Valuation of Patents using Stock Market Responses

By

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Professor Brian Wright, Chair
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Abstract

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Patent valuation is of vital importance. This dissertation develops two patent valuation measures using abnormal stock market returns to patentee firms in time windows around grant and publication, respectively. The methodologies innovatively involve dynamics in the probability of grant, provide a way to estimate the patent value as early as the publication of the patent applications, and extend the valuation focus from patents to abandoned patent applications. The results provide important insights on the value of patents at publication and at grant, and the value of abandoned patent applications at publication. The results also shed light on the distribution of aggregate patent value, which has great potential to be used in R&D accounting. Moreover, the dissertation provides important and interesting findings about the relationship between patent value and grant lag. Furthermore, the dissertation also has important inferences on information flow in the patent application process at the USPTO.

The measure of value at grant extends Kogan, Papanikolaou, Seru, and Stoffman (2017) (hereafter KPSS) to take advantage of information made available by the switch (for most publications) from publication at grant to publication eighteen months from filing. It uses a dynamic model on the changing probability of grant of a patent application as the lag from publication increases. Further, it focuses on sole-grant patents: the patents that are granted as the only patent for its assignee on the day of grant. The measure of value at publication is a unique contribution of this dissertation. I use it to measure the value of both patents and abandoned applications.

The results show that if the dynamic decline in grant probability is ignored, as in KPSS, the average value of patents is overestimated by over 50%. The bias varies with the grant lag. However, with a dynamic probability of grant, the distributions of the value of patents with pre-grant publication and the value of patents for which the patentee opts to forego foreign applications in exchange for the right to delay publication until grant are similar. Moreover, with a dynamic probability of grant, the distributions of patent values at publication and patent values at grant are very similar. This implies that the market is risk-neutral and rational, and on average makes good patent value estimations at publication and grant.

I use the estimated value to explore the relationship between patent value and the lag from publication. I find that (1) patent value at publication is not correlated with grant lag, indicating that the market participants cannot predict how long it will take for a patent application to get granted given the information available at the time of publication; (2) if the dynamic decline in grant probability is ignored (as in KPSS), the value of patents increases with the grant lag, (3) with a dynamic probability of grant, the value of patents does not tend to increase with grant lag. Indeed, the value tends to decrease modestly with lag from publication. In other words, more valuable patents tend to be granted somewhat earlier than less valuable ones.

I explore the distribution of aggregate value and its potential for R&D accounting. I find that even if the estimate of value for each patent can have errors, according to the Central Limit Theorem, the aggregate value of patents can be quite accurate, with a narrow 95% confidence interval. Back-of-the-envelope calculations of aggregate patent value by year and aggregate patent value by CPC section are provided. This finding is important in providing crucial empirical verification for the validity of the KPSS model of patent valuation, as modified to include dynamic evolution of the probability of grant.

The distribution of the value of patents and the value of abandoned applications at publication are similar, although the value of abandoned applications tends to be slightly lower than the value of granted patents. Most of the differences in distribution happen on the low-value part, while the high-value part of the distribution is very similar. This similarity still holds when controlling for the year of filing, CPC section, and assignee firm. The results suggest that the value of patent applications at publication is not importantly correlated with the probability of grant. This indicates that stock market participants cannot predict with accuracy at the time of publication whether a patent application will be granted or not. However, upon publication, they can make a virtually unbiased prediction of application value if granted. It also implies that when making decisions on patent grants, the USPTO focuses on patent validity, instead of patent value conditional on grant.

The dissertation also has important inferences on information flow in the patent application process at the USPTO. I find that publication and grant are the two important events with information flow on patent value and probability of grant. At the time of publication, market participants form an initial estimation of patent value but cannot predict whether a patent application will be granted or not. At the time of grant, the market participants update the probability of grant to 100% and update their patent value estimation based on the final version of the patent and other available information. Before publication, there is little information flow because of the lack of information on the existence and the details of patent applications. After publication and before grant, the conditional probability of grant decrease with the time lag from publication but there is little information flow about patent value since the market participants cannot obtain access to real-time updates on patent application details without significant extra efforts or private information sources.

Table of Contents

List of Figures

List of Tables

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1 Introduction

1.1 Motivation

Patents have long been an important measure of innovation productivity. However, the number of patents alone, a popular measure, is not a sufficient measure since different patents can have very different values. To value patents, there are multiple measurement strategies. These include (1) using citations as a proxy; (2) using payments to issue the patent and payments to maintain the patent at 4 years, 8 years, and 12 years from the patent grant as measures of minimum conditional expectations of future value at 4 years, 8 years, and 12 years from grant; (3) value from sales/auctions of patents; (4) license revenue. Each of these has significant problems. More specifically, to get a value measure, citations need to be converted to dollar value, and this step can introduce considerable complexity and bias. Using the payments for patent issues and renewal fees only provides a lower bound of the patent value and this lower bound can be much smaller than the actual patent value in many cases. Sales/auctions of patents are rare and license revenue is frequently confidential information not available to the public.

Coming up with a more accurate measure that enables comparisons across time and fields has become more and more important as innovations have become an increasingly important part of a firm's capital stock, crucial for its success. Kogan, Papanikolaou, Seru, and Stoffman (2017) (hereafter KPSS) develops a model to estimate the value of patents by measuring the stock market responses around patent grants. However, KPSS gives only one value estimate for each patent and the value estimates are difficult to validate without external sources.

This dissertation attempts to provide a more accurate measure of the economic value of patents at grant and develop a new measure of the value of patent applications at publication, for both patented and unpatented applications, by assessing the stock market response of the focal firm around the patent event dates, including both patent grant and patent application publication. With estimates of the value of the granted patent at grant and the value of the granted patent estimated at the prior publication of its application prior, I can compare the two measures and provide crucial empirical verification of the validity of crucial assumptions of the model of patent valuation in KPSS.

In this dissertation, I am also interested in estimating aggregate patent value, which can be very useful for R&D accounting. With the individual patent value estimates generated in this study, I can then explore the distribution of the aggregate value of these patents, test for its accuracy, and do back-of-the-envelope calculations to show the total annual value of patents granted, their changes over time, and distribution across different fields.

This dissertation also attempts to take a closer look at the abandoned applications, which have received little attention. I am interested in whether the market participants can predict which patent applications are more likely to be abandoned, what is the value of abandoned applications if granted, and what is the remaining value of abandoned applications after abandoned. Answering these questions can improve the understanding of patent application value, as well as the USPTO decision criteria.

Finally, the dissertation attempts to explore the information flow during the patent application process at the USPTO. It is worth exploring when market participants generate their estimates of patent value and probability of grant, as well as when and how these estimates are updated. Answering these questions will shed light on the understanding of information flow in the patent application process.

The dissertation explores the research questions discussed above and the empirical results reveal important and interesting findings.

1.2 Background

First, some background on patents and the patent application process in the United States. A patent gives its owner the right to sue for infringement of anyone who makes, uses, sells, or offers the invention in the country where the patent has been issued, or imports, or offers to import the invention into that country (35 U.S.C. § 271). The patent holder makes the innovation public in exchange for a temporary monopoly right.

Patents are widely used as a measure of innovation output. Millions of patent applications have been filed and approved in the past few decades. The number of patent applications is increasing significantly over time. In the United States, the responsible department is the United States Patent and Trademark Office (USPTO). To obtain a patent for an invention, the inventor files an application at the USPTO. It is worth noting that the "first to file" policy applies: the inventor must be the first to file an application on a specific invention to be eligible for a patent on the invention. After receiving the patent application, the USPTO assigns the application to an examiner in that specific field. The assigned examiner reviews the application, makes the first office action decision, and communicates that decision to the applicant, who must respond within a given period. During the process, the applicant has the right to abandon the application at any time. Most applications will be published by the USPTO within 18 months from application filing. All publications occur on Thursdays. Before grant, there are usually one or more rounds of interactions between the examiner and the applicant. If a patent application is accepted, the grant information is released to the public on a Tuesday at midnight Eastern time.

Austin (1993) is the first to use stock market responses to explore the effect of patent grants on patent-holding firms and their rivals, using patent data on large biotechnology firms. The data sample is very small, with less than 200 patents, and the results are mostly qualitative. However, the idea is innovative and inspires further studies. Hall, Jaffe, and Trajtenberg (2005) find a significant positive effect of patent citations on a firm's market value by estimating Tobin's Q equations on citations to the firm's patents. However, instead of using daily stock market data, they use lower-frequency data and are not able to identify the value of individual patents. Patel and Ward (2011) relate firms' market return on equity to information about patent citation patterns. Using an event study method, they obtain the dollar value of patent citations to the patent-owning firm. They are innovative in using the daily CRSP security returns to measure abnormal returns due to patent-relevant events.

KPSS measures the economic value of patents by extracting the grant-related part of abnormal stock market returns in a three-day time window starting from the patent grant date and then scaling it by a constant. This method implicitly assumes that all patent applications have the same probability of grant. Grant is determined purely by luck, not by observable indicators of quality. This method also implicitly assumes that the value of grant is known before the application is revealed at publication, which for most of the sample used by KPSS occurs simultaneously with grant.

1.3 Contributions

Extending KPSS, I incorporate the dynamics in the probability of grant and construct a model to estimate patent value from abnormal stock market returns to the patentee firm in a window around grant. In contrast to KPSS, but more consistent with their basic methodology, I focus on sole-grant patents: the patents that are granted as the only patent for its assignee on the day of grant. Unlike KPSS, I recognize the changing probability of grant of a patent application as the lag from publication increases. I find that the probability of grant changes considerably with the time lag between publication and grant. As the time lag increases, the probability that the application will ever be granted decreases. If the dynamic decline in grant probability is ignored, as in KPSS, the value of sole-grant patents is overestimated by over 50% on average. The bias varies with the grant lag.

I then use the estimated value to explore the relationship between patent value and the lag from publication. If the dynamic decline in grant probability is ignored (as in KPSS), the value of patents increases with the grant lag, in other words, apparently more valuable patents take longer to be granted than less valuable ones, supporting the finding of Johnson and Popp (2003), and Popp et al. (2004), etc. However, after recognizing the dynamics of the probability of grant, the results show that the value of patents does not tend to increase with grant lag. Indeed, the value tends to decrease modestly with lag from publication. In other words, more valuable patents tend to be granted earlier than less valuable ones. This finding supports the findings of Regibeau and Rockett (2009), Harhoff and Wagner (2009), etc.

Moreover, I compare the value of patents with a pre-grant publication with patents for which the patentee opts to forego foreign applications in exchange for the right to delay publication until granted. The results show that the effects of grant on published and unpublished patents are different. For published patents, since they are already known to the public due to their prior publication, at grant, the market participants update the probability of grant to one and update the value of patent estimation to reflect the changes between publication and grant. On the other hand, for unpublished patents, since they are never published before grant, market participants appear to have very little information on their existence, much less the details, and thus cannot form an initial probability of grant and value of patent estimation before grant. At grant, the market participants realize the existence of the patent, set the probability of grant to one, and form a value estimation of the patent. Thus, different grant effects apply to published and unpublished patents, and different methodologies need to be used in the valuation of published and unpublished patents using stock market response at grant. The results also show that, when appropriate methodologies are used, the distributions of published and unpublished patent values appear very similar. This finding has important implications for KPSS. In KPSS, most patents are filed before Nov 29, 2000, and thus are not required to publish before grant, while the others are filed on or after Nov 29, 2000, and thus are required to either publish before grant or forego foreign applications in exchange for the right to delay publication until grant. KPSS treats the two sets of patents with the same methodology. However, according to the findings in this dissertation, it is inappropriate.

