on the signaling function of patents among startups in a limited number of industries, our research paints a more holistic picture, encompassing all Japanese manufacturing companies across sectors. This research also provides new insights into the role of patents as an effective signal of firms' performance to IPO investors amid information friction between the two parties. Lastly, we present fresh evidence that the effect of the patent signal on IPO outcomes could depend on the technology intensity of a company's industry. While its benefit may be negligible among high-tech companies, low-tech firms may profit greatly and enjoy an increased likelihood of attracting external financing through an IPO.

Further research addressing the limitations of our study and validating our findings could greatly benefit international economic scholarship.

References

Al-Shammari, H. A., Ross, O. W., & Yousuf, H. A. (2013). Firm internationalization and IPO firm performance: The moderating effects of firm ownership structure. *International Journal of Commerce and Management*, *23*(3), 242–261.

Arora, N., & Singh, B. (2019). Impact of Auditor and Underwriter Reputation on Underpricing of SME IPOs in India. *Management and Labour Studies*, *44*(2), 193–208.

Artz, K. W., Norman, P. M., Hatfield, D. E., & Cardinal, L. B. (2010). A longitudinal study of the impact of R&D, patents, and product innovation on firm performance. *The Journal of Product Innovation Management*, *27*(5), 725–740.

Barth, M. E., & Kasznik, R. (1999). Share repurchases and intangible assets. *Journal of Accounting and Economics*, *28*(2), 211–241.

Basir, N. (2020). Reputation Enhancing Through Patent Portfolios: An Exploration of Lapsed Patents and IPOS. *Corporate Reputation Review*, *23*(1), 42–56.

Baum, H. S. (2000). Fantasies and Realities in University-Community Partnerships. *Journal of Planning Education and Research*, *20*(2), 234–246.

Beatty, R. P. (1989). Auditor Reputation and the Pricing of Initial Public Offerings. *The Accounting Review*, *64*(4), 693–709.

Bruton, G. D., Chahine, S., & Filatotchev, I. (2009). Founders, Private Equity Investors, and Underpricing in Entrepreneurial IPOs.

Entrepreneurship Theory and Practice, *33*(4), 909–928.

Certo, S. T., Daily, C. M., & Dalton, D. R. (2001). Signaling Firm Value through Board Structure: An Investigation of Initial Public Offerings. *Entrepreneurship Theory and Practice*, *26*(2), 33–50.

Chan, K. H., Mo, P. L. L., & Zhang, W. (2021). Do Abnormal IPO Audit Fees Signal IPO Audit Quality and Post-IPO Performance? A Principal-Agent Analysis Based on Evidence from China. *Journal of International Accounting Research*, *20*(1), 1–29.

Cohen, B. D., & Dean, T. J. (2005). Information asymmetry and investor valuation of IPOs: top management team legitimacy as a capital market signal. *Strategic Management Journal*, *26*(7), 683–690.

Cohen, W., Nelson, R., & Walsh, J. (2000). *Protecting Their Intellectual Assets: Appropriability Conditions and Why U.S. Manufacturing Firms Patent (or Not)*. doi: 10.3386/w7552.

Coursey, C. C. (2009). Battling the patent troll: tips for defending patent infringement claims by non-manufacturing patentees. *The American Journal of Trial Advocacy*, *33*, 237.

Deeds, D. L., Decarolis, D., & Coombs, J. E. (1997). The impact of firmspecific capabilities on the amount of capital raised in an initial public offering: Evidence from the biotechnology industry. *Journal of Business Venturing*, *12*(1), 31–46.

Eisenhardt, K. M., & Schoonhoven, C. B. (1990). Organizational Growth: Linking Founding Team, Strategy, Environment, and Growth Among U.S. Semiconductor Ventures, 1978-1988. *Administrative Science Quarterly*, *35*(3), 504–529.

Feldman, R., & Frondorf, E. (2015). Patent demands and initial public offerings. *Stan. Tech. L. Rev.*, *19*, 52.