I then expand my focus beyond patent grant, to another important patent event, patent application publication. According to the requirement of the American Inventor's Protection Act (AIPA), most patent applications, with few exceptions, filed on or after Nov 29, 2000, are published by 18 months from filing. At the time of publication, patent application files are made available to the public, so the market can obtain detailed information about a patent application, even before it is granted or abandoned. Thus, patent application publication is an important event to study. However, the effects of patent application publication have not been given much attention in the literature.

I examine the information flow around the date of patent publication and develop a second patent value measure based on abnormal stock market response in the publication window. The results reveal important information about how and when the stock market obtains knowledge about the value of the invention if patented. The results show that the patent publication event is of vital importance. The patent publication is the time point when the public gains accurate information about the value of the invention and the value of its patent if granted and generates their initial estimate of patent value.

I then combine the results with those about patent grant and compare the two patent value measures: value at grant and value at publication. I find that after including the dynamics of the probability of grant, patent value at publication and value at grant are similar, especially for the high-value patents that account for over 90% of the aggregate value. This implies that the market is risk-neutral and rational, and on average makes good patent value estimates at publication and grant. This finding is important in providing crucial empirical verification for the validity of the KPSS patent valuation approach using stock market responses, as modified to include dynamic evolution of the probability of grant and restricted to sole-event publication and grant observations. (KPSS provides just one value estimate for each patent, so the validation of their results must rely on other sources of patent value information, which are difficult to obtain for large samples.) My study develops two value estimates focusing on different patent events. The two estimates turn out to give different but virtually unbiased results for individual patents, and very accurate aggregate results. This provides strong support for the validity of the overall approach I use for estimating patent value from stock market responses.

I also investigate the relationship between patent value at publication and grant lag and find that patent value at publication is not correlated with grant lag, indicating that the market participants cannot predict how long it will take for a patent application to get granted based on the information available at the time of publication.

I also explore the distribution of aggregate value and discuss its potential for R&D accounting. I find that most of the aggregate patent value comes from high-value patents. The 20% highest value patents contribute to over 80% of aggregate patent value while the 20% least valuable patents contribute less than 1%. I also establish that, using the methodology of this study, even though the estimated value of individual patents are highly variable, for large samples the aggregate value of patents can be quite accurate, consistent with the Central Limit Theorem. This finding has important potential in R&D accounting. The methodology presented here has the advantage of high accuracy and high flexibility. It can be used to account for the value of patented R&D for individual firms, for a certain sector, for a certain year, or even for a nation. As an example, I did back-of-the-envelope calculations of aggregate patent value by year and aggregate patent value by CPC section. The results shed light on aggregate patent value amount, its change over time, and its distribution across sections.

Then I extend my focus from successful patent applications to failed patent applications, revealed as abandoned applications. This group of patent applications has received little attention in the literature but can play an important role in understanding the information flow associated with the patent decision-making process. I measure the value at publication, conditional on grant, of these subsequently abandoned applications. I find the distributions of the value of patented applications and the value of abandoned applications at publication are similar, while the value of abandoned applications tends to be slightly smaller than the value of patented applications. Most of the difference in value occurs in the lowest 20th percentiles. The remainder of the value distributions are very similar. This similarity in value distributions still holds when controlling for the year of filing, section, and assignee firm.

The results suggest that the underlying value of patent applications conditional on grant does not depend importantly on whether they are later granted or not. In other words, the value of patent applications at publication is essentially uncorrelated with the probability of grant. This indicates the stock market participants cannot predict with accuracy at the time of publication whether a patent application will be granted or not. It also implies that the USPTO patent examiners, when making decisions on patent grants, focus on patent validity, instead of patent value conditional on grant, consistent with the citations-based inferences of Sun and Wright (2022).

I develop a simplified model and use empirical data to test whether a patent application after it is abandoned, has any private value to the firm that owns it. The results show that patent applications, after abandonment, have very low, if any, private value for the firm that owns them[1]. The findings have important implications for patent-relevant studies and policy analysis.

[1] There is little related evidence about the implications of failure to receive a patent. In a survey of Australian firms, Webster and Jensen (2011) find that patentees persist in the development of many inventions even if the patent application is rejected.

Last but not least, this dissertation has important implications for information flow during the patent application process at the USPTO. The results indicate that, at the time of publication, market participants form an initial estimate of the value of the invention but cannot predict whether a patent application will be granted or not. At the time of grant, the market participants update the probability of grant to one and update their patent value estimate based on the final version of the patent and other available information (e.g., remaining patent life, pre-grant citations, etc.). Before publication, market participants appear to have very little information on the existence, much less the details, of patent applications. After publication and before grant, the conditional probability of grant decreases with the time lag from publication but there is little other information flow relevant to patent value since the market participants cannot obtain access to real-time updates on patent application details (e.g., changes in claims, interactions with the USTPO examiner) without significant extra effort or access to private information sources.

1.4 Structure of the Dissertation

The remainder of the dissertation is structured as follows. Chapter 2 describes the construction of the data set. Chapter 3 sets up my dynamic patent valuation framework and estimates the value at grant, producing new results regarding the relation of patent value to grant lag, the distribution of aggregate patent value, and the relative value of patents to patentees who opt to delay publication until grant. Chapter 4 develops a new methodology and estimates the patent value at publication, providing new results regarding the comparison of patent value at grant and patent value at publication, the relation between the patent value at publication and grant lag, and back-of-the-envelope calculations of aggregate patent value by year and by CPC section. Chapter 5 measure the value of abandoned applications at the time of publication, providing new findings on the value comparison of abandoned and patented applications, and providing inferences on the USPTO patenting process, market participants' ability to predict patent grant, and private value of an application after its abandonment. Chapter 6 summarizes the important inferences on information flow in the patent application process at the USPTO, provides explanations of the reasoning behind the inferences, and refers to the supporting evidence of the inferences using empirical results in Chapters 3, 4, and 5.

2 Data

This chapter describes the data source and data pre-processing. It includes two major parts: (1) filtering for the patents of interest and matching patents with their firm assignee's permno (a unique permanent security identification number assigned by CRSP to each security), and (2) filtering and preprocessing CRSP daily stock market data.

2.1 Patent Application Data

I use the data for patent applications from USPTO Patent Examination Research Dataset (PatEx). The data contains detailed information on more than 12.5 million patent applications from the beginning of the Public Patent Application Information Retrieval (PAIR) database to mid-2022. The data covers most of the relevant information, including characteristics of inventions, applicants, assignees, patent identification number, filing date, publication date, status codes, and dates for all actions taken throughout the examination process. I focus on patent applications filed on or after 2001 since the American Inventors Protection Act (AIPA) was enacted on Nov 29, 2000. Until this date, patents were generally published on the day of the grant. Subsequently, most patent applications have been published by 18 months from filing. My project regards patent publication as an important event to study, thus using data after Nov 29, 2000, becomes essential.

Since this paper examines the stock market changes related to patenting events, identifying the firm associated with a patent application is vital. To do this, I first adopt the disambiguated assignee data for patent publications and patent grants from PatentsView, which provides state of art data on U.S. patent applications. Then I use the data of Kogan, Papanikolaou, Seru, and Stoffman (2017) (hereafter KPSS) for matching purposes (i.e., matching patents with assignee's permno code in the stock market).

In this study, I am interested only in patent applications that are

- utility patent applications;
- filed on or after Nov 29, 2000;
- either published or granted; and
- not foreign priority patent applications.

With these criteria, I am left with ~3.95 million patent applications, ~3.57 million of which are published, ~2.85 million applications are granted and ~1.09 million are abandoned.

On the other hand, I am interested only in publications/grants for which

- there is a sole assignee, and
- the assignee is a public firm.

I develop a method to match patents to public firms' permno code. I first merge KPSS and the patent data and generate matches between assignees and permno using existing information. In this initial match, some assignees are matched with more than one permno. For this paper, I need to match one assignee to only one permno. So, I use the following criteria:

- for assignees with only one permno matched, keep the match.
- for assignees with more than one permno matched, use the permno that is matched with the assignee most frequently.

Then I manually exclude some assignees that are not public firms traded on the U.S. stock market. Finally, to reduce mismatching, when one permno is matched to more than one assignee, I keep the match that appears most frequently or appears more frequently than 90% of all matches. In the end, I establish matches between 3,402 assignees and 3,251 permno.

Using these matches, I successfully match ~1.52 million patent applications with permno. More specifically, ~1.33 million patents (all granted) are matched with permno based on their assignee at grant. About 0.71 million patent applications (either granted or abandoned) are matched with permno based on their assignee at publication. For these patent applications with permno at publication matched, ~0.54 million, or 76%, are granted patents and ~0.17 million, or 24%, are abandoned applications.

The final patent application data set includes information on the application number, patent number (if applicable), filing date, publication date, grant date (if applicable), abandoned date (if applicable), assignee's name, assignee's permno, and CPC class information.

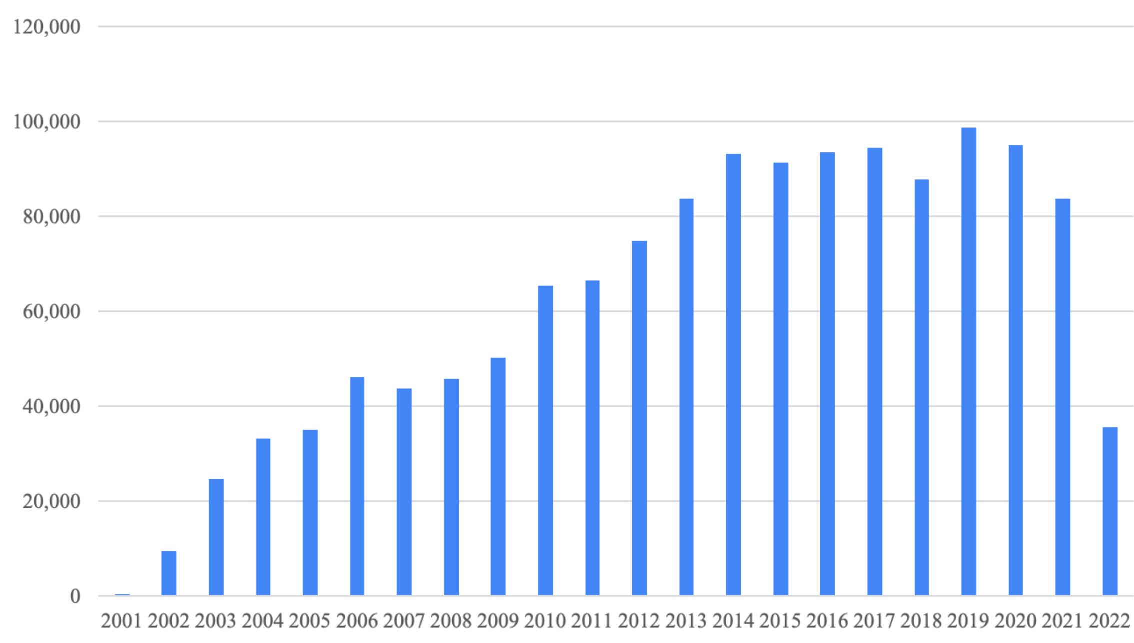

Figure 2. 1 Number of Patents Granted to U.S. Public Firms: by Year[2]

Figure 2.1 displays the number of patents granted in different years. As this study focuses

[2] This figure only includes the number of patents satisfying the selection criteria of this study. There are more patents granted each year if no selection criteria are applied.

on the patent applications filed on or after Nov 29, 2000, and the patent application process takes a long time, the number of patents granted in the first several years, i.e., 2001-2005, is relatively small. It is also noteworthy that the number of patents granted declines sharply in 2022. This is because the data set only includes patent grant data until Jun 21, 2022. The figure shows that the number of patents granted to U.S. public firms increased rapidly between 2007-2014, then remains stable at a high value, about 95,000 per year, between 2015-2020. The year 2021 experiences a slight decline in the number of patents granted. A possible reason for this decline is the pandemic.

Table 2.1 displays the number of patents in different CPC sections. The number of patents varies substantially across different CPC sections. Section G, Physics, and Section H, Electricity, have the largest number of patents, close to 500 thousand. Section D, Textiles; Paper, has the smallest number of patents, only about 4 thousand.

Table 2. 1 Number of Patents in each CPC Section

CPC Section	# of Patents[3]
A Human Necessities	114,092
B Performing Operations; Transporting	102,375
C Chemistry; Metallurgy	79,861
D Textiles; Paper	4,273
E Fixed Construction	21,923
F Mechanical Engineering; Lighting; Heating; Weapons; Blasting	61,937
G Physics	488,009
H Electricity	480,346

2.2 Daily Stock Data

I collect CRSP daily stock data for 3,306 permno from 2000/1/1 to 2022/3/31 (the latest date available in Wharton CRSP annual update). The data has 11,121,812 rows, and includes permno, date, company name (comnam), closing price (prc), trading volume (vol), holding period return (ret), share outstanding (shrout, in thousands), and value-weighted return of market portfolio (vwretd). I add three more variables:

- Abnormal return: a firm's abnormal return is defined as the firm's return minus the value-weighted return of the market portfolio.[4]

$$R = ret - vwretd \tag{2.1}$$

[3] The table only includes the number of patents satisfying the selection criteria of this study. There are more patents granted in each CPC section if no selection criteria are applied.

[4] The definition of abnormal return is adopted in KPSS to avoid estimating firms' stock market beta.

- Turnover rate (%):

$$h = (vol*100)/(shrout*1000) \tag{2.2}$$

- Capitalization (million dollars):

$$cap = prc*shrout/1{,}000 \tag{2.3}$$

3 Valuation of Patents Using Stock Market Response at Grant

3.1 Introduction

In this chapter, extending Kogan, Papanikolaou, Seru, and Stoffman (2017) (hereafter KPSS), I construct a dynamic model to estimate patent value from abnormal stock market returns to the patentee in a window around grant. In contrast to KPSS, I focus on sole-grant patents: the patents that are granted as the only patent for its assignee on the day of grant and take into consideration the changing probability of grant of a patent application as the lag from publication increases. I then use the estimated value to explore the relationship between patent value and the lag from publication. Moreover, I compare the value of patents with a pre-grant publication with patents for which the patentee opts to forego foreign applications in exchange for the right to delay publication until granted. Finally, I explore the distribution of aggregate value and talk about its potential for R&D accounting. The results of this chapter are revisited in the following chapters.

The remainder of the chapter is structured as follows. Section 3.2 sets up the analytical framework and empirical strategies I use to study the economic value of patents. Section 3.3 describes the data. Section 3.4 shows the results and briefly discusses some potential concerns that might arise. Section 3.5 provides robustness checks. Section 3.6 concludes.

3.2 Model and Methodology

I focus on three main elements. The first element is a dynamic model on the conditional probability of grant changing with the time lag between publication and grant. This dynamic model is a unique contribution of this paper and plays an essential role in patent valuation.

The second element is the event study methodology for patent valuation at grant. This part follows the lead of the seminal contribution of KPSS. In contrast to that paper, I focus on patents that are granted as the only patent to its assignee on the day of grant. In KPSS, multiple patents granted to the same assignee firm on the same date are treated as sharing the same average value. However, these patents can be very different in many ways, for example, filed in different years, with different inventors, in different CPC classes, examined by different examiners, and receiving different numbers of citations. Besides, in KPSS, all the patent grant events to a firm share the same signal-to-noise ratio. However, a multiple-grant event could have a different signal-to-noise ratio from a sole-grant event (See more details in Section 3.5.1). Focusing on sole-grant events makes the valuation of each patent more reliable and more accurate.

Third, I focus on a sample of patents issued since Nov 29, 2000, when most applications began to be published by 18 months after application. Although data used by KPSS include observations with filing dates after Nov 29, 2000, they do not recognize the implications of this change for their empirical approach, as recognized in the methodology of this paper.

3.2.1 Model Probability of Grant Dynamics

The focus here is on the conditional probability of a patent grant just before its grant; this probability is important for inferring patent value from the stock market reaction around the day of grant. I assume that the probability that a patent will ever be granted should decline over time assuming abandonment information is not known to the public in a timely fashion. Under this assumption, the model predicts that ceteris paribus, the stock market reaction on the day a patent is granted should increase with the time lag from filing to grant.

Before starting to describe the model in detail, it is important to keep in mind that grants are announced once a week, almost always on Tuesdays. An essential assumption for the model is that market participants know the market value of the patent before the announcement of the grant, at midnight of the Tuesday of the grant.

Consider a dynamic model where the market updates the conditional probability that a patent will ever be granted, on every eligible Tuesday (every Tuesday after the application is published). I continue to assume, for now, that the probability of grant on a given eligible Tuesday is the same across years in the sample (from 2000 to 2022). On the first eligible Tuesday, the patent application has the average probability of grant of all patents (the unconditional probability that the patent will ever be granted). Assume for now that abandonment of patent applications is not observed by stock market participants in a timely fashion. The validity of this assumption can be tested using empirical data.

Intuitively, after many Tuesdays have gone by if the patent application is still ungranted, observers might not know the conditional probability of grant on any given Tuesday after the first one, but they know it should be no higher than the unconditional probability. In other words, the probability that the patent will ever be granted should decline as the number of Tuesdays increases.

The model predicts that if the conditional probability that the application will ever be granted declines over time, ceteris paribus, the corresponding stock market reaction on the day the patent j is granted should increase with the number of Tuesdays, for a patent of a given value, gross of research costs. To give some intuition, consider patents granted near the last Tuesday people consider to be a conceivable grant date for a patent. When it comes to the last eligible Tuesday, almost all the applications that will ever be granted have been granted, so the probability of a later grant is negligible. Thus, for the patents that are granted near the last eligible Tuesday, the change in stock market value should be close to the total value of the patent because the conditional probability that the patent would ever be granted is so small just before midnight of the grant Tuesday. Using a universal unconditional probability of grant as in KPSS will over-value most patents substantially.

I can approximate the probability of grant dynamics using patent application data in my sample (Nov 29, 2000 – March 31, 2022).

$$\pi_t = \frac{number\ of\ applications\ granted\ on\ or\ after\ the\ t^{th}\ Tuesday}{number\ of\ all\ applications - number\ of\ applications\ granted\ before\ the\ t^{th}\ Tuesday} \tag{3.1}$$

3.2.2 Identify Patent Grant Window

To conduct the event study properly, first I need to identify the information event and choose the event window around patent grant. To guide my decision, I examine the pattern of trading volume for the stocks of firms that have published at least one patent application during the examination period (Nov 29, 2000 – March 31, 2022). I focus on the ratio of daily volume to shares outstanding, i.e., the share turnover rate, h. I compute the abnormal share turnover around patent grant, from one day before patent grant (Monday) to three days after patent grant (Friday), after adjusting for firm-year and calendar-day fixed effects.

I run the following regression and report the coefficient estimates b_l, l = -1, 0, 1, 2, 3

$$h_{ft} = a_0 + \sum_l b_l I_{ft+l} + cZ_{ft} + u_{ft} \tag{3.2}$$

where

- the indicator variable I_{ft+l} takes the value one if firm f has one or more patents granted on day $t + l$;
- the vector of controls Z_{ft} includes firm-year and calendar-day fixed effects;
- standard errors are clustered by year.

I select the grant event window as the consecutive days with positive abnormal share turnover around the patent grant date.

3.2.3 Measure Stock Market Response

After identifying the grant event window, the next step is to measure the stock market response.

In practice, a patent can be,

- granted alone as the only patent of its assignee firm on the day of grant, or
- granted with other patents with the same assignee firm on the same date.

The first case is more straightforward. As the only patent granted on that day, the stock market signal related to patents on that date is purely from that sole patent, thus the stock market response to the patent can be estimated following the method used by KPSS. The second case is harder to investigate because when multiple patents are granted on the same date, the stock market signal related to patents on that date is a mixture of signals from all the patents granted to the patentee firm on that date. It is hard to separate the signals from different patents. Thus, it becomes difficult to estimate the stock market response to each patent. KPSS uses one constant signal-to-noise ratio for both sole-grant events and multiple-grant events. The implicit assumption in KPSS is that multiple-grant events have the same signal-to-noise ratio as sole-grant events. However, in multiple-grant events, there are multiple signals related to multiple patents and only one noise term. In contrast, in sole-grant events, there is only one signal related to one patent and still one noise term. Thus, multiple-grant events should have a higher signal-to-noise ratio than sole-grant events. I test this empirically in Section 3.5.1 and the results support this point.

KPSS estimates the value of patents granted on multiple-grant events by dividing the total value related to patents by the number of patents granted on the same date. This essentially assumes patents granted to the same firm on the same date have the same value.

This assumption seems dubious for my dataset. I take a closer look at the patents granted on the same date with the same firm assignee. I find these patents can be in different fields, are often assigned to different patent examiners, and usually have different numbers of forward citations. Their lags from publication to grant are also usually different. There is no strong evidence that these patents should have the same value.

As there is currently no ideal method to separate the value of different patents granted on the same date to the same firm, let's focus for now on sole-grant patents, i.e., the patents that are the only patent granted to their assignee firm on the grant date. For these patents, I use KPSS's methodology to measure the stock market response to patent grant.

The abnormal return R of a public firm[5] in a sole-grant event window is comprised of two parts: the part that is related to the value of the patent, v, and the part that is unrelated to the patent, ε.

$$R_j = v_j + \varepsilon_j \tag{3.3}$$

where v_j is a fraction of the assignee firm's market capitalization. The change in the firm's market capitalization that is related to the patent can be obtained by multiplying v_j with the firm's market capitalization right before the event.