Gomulya, D., Jin, K., Lee, P. M., & Pollock, T. G. (2019). Crossed wires: Endorsement signals and the effects of IPO firm delistings on venture capitalists' reputations. *Academy of Management Journal. Academy of Management*, *62*(3), 641–666.

Graham, S. J. H., & Sichelman, T. (2008). Why do start-ups patent. *Berkeley Tech. LJ*, *23*, 1063.

Guiso, L. (1998). High-tech firms and credit rationing. *Journal of Economic Behavior & Organization*, *35*(1), 39–59.

Gujarati, D. N., & Porter, D. C. (1999). *Essentials of econometrics* (Vol. 2). Irwin/McGraw-Hill Singapore.

Hall, B. H., & Ziedonis, R. H. (2001). The Patent Paradox Revisited: An Empirical Study of Patenting in the U.S. Semiconductor Industry, 1979-1995. *The Rand Journal of Economics*, *32*(1), 101–128.

Heeley, M. B., Matusik, S. F., & Jain, N. (2007). Innovation, Appropriability, And The Underpricing Of Initial Public Offerings. *Academy of Management Journal*, *50*(1), 209–225.

Higgins, M. C., & Gulati, R. (2001). *Getting off to a good start: the effects of top management team affiliations on prestige of investment bank and IPO success*. Working paper.

Higgins, M. C., & Gulati, R. (2006). Stacking the deck: the effects of top management backgrounds on investor decisions. *Strategic Management Journal*, *27*(1), 1–25.

Higgins, M. J., Stephan, P. E., & Thursby, J. G. (2011). Conveying quality and value in emerging industries: Star scientists and the role of signals in biotechnology. *Research Policy*, *40*(4), 605–617.

Hsu, D. H., & Ziedonis, R. H. (2008). Patents As Quality Signals For Entrepreneurial Ventures. *Proceedings: A Conference of the American Medical Informatics Association / ... AMIA Annual Fall Symposium. AMIA Fall Symposium*, *2008*(1), 1–6.

Johan, S. A. (2010). Listing standards as a signal of IPO preparedness and quality. *International Review of Law and Economics*, *30*(2), 128–144.

Lange, J. E., Bygrave, W., Nishimoto, S., Roedel, J., & Stock, W. (2001). Smart money? The impact of having top venture capital investors and underwriters backing a venture. *Venture Capital*, *3*(4), 309–326.

Lemley, M. (n.d.). *Reconceiving Patents in the Age of*

Venture Capital. doi: 10.31235/osf.io/sdtmj

Lemley, M. A. (2000). Rational ignorance at the patent office. *Nw. UL Rev.*, *95*, 1495.

Leone, A. J., Rock, S. K., & Willenborg, M. (n.d.). Disclosure of Intended Use of Proceeds and Underpricing in Initial Public Offerings. In *SSRN Electronic Journal*. doi: 10.2139/ssrn.384620.

Levin, R. C., Klevorick, A. K., Nelson, R. R., Winter, S. G., Gilbert, R., & Griliches, Z. (1987). Appropriating the Returns from Industrial Research and Development. *Brookings Papers on Economic Activity*, *1987*(3), 783–831.

Long, C. (2002). Patent Signals. *The University of Chicago Law Review. University of Chicago. Law School*, *69*(2), 625–679.

Megginson, W. L., & Weiss, K. A. (1991). Venture capitalist certification in initial public offerings. *The Journal of Finance*, *46*(3), 879–903.

Megginson, W. L., & Weiss, K. A. (1991). Venture capitalist certification in initial public offerings. *The Journal of Finance*, *46*(3), 879–903.

Motohashi, K. (2008). Licensing or not licensing? An empirical analysis of the strategic use of patents by Japanese firms. *Research Policy*, *37*(9), 1548–1555.

Ozmel, U., Reuer, J. J., & Gulati, R. (2013). Signals across Multiple Networks: How Venture Capital and Alliance Networks Affect Interorganizational Collaboration. *Academy of Management Journal*, *56*(3), 852–866.