I assume that

- v_j is distributed according to a normal distribution truncated at 0, $v_j \sim N^+(0, \sigma^2_{vfy})$;
- ε_j is normally distributed, $\varepsilon_j \sim N(0, \sigma^2_{\varepsilon fy})$;
- Both σ^2_{vfy} and $\sigma^2_{\varepsilon fy}$ are allowed to vary proportionally across firms and years[6].

Define the signal-to-noise ratio δ as

$$\delta = \frac{\sigma^2_{vfy}}{\sigma^2_{vfy} + \sigma^2_{\varepsilon fy}} \tag{3.4}$$

Given the above assumptions, the conditional expectation of v_j on R_j is

[5] The abnormal return is defined as the firm's return minus the return on the market portfolio.
[6] The first distributional assumption is due to John Cochrane. All three assumptions are adopted in KPSS.

$$E\left[v_j \mid R_j\right] = \delta R_j + \sqrt{\delta}\sigma_{\varepsilon fy} \frac{\phi\left(-\sqrt{\delta}\frac{R_j}{\sigma_{\varepsilon fy}}\right)}{1 - \Phi\left(-\sqrt{\delta}\frac{R_j}{\sigma_{\varepsilon fy}}\right)} \tag{3.5}$$

where ϕ and Φ are the standard normal pdf and cdf, respectively.

To estimate the change in the focal firm's market capitalization that is related to patent grant, it is sufficient to estimate δ and $\sigma^2_{\varepsilon fy}$. Since published patents and unpublished patents can be different inherently, I separate the data sample for published and unpublished patents and estimate the parameters for these two kinds of patents separately. In the estimation, I assume the market participants are risk neutral.

To estimate δ, I regress the log-squared abnormal returns on grant-day dummy I_{ft},

$$log\left(R_{ft}\right)^2 = \gamma I_{ft} + cZ_{ft} + u_{ft} \tag{3.6}$$

where Z includes day-of-week and firm-year fixed effects.

I approximate the value of δ, the signal-to-noise ratio, by

$$\hat{\delta} = 1 - e^{-\hat{\gamma}} \tag{3.7}$$

$\sigma^2_{\varepsilon fy}$ can be estimated nonparametrically. I first calculate σ^2_{fy} using the realized mean abnormal squared returns, which in turn is a function of σ^2_{vfy} and $\sigma^2_{\varepsilon fy}$. Then I estimate $\sigma^2_{\varepsilon fy}$ using σ^2_{fy}, the fraction of trading days that are sole-grant event days d_{fy}, number of days in an event window n, and $\hat{\gamma}$,

$$\sigma^2_{\varepsilon fy} = n\sigma^2_{fy}\left(1 + nd_{fy}\left(e^{\hat{\gamma}} - 1\right)\right)^{-1} \tag{3.8}$$

Then I use the estimated $\hat{\delta}$ and $\sigma^2_{\varepsilon fy}$ to find out the conditional expectation of v_j on R_j. Finally, I multiply this conditional expectation of v_j by the firm's market capitalization right before the patent grant to reveal the changes in the firm's market capitalization ΔV_j that is related to the patent grant.

3.2.4 Estimate Patent Value

The basic equation for measuring patent value using stock market response at grant is:

$$\xi_{jg} = (1 - \pi_n)^{-1} * \Delta V_{jg} \tag{3.9}$$

where

- ξ_{jg} is the value of patent j at grant,
- π_n is the conditional probability of grant right before the patent issuance day,
- ΔV_{jg} is the firm's stock market capitalization change related to the patent j's issuance.

The intuition is as follows: assuming the market participants know the value of the application j if granted, but they do not know whether the application will be granted or not. The market participants know the conditional probability that patent j will ever be granted given it is not granted in the first $(t-1)$ eligible weeks to be π_t ; this expectation is updated on every eligible Tuesday. Define the grant lag as the time lag (measured in the number of weeks) between publication and grant. If the grant lag for patent j is n weeks, then before the patent grant, the stock market price only incorporates the expected value of the patent: $\pi_n * \xi_{jg}$. After the patent grant, the stock market price incorporates the full value of the patent: ξ_{jg}. Thus, ΔV_{jg}, the change in stock market capitalization related to patent j around the grant date, reflects the difference between ξ_{jg} and $\pi_n * \xi_{jg}$.

3.3 Data

I match the CRSP daily stock data and patent data using the permno of firm assignee at grant and patent grant date. In the matched dataset, only 13.6% of patents are granted as the only one for its assignee firm on its grant date. More detailed descriptions of the construction of the dataset are available in Chapter 2.

3.4 Results and Discussion

3.4.1 Probability of Grant

3.4.1.1 Unconditional Probability of Grant

I first estimate the unconditional probability of grant at publication. To do this, I use the applications with a public firm assignee at the time of publication and exclude applications after 2017 to avoid truncation problems (some applications may not receive a final decision by the date of data collection). Out of the 663,326 patent applications satisfying the selection criteria, 502,236 patents are granted, suggesting a 75.7% probability of grant. Probability of grant varies across years, firms, and CPC classifications.

The probability of grant varies across years, from 68% to 84%.

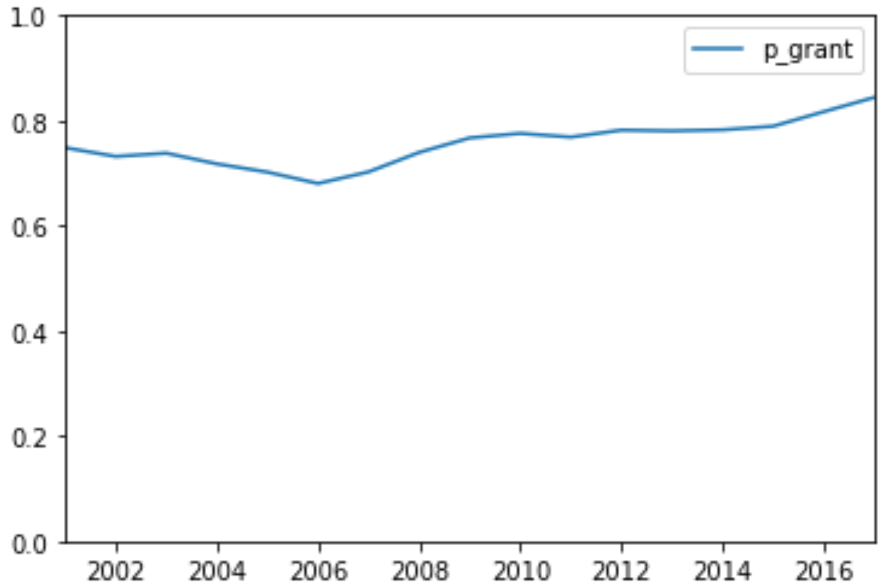

Figure 3. 1 Probability of Grant by Year of Filing

The probability of grant also varies across firms. The estimated probability of grant for 2,961 firms ranges from 0 to 1, with the median equal to 70%. As the number of applications increases, the distribution of the probability of grant becomes more concentrated, and the median increases.

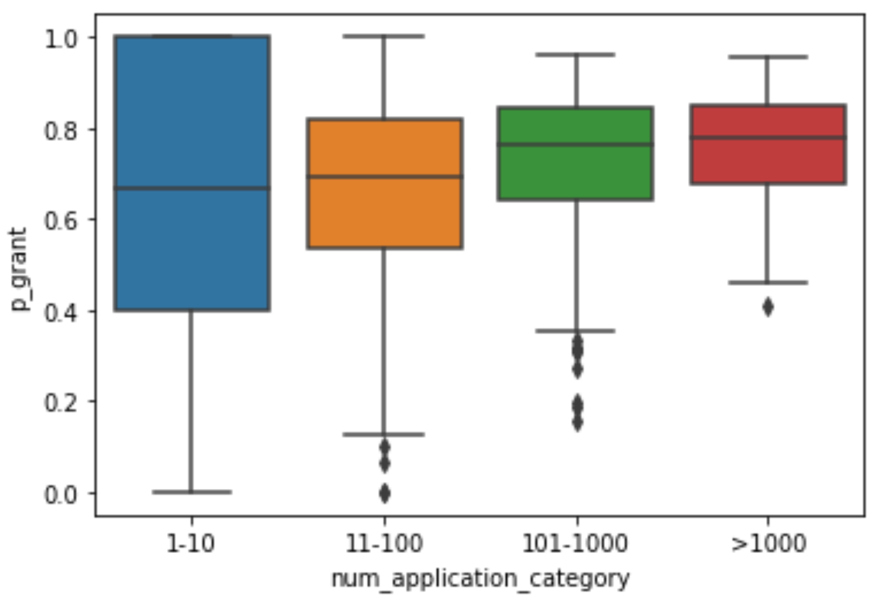

Figure 3. 2 Distribution of Probability of Grant by Firm by Number of Applications

The probability of grant for a given firm also changes over decades. The probability of grant in the 2010s is higher than that in the 2000s on average. The results are shown in Figure 3.3.

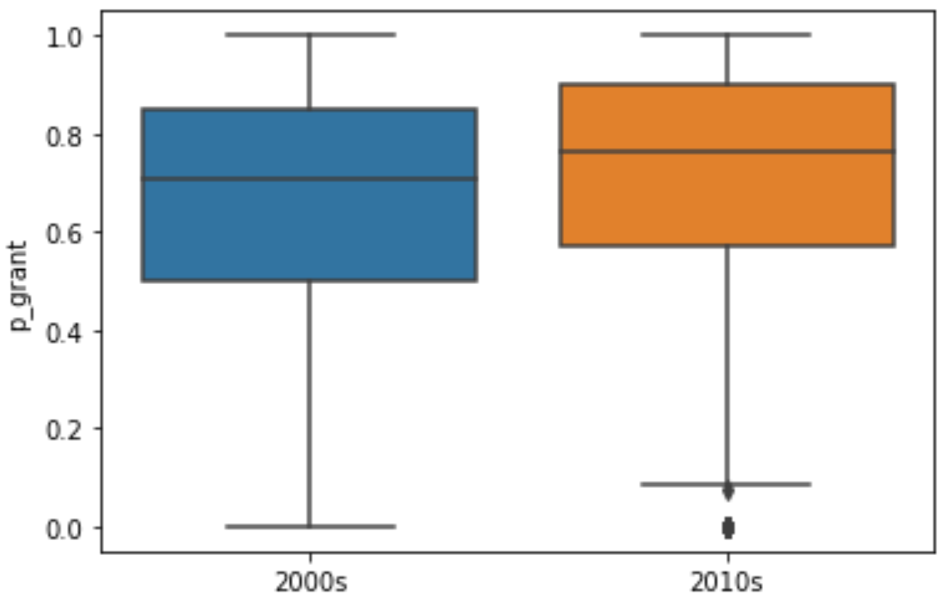

Figure 3. 3 Distribution of Probability of Grant by Firm by Decade

I take a closer look at 20 actively patenting firms (> 5,000 applications) and find that the probability of grant changes for a given firm over different years. (Only years with at least 100 applications are included to ensure probability is well defined.) The results are shown in Figure 3.4.

Grant rate also varies by CPC classifications. I organize the patent applications by CPC section and calculate the probability of grant in 8 different CPC sections. The results are shown in Table 3.1. I also organize the patent applications by CPC class and calculate the probability of grant in each of the 125 CPC classes. Figure 3.5 shows the range and the distribution of the probability of grant in different CPC classes. Similarly, I organize the patent applications by CPC subclass and calculate the probability of grant in each of the 608 CPC subclasses. The range and distribution of the probability of grant in different CPC subclasses are shown in Figure 3.6.

Table 3. 1 Probability of Grant in Different CPC Sections

CPC Section	Probability of Grant
A Human Necessities	67%
B Performing Operations; Transporting	77%
C Chemistry; Metallurgy	62%
D Textiles; Paper	70%
E Fixed Construction	79%
F Mechanical Engineering; Lighting; Heating; Weapons; Blasting	78%
G Physics	76%
H Electricity	81%

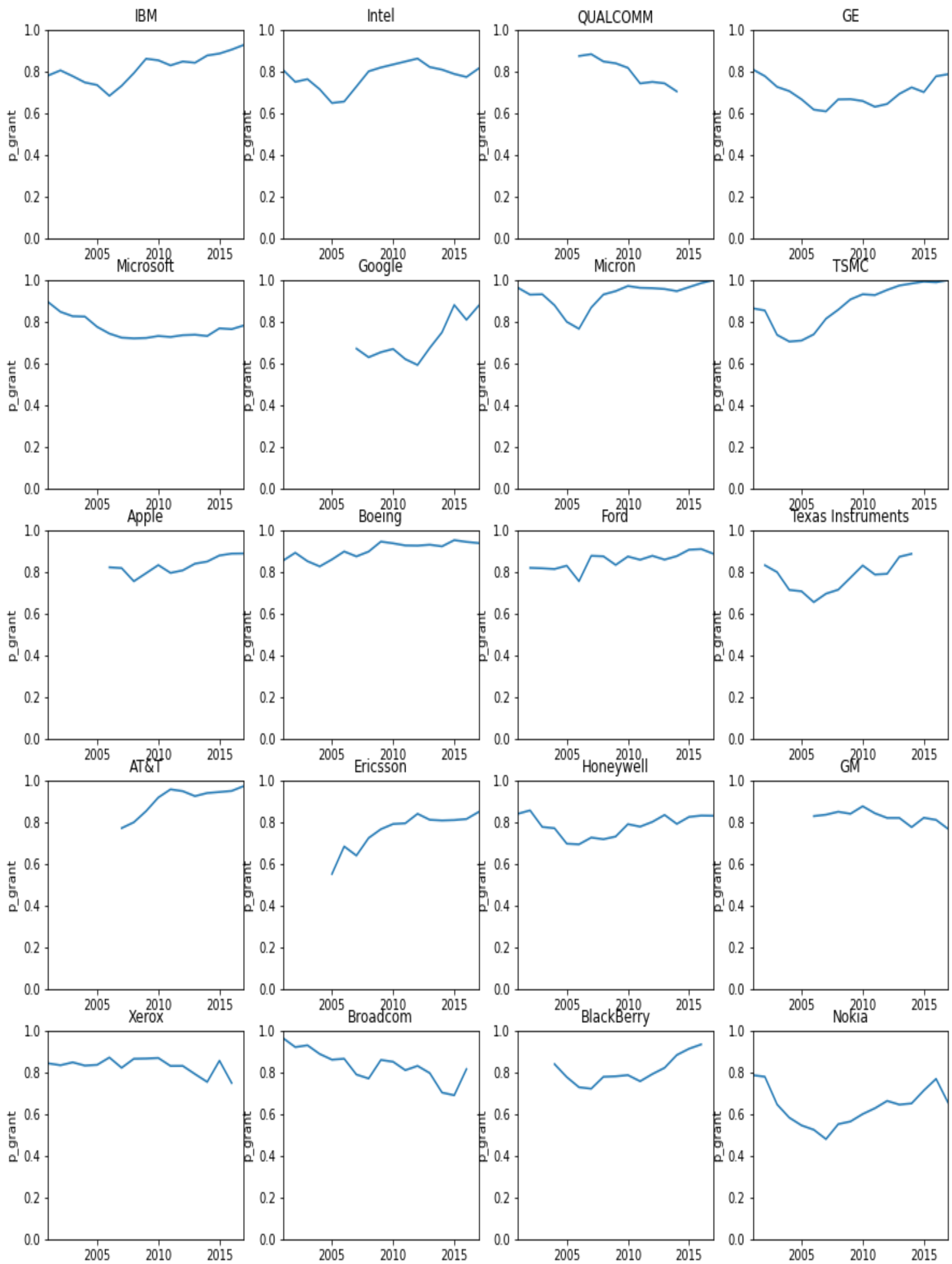

Figure 3. 4 Probability of Grant by Firm by Year

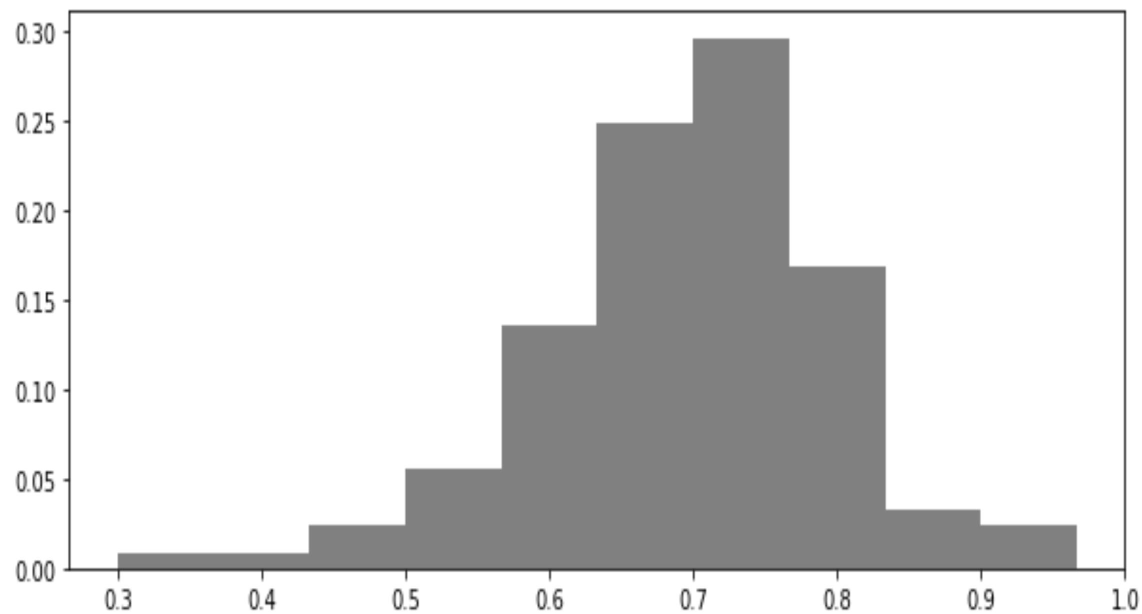

Figure 3. 5 Distribution of Probability of Grant in Different CPC Classes

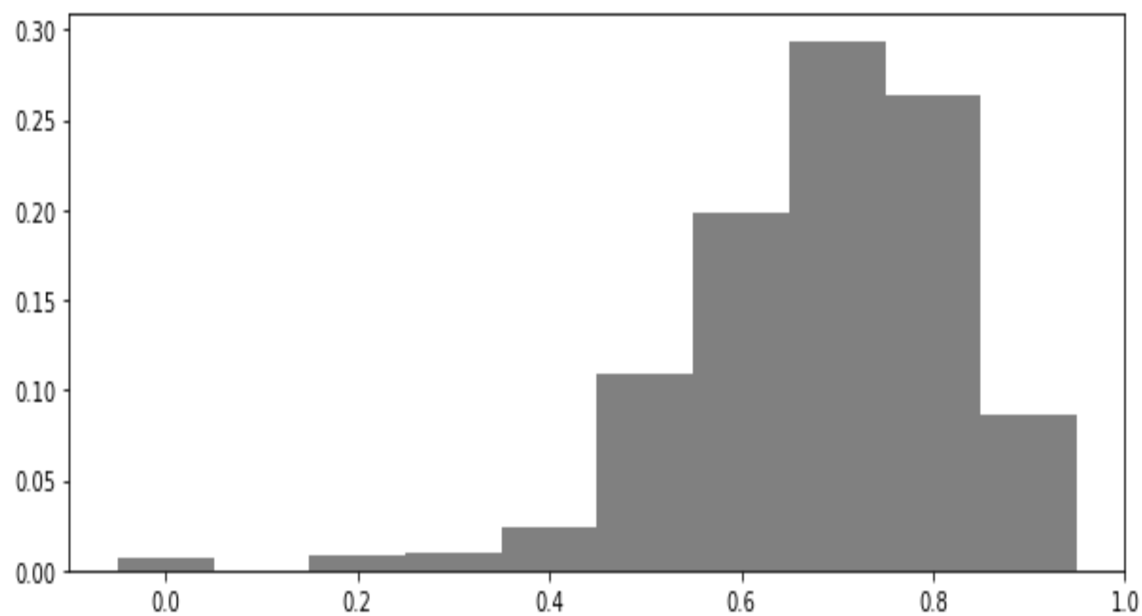

Figure 3. 6 Distribution of Probability of Grant in Different CPC Subclasses

3.4.1.2 Conditional Probability of Grant

Figure 3.7 shows the distribution of grant lag (the time lag between publication and grant, measured in the number of weeks). It shows that most patents are granted within 200 weeks from publication, while some patents can have an extra-long grant lag, e.g., 600 weeks.

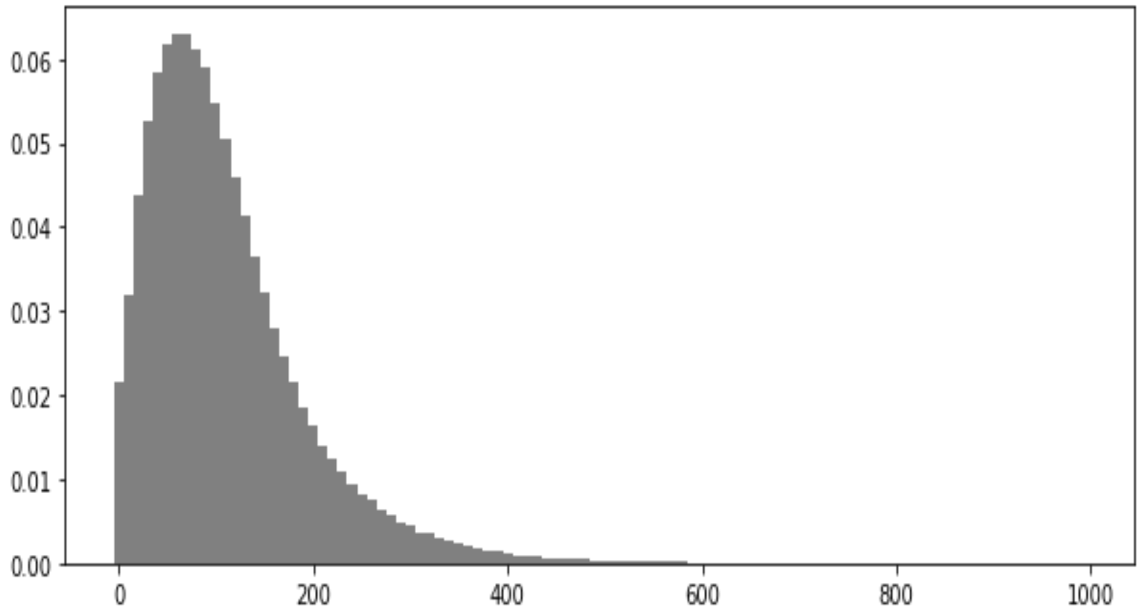

Figure 3. 7 Distribution of Grant Lag (weeks)

Figure 3.8 shows the realized empirical distribution of the conditional probability that a patent application will ever be granted if it is not issued within a certain number of Tuesdays, assuming abandonment is not immediately observable by the public[7]. This assumption is reasonable because the abandonment of patent applications is not announced to the public in the same manner as the publication of patent applications or the grant of patents. Instead, abandonment information is updated in the PAIR system when an applicant does not respond to an examiner within a specified time, as long as six months. Individuals need to check for abandonment by themselves using the system. The PAIR system allows for only one search at a time, which makes it infeasible for stock market participants to obtain sufficient information on all patent abandonments promptly.