Pukthuanthong-Le, K., & Walker, T. (n.d.). *Pre-IPO insider ownership and underpricing: High-tech versus low-tech IPOs*. Retrieved August 12, 2021, from http://www.financialdecisionsonline.org/current/PukthuanghongWalkerSummer2008.pdf

Ritter, J. R., & Welch, I. (2002). A review of IPO activity, pricing, and allocations. *The Journal of Finance*, *57*(4), 1795–1828.

Stuart, T. E., Hoang, H., & Hybels, R. C. (1999). Interorganizational Endorsements and the Performance of Entrepreneurial Ventures. *Administrative Science Quarterly*, *44*(2), 315–349.

Useche, D. (2014). Are patents signals for the IPO market? An EU–US comparison for the software industry. *Research Policy*, *43*(8), 1299–1311.

Zhou, L. (jolly), & Sadeghi, M. (2019). The impact of innovation on IPO short-term performance – Evidence from the Chinese markets. *Pacific-Basin Finance Journal*, *53*, 208–235.

Ziedonis, R. H. (2004). Don't Fence Me In: Fragmented Markets for Technology and the Patent Acquisition Strategies of Firms. *Management Science*, *50*(6), 804–820.

Appendix 1.
TSE New Industry Code

Manufacturing	Non-Manufacturing
1. Construction	1. Electric Power & Gas
2. Foods	2. Land Transportation
3. Textiles & Apparels	3. Marine Transportation
4. Pulp & Paper	4. Air Transportation
5. Chemicals	5. Warehousing and Harbor Transportation
6. Pharmaceutical	6. Information & Communication
7. Oil & Coal Products	7. Wholesale Trade
8. Rubber Products	8. Retail Trade
9. Glass & Ceramic Products	9. Banks
10. Iron & Steel	10.Securities & Commodity Futures
11. Nonferrous Metals	11.Insurance
12. Metal Products	12.Other Financing Business
13.Electric Appliances	13. Real Estate
14.Transport Equipment	14. Service
15.Precision Instruments	15. Unclassifiable
16.Other Products	

Appendix 2.
Summary Of Varaiables And Expected Sign

Variable	Definition	Expected Sign
Independent Variable:		
LN(Patent +1)	Natural Logarithm of Number of patents applied for by the firm in last five years until IPO;	+
LN(Patent+1)*High -tech	The interaction between High-tech Dummy and Natural Logarithm of Number of patents applied for by the firm in last five years until IPO	-
LN(Patent+1)*Low -tech	The interaction between Low-tech Dummy and Natural Logarithm of Number of patents applied for by the firm in last five years until IPO	+
Dependent Variable:		
LN(Total Proceed)	Natural Logarithm of Total proceeds: the total amount of money collected at IPO;	

Control Variable:		
LN(Total Asset)	Natural Logarithm firm assets in one year prior to the IPO;	+
LN(Age)	Natural Logarithm of the difference in years between IPO year and the firm's founding year;	+
Debt Ratio	The ratio between Total Debt and Total Asset of the company in the year before IPO;	+
Underpricing	Underpricing is measured as the percentage change in stock price during the first day of trading for the IPO;	-
UW Dummy	Dummy variable assigned a value of 1 if the underwriter for the IPO company is one of these three underwriters in Japan: Daiwa Securities, Nomura Securities, SMBC Nikko Securities, and 0 otherwise;	+
STOCK Dummy	Dummy variable assigned a value of 1 if the IPO company listed in TSE1 and TSE2, otherwise;	+
High-tech Dummy	Dummy variable assigned a value of 1 if IPO company is High-tech company and 0 otherwise;	+
Low-tech Dummy	Dummy variable assigned a value of 1 if IPO company is Low-tech company and 0 otherwise;	+
Year Dummies	Dummies years from 'Year2000' to 'Year2015' to account for IPO years	