As shown in Figure 3.8, the conditional probability of grant declines significantly over time. This is consistent with my dynamic hypothesis.

[7] This assumption is important as it affects the method of estimating the empirical conditional probability of a patent will ever be granted given it is not granted in the first *t-1* weeks. If market participants observe that a patent has not already been granted, there are two possible inferences. The first is that the patent has already been abandoned, the second is that the patent is still pending. If I assume that market participants do not know the patent withdrawal information, then they do not know which is the case. So, their estimated conditional probability that a patent will ever be granted given that it has not already been granted should be the product of the probability that the patent is not yet abandoned and the probability that a patent will ever be granted given that it has not already been abandoned nor granted. Both probabilities can be approximated using the corresponding fractions from the empirical data. On the other hand, if the market participants know about the abandonment immediately, then the estimated conditional probability that a patent will ever be granted given that it has not already been granted should be the second part only, i.e., the probability that a patent will ever be granted given that it has not already been abandoned nor granted. Thus, assumptions on awareness of abandonment are essential for empirical estimation of the conditional probability.

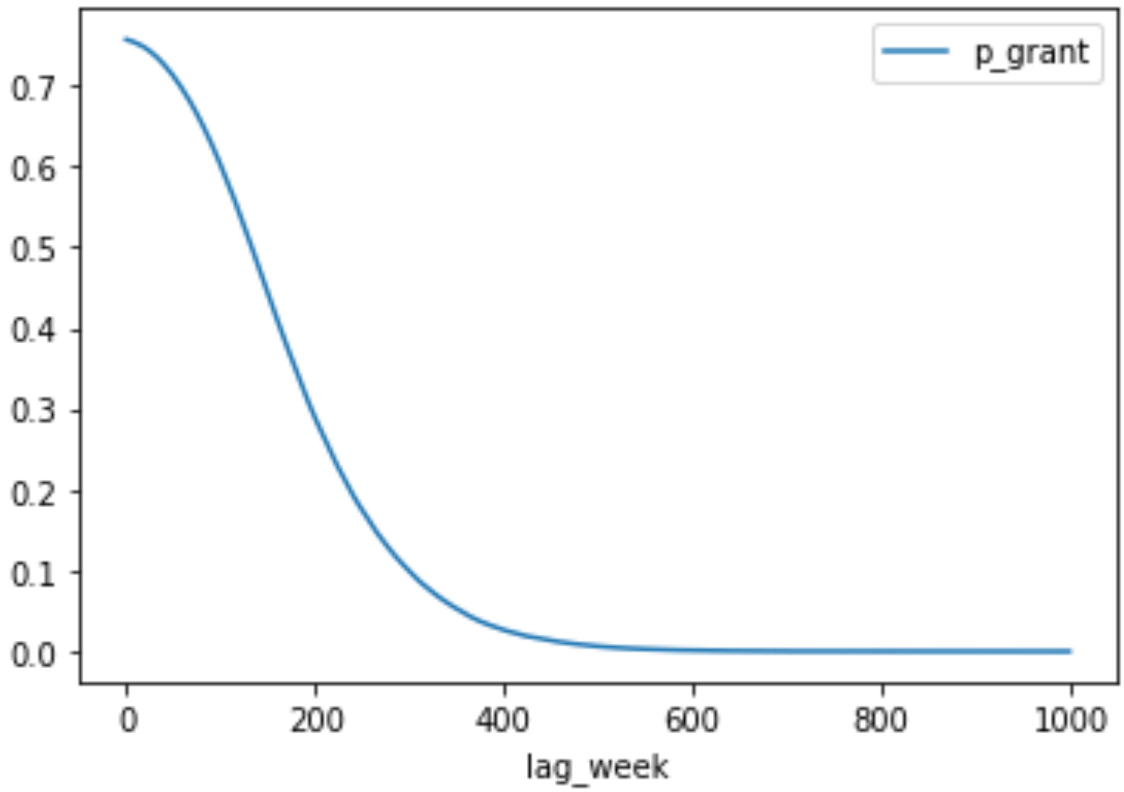

Figure 3. 8 Empirical Approximation of Conditional Probability of Grant on Lag (weeks)

3.4.2 Event Window

As shown in Figure 3.9, there is an increase in share turnover rate around patent grant, with most of the increase taking place on the first two days following the grant. This indicates that patent grant conveys important information to the market. Table 3.2 reports the coefficient estimates b_l, l = -1, 0, 1, 2, 3 (and 90 percent intervals) for specifications as described in Equation (3.2).

The trend looks like that reported in KPSS, but the observed share turnover rate increase is smaller and less significant than that in KPSS. This could be because KPSS used all patents granted from 1926 to 2010 while this paper focuses on patents filed after AIPA. Before the AIPA was enacted in late 2000, most patents were not revealed to the public until granted. Thus, KPSS estimates a combination of grant and publication effects. In this study, I only use the patents filed after Nov 29, 2000, when most patents are published 18 months after filing. In this case, the estimated grant effect is not combined with the publication effect. So, the observed abnormal share turnover turns out to be smaller and less significant. It is worth keeping in mind that the stock market prices can still adjust to the information of patent grant even without a significant increase in share turnover rate.

Based on the observations, I choose a two-day event window, including the two days right after the grant, [t+1, t+2], for the patent grant event.

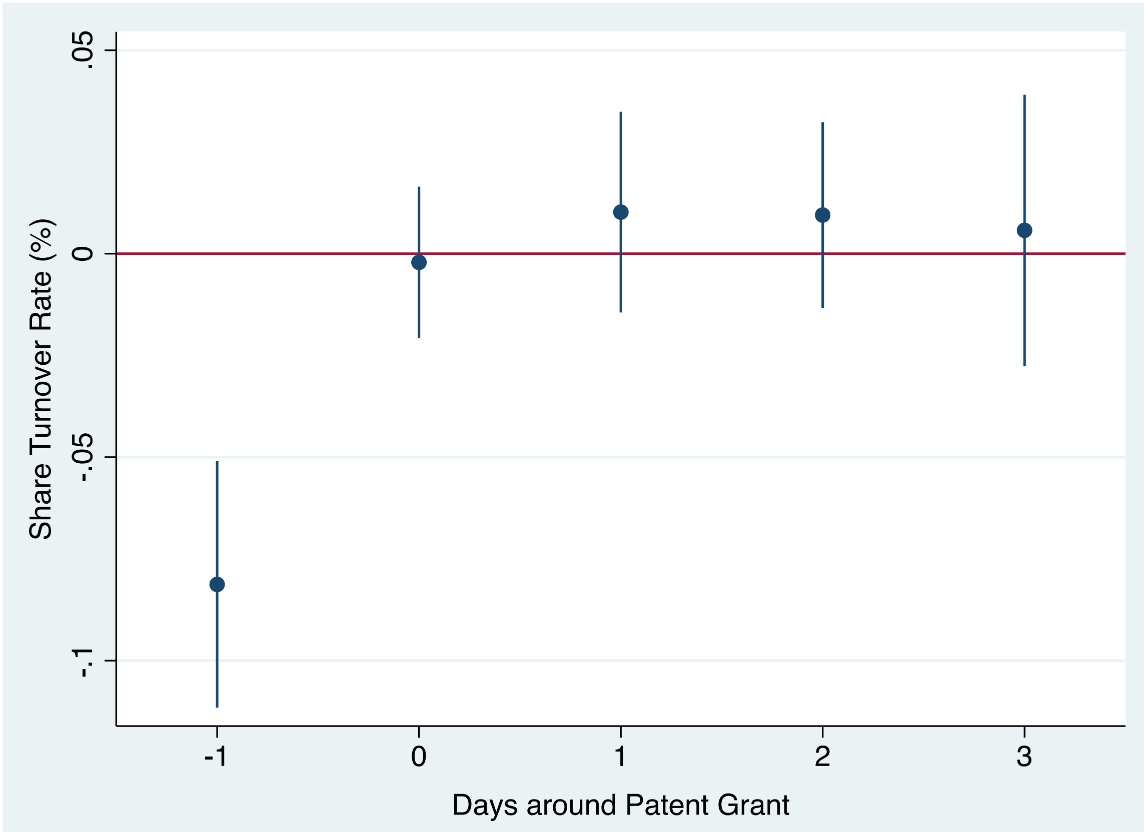

Figure 3. 9 Abnormal Share Turnover Around Patent Grant

Table 3. 2 Coefficient Estimates for Grant Window

	Coef.	Robust Std. Err.	90% Conf. Interval	
b_{-1}	-0.081	0.018	-0.118	-0.045
b_0	-0.002	0.011	-0.025	0.020
b_1	0.010	0.014	-0.020	0.040
b_2	0.010	0.013	-0.018	0.037
b_3	0.006	0.019	-0.034	0.046
cons	1.107	0.001	1.104	1.109

3.4.3 Stock Market Response

I estimate the stock market value change related to grant following the estimation strategies described in Section 3.2, using the two-day event window identified in Section 3.4.2. The results are listed in Table 3.3. As shown in Table 3.3, unpublished patents have a much higher and more significant signal-to-noise ratio than published patents. A potential explanation is that grant of unpublished patents involves the combination of publication effect and grant effect, while the grant of published patents only involves grant effect.

Table 3. 3 Parameter Estimates for Equations (3.6)

γ	Coef.	Std. Err.	p-value
Published	0.008	0.007	0.302
Unpublished	0.034	0.017	0.052

Table 3.4 shows the stock market value change related to patent grant. The median value is in the magnitude of several million dollars. The mean is much higher than the median since some extremely valuable patents significantly lift the average. The variance is huge, indicating considerable differences across the value of various patents. The median stock market value change related to unpublished patents is much higher than that of published patents. Figure 3.10 shows the distribution of the market value change related to grant of published patents and unpublished patents.

Table 3. 4 Stock Market Value Change Related to Patent Grant (million $)[8]

	Published	Unpublished
Median	2.62	6.33
Mean	11.08	26.82
SD	27.32	69.07
Percentiles		
p1	0.04	0.09
p5	0.15	0.34
p10	0.28	0.71
p25	0.83	2.16
p50	2.62	6.33
p75	8.74	20.41
p90	27.12	63.74
p95	51.40	119.64
p99	134.58	342.56
# of Obs.	118709	19125

[8] All dollar values in this dissertation are deflated to 1982 (million) dollars using the CPI.

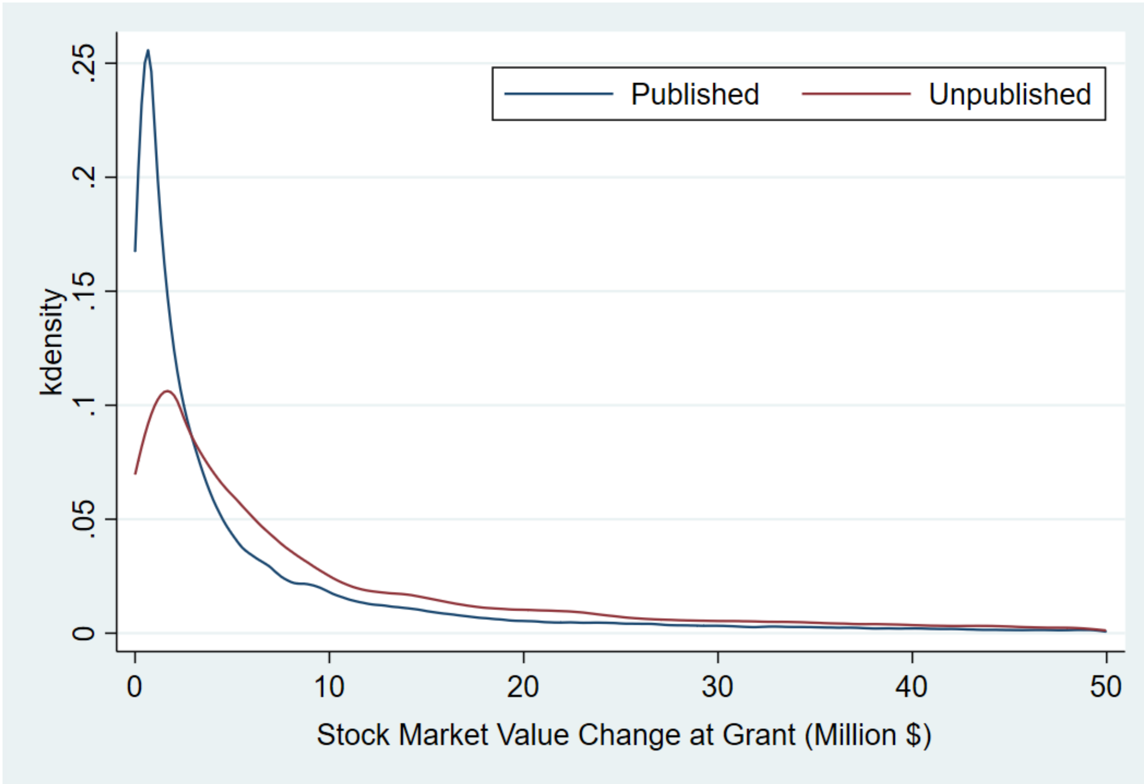

Figure 3. 10 Distribution of Market Value Change Related to Patent Grant

3.4.4 Patent Value

The estimated value for patents that have been published before granted is derived from Equation (3.9), using stock market value change related to grant and the conditional probability of grant, which decreases with the grant lag. For the patents that have never been published before granted, the market may not realize the existence of these patents or only have very limited information on these patents until their grant. Thus, such grant events may reveal two kinds of important information: first, the patent's value, and second, the patent's issuance. Therefore, if I assume the market doesn't know the existence of the unpublished patent before its grant, then at the time of grant, the stock market value change should reflect the full value of the patent. Thus, for the unpublished patents, I estimate their value using the stock market value change related to its grant. The estimated patent values at grant are shown in Table 3.5. The paper estimated grant value for 118,709 published patents and 19,125 unpublished patents. The estimated median values of published and unpublished patents are very similar, 6.60 million dollars and 6.33 million dollars, respectively. Figure 3.11 shows the distribution of patent value. The distribution of the estimated patent value of published patents is very close to that of unpublished patents.

Table 3. 5 Patent Value at Grant (million $)

	Published	Unpublished
Median	6.60	6.33
Mean	29.73	26.82
SD	81.14	69.07
Percentiles		
p1	0.08	0.09
p5	0.33	0.34
p10	0.64	0.71
p25	1.98	2.16
p50	6.60	6.33
p75	21.93	20.41
p90	68.94	63.74
p95	133.74	119.64
p99	382.93	342.56
# of Obs.	118709	19125

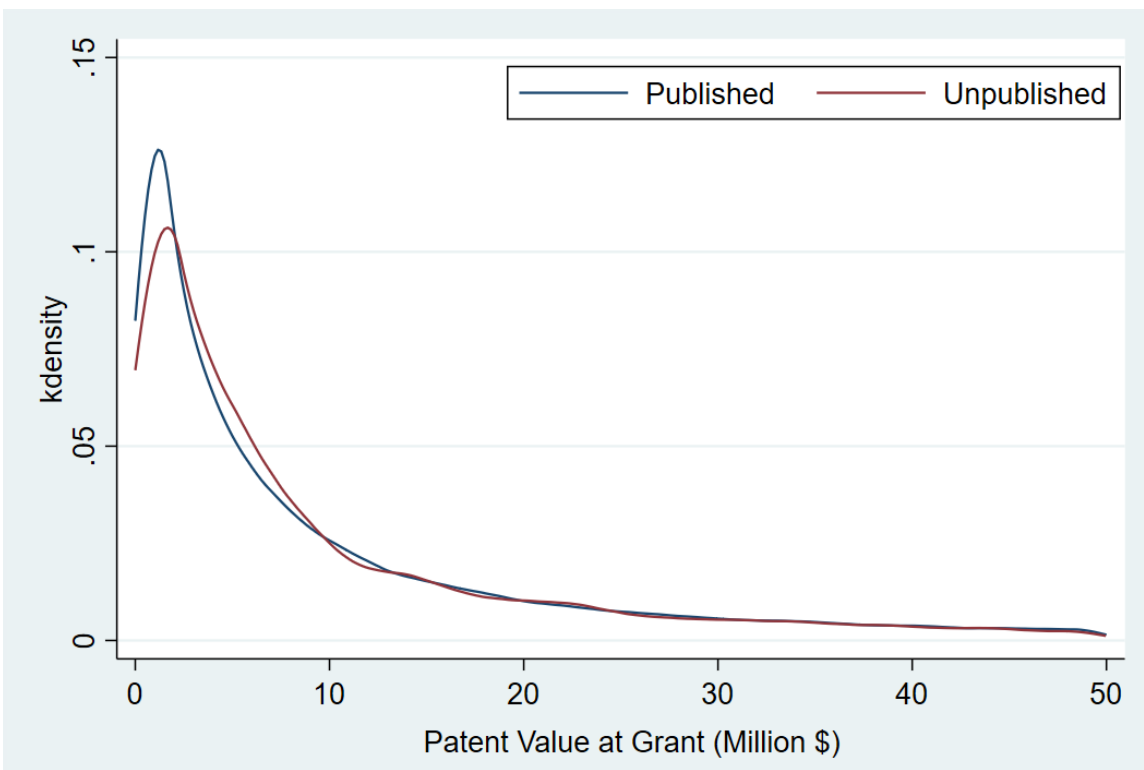

Figure 3. 11 Distribution of Patent Value at Grant

3.4.5 Importance of the Conditional Probability Dynamics

My dynamic probability model predicts that the estimated stock market response around the patent grant date increases with grant lag (i.e., the number of weeks between publication and grant). I test this by regressing the log of stock market response related to grant ΔV_{jg} on the grant lag lag_j, controlling for firm-year fixed effects.

$$ln\, \Delta V_{jg} = a + blag_j + cZ_{ft} + u_{ft} \tag{3.10}$$

Table 3.6 shows the regression results. The results reveal a significant positive relationship, which is consistent with my model's prediction. This emphasizes the need to use conditional probability instead of the unconditional probability of grant when estimating the value of a patent.

Table 3. 6 Regression Results of Equation (3.10)

	Coef.	Robust Std. Err.	p-value
lag_j	0.00064	0.00002	0.001
cons	0.97228	0.00238	0.000
# of Obs.	111,912		

To show how much bias can be introduced by ignoring the dynamic process, I replace the conditional probability of grant in Equation (3.9) with the unconditional probability of grant and calculate the pseudo patent value.

$$\xi_{jg\_pseudo} = (1 - \pi)^{-1} * \Delta V_{jg} \tag{3.11}$$

A comparison of the results from the two different methodologies is shown in Table 3.7. The last column of the table includes the distribution of differences (%) between the pseudo value and the actual value of patents. The results indicate that ignoring the conditional probability of grant will overestimate the value of most patents substantially. The median of this overestimation is over 50%. Using the conditional probability approach makes a significant improvement in the accuracy of patent economic value estimates compared to the unconditional probability approach.

Table 3. 7 Patent Value at Grant: Unconditional vs. Conditional Probability of Grant

	Value with Conditional Probability (million $)	Value with Unconditional Probability (million $)	Difference
Median	6.60	10.78	52.8%
Mean	29.73	45.62	80.5%
SD	81.14	112.42	77.5%
Percentiles			
p1	0.08	0.15	0.5%
p5	0.33	0.61	3.0%
p10	0.64	1.17	6.6%
p25	1.98	3.40	19.2%
p50	6.60	10.78	52.8%
p75	21.93	35.97	120.9%
p90	68.94	111.61	204.6%
p95	133.74	211.52	250.0%
p99	382.93	553.83	298.5%
# of Obs.	118709	118709	118709

3.4.6 Patent Value and Grant Lag

Patent value can change as grant lag increases. On the one hand, patent life remains after grant decreases with grant lag, so ceteris paribus, the value of a patent could also decrease with grant lag. For example, if a patent is granted after 6 years from filing, the effective patent life falls from 20 years to only 14 years. On the other hand, applicants with high-value patents may be willing to bear the cost of more persistent interactions with the examiner, so maybe high-value patents will tend to be granted later. Several studies have investigated the relationship between patent value and examination time. The empirical evidence is contradictory. Johnson and Popp (2003) and Popp et al. (2004) use citations as a proxy of patent value and find that valuable patents take longer to be granted than less valuable ones, while Regibeau and Rockett (2009)'s study on the USPTO and Harhoff and Wagner (2009)'s study on the European Patent Office (EPO) find valuable patents are granted earlier than less valuable ones.

To shed more light on the relationship between patent value and grant lag using empirical evidence, I regress the log of patent value on grant lag, controlling for firm-year fixed effects.

$$ln\, \xi_j = a + blag_j + cZ_{ft} + u_{ft} \tag{3.12}$$

I currently have two value estimations for each patent, the value estimated at grant with conditional probability of grant ξ_{jg}, and the value estimated at grant with the unconditional probability of grant ξ_{jg_pseudo}. I regress the log of each of them on grant lag. The results are shown in Table 3.8.

Table 3. 8 Regression Results on Log Patent Value and Grant Lag

	$ln(\xi_{jg\_pseudo})$	$ln(\xi_{jg})$
lag_j	.00066*** (.00005)	-.00409*** (.00005)

The results suggest that:

- Patent value at grant, if not adjusted for changes in the probability of grant with grant lag, increases with grant lag.
- Patent value at grant, if adjusted for changes in the probability of grant with grant lag, decreases with grant lag.

Some potential explanations are:

- Ignoring the probability of grant changes with grant lag leads to an overestimation of patent value for a given observed change in stock market capitalization, especially for the ones with long grant lag, thus leading to the spurious relationship between patent value and grant lag.
- Effective patent life decreases with grant lag, so the value of a patent could also decrease with grant lag. For example, if a patent is granted after 6 years from filing, the effective patent life falls from 20 years to only 14 years.
- Patents that take longer to grant may have more interactions with the examiner. The patent claims may change during the examination process. Longer examination periods may be related to bigger changes in the patent claims, for example, significantly narrowing the claims of the patent, thus leading patent value to decrease.

3.4.7 Aggregate Patent Value

I am interested in the distribution of aggregate patent value at grant. To investigate the distribution, I rank patents using value at grant from low to high and calculate the fraction of aggregate patent value by fraction of patents. The results are shown in Figure 3.12.

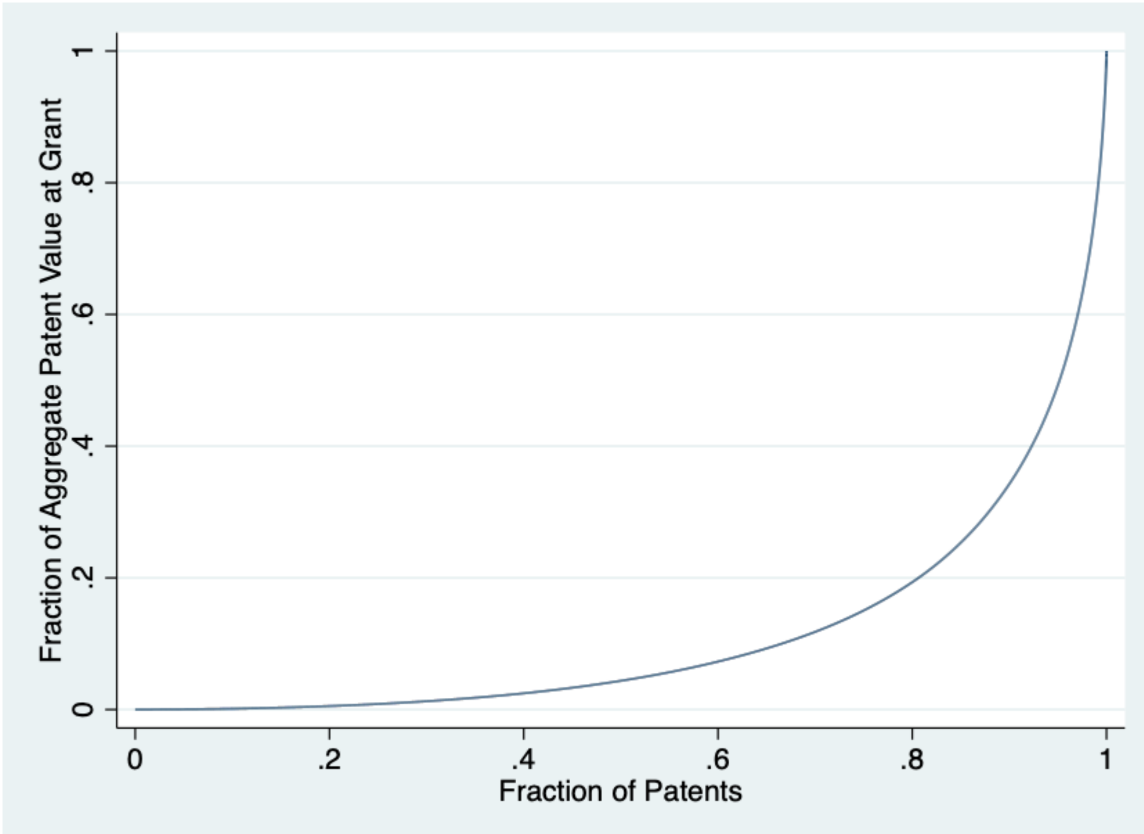

Figure 3. 12 Fraction of Aggregate Patent Value at Grant by Fraction of Patents

Figure 3.12 indicates that most of the aggregate patent value at grant comes from high-value patents. The 20% least valuable patents contribute less than 1% of aggregate patent value, while the 20% most valuable patents contribute over 80% of aggregate patent value.

The results of patent valuation can also help with R&D accounting. To estimate the total value of all the sole-grant patents, I can sum up the estimated value of all these patents. Similarly, for people/firms/institutions who are interested in the total value of all sole-grant patents in a certain year, within a certain CPC class, or granted to a certain firm, it is easy to generate an estimate using the sum of the value of relevant patents. If the people/firms/institutions are interested in the total value of all patents (including both sole-grant patents and multiple-grant patents), with only one additional assumption, i.e., assuming the distribution of values of multiple-grant patents is the same as the distribution of values of sole-grant patents, I can approximate the total value of all patents of interest using the mean value multiplied by the number of patents.

Using the sum of patent value has a big advantage. That is, even if the estimated value for each patent can be imprecise (as indicated by comparison of the value estimated at publication and value estimated at grant), the sum of the value of many patents can be quite accurate, given the distribution of patent value has limited variance and value of different patents are not too highly correlated. And as the number of patents increases, the sum of the value of patents becomes more accurate.

To illustrate this, let's consider a simple example. Assume that there are N patents, the value of patents are independent and identically distributed random variables each having mean μ and standard deviation σ. Note that the distribution does not need to be normal. It only requires that the mean and the standard deviation are finite. Then, according to Central Limit Theorem, when N is large, the sum of the value of the N patents is approximately normal with mean $N\mu$ and variance $N\sigma^2$. The standardized distribution of the sum of patent value is approximately standard normal. The 95% confidence interval of the sum of patent value is $[N\mu-2\sqrt{N}\sigma, N\mu+2\sqrt{N}\sigma]$. When N is large, the variance of the sum of patent value is relatively very small compared to the mean of the sum of patent value, making the estimate of the total value of patents highly accurate.

Let's take a numerical example. For example, I am interested in estimating the total value of 1,000 patents. Let's assume the value of each patent follows the empirical distribution estimated in Section 3.4.4, with mean of 29.73 million dollars and standard deviation 81.14 million dollars. Then the total value of these 1,000 patents is approximately normal with mean 29.73 billion dollars and standard deviation 2.57 billion dollars. The 95% confidence interval is [24.59, 34.87] billion dollars. This is to say, even when the distribution of the value of individual patents has a very high variance, the distribution of the sum still has a relatively small variance if N is large. So that it is very likely to obtain an estimated total value with high accuracy. When N is even larger, the estimated total value is even more accurate. For example, if I am interested in the total value of 10,000 patents, with the same distribution assumption, the total value is approximately normal with mean 297.3 billion dollars and standard deviation 8.1 billion dollars. The 95% confidence interval is [281.1, 313.5] billion dollars. The confidence interval is relatively small compared to the mean. In other words, the total value of patents can be estimated with much higher precision than the value of one patent.

This finding has important potential to be used in R&D accounting. It has the advantage of high accuracy and high flexibility. For example, it can be used to account for the value of R&D for individual firms, for a certain sector, or even for a nation.

3.5 Robustness Checks

3.5.1 Test for Differences in Signal-to-Noise Ratios

I would like to test whether the signal-to-noise ratio is the same for multiple-grant events and sole-grant events, so I added an indicator variable I_{mft}, which equals 1 if there are multiple patents granted to firm f on date t.

For sole-grant events, I am interested in testing if the signal-to-noise ratio is the same for patents that were published before the grant and patents that were never published before the grant. I include an indicator variable I_{nft}, which equals 1 if the sole-grant patent never got published before its issuance.

For grant events, I regress the log squared abnormal returns on three dummies: grant-day dummy I_{ft}, multiple-grant-day dummy I_{mft}, and sole-unpublished-grant-day dummy I_{nft}.

$$log\left(R_{ft}\right)^{2} = \gamma I_{ft} + \gamma_m I_{mft} + \gamma_{np} I_{nft} + cZ_{ft} + u_{ft} \quad (3.13)$$

If γ_m is significantly different from zero, it indicates that the signal-to-noise ratio of multiple-grant events is different from that of sole-grant events. If γ_{np} is different from zero, it suggests that sole-grant patents that never got published before issuance and sole-grant patents published before issuance introduce different signal-to-noise ratios on their issuance day.

The model estimates $\hat{\gamma} = 0.010$ for sole-grant patents published before grant. The coefficient of multiple-grant indicator γ_m is significantly different from zero (with p-value = 0.009), indicating that the signal-to-noise ratio of multiple-grant events is different from that of sole-grant events. Note that the purpose of including the multiple-grant indicator is to show the multiple-grant events have a different signal-to-noise ratio from the sole-grant events. To estimate the signal-to-noise ratio of different kinds of multiple-grant events (e.g., two patents granted together, three patents granted together, etc.), a more complicated methodology must be used.

I observe a much higher γ_{np}= 0.031 which is significant at the 10% level. This implies that the grant of a patent that has never been published before grant can lead to a much higher signal-to-noise ratio than the grant of a patent that has been published before grant.

The possible reason for this is that as the patent has never been published before grant, people have limited information on the patent, at the time of grant, people realize two things at the same time, first, the details of the patent, and second, the patent has been granted. So, the patent grant serves not only the function of confirming the patent's grant but also delivering information about the patent details. This latter function is usually served by publication events for the patents that have been published before the grant. So, it is very likely that the grant effect of unpublished patents is a combination/mixture of the grant effect and the publication effect. This situation is like patent grant before the AIPA was enacted in late 2000 when the majority of patents were not revealed to the public until granted. For those patents, their grant effects could be a mixture of grant and publication effects, too.

Table 3. 9 Parameter Estimates for Equations (3.13)

	Coef.	Std. Err.	p-value
γ	0.010	0.007	0.169
γ_{np}	0.031	0.019	0.100
γ_m	0.026	0.010	0.009

3.5.2 Alternative Distribution Assumption

For the robustness check, instead of the truncated normal assumption, I include an alternative distribution assumption for v_j. I assume that v_j is exponentially distributed with parameter $1/\sigma_v$, keeping all other assumptions unchanged, the conditional expectation of v_j given R_j is

$$E[v|R] = R + \sigma_\varepsilon\left(\sqrt{\frac{2}{\pi}}\frac{exp(-\tilde{R}^2/2)}{G^c(\tilde{R}/\sqrt{2})} - \frac{\sigma_\varepsilon}{\sigma_v}\right) \tag{3.14}$$

where G^c is the complementary error function and

$$\tilde{R} = \frac{\sigma_\varepsilon}{\sigma_v} - \frac{R}{\sigma_\varepsilon} \tag{3.15}$$

Using the same signal-to-noise ratio estimated from empirical data, I calculate the value of patents with the exponential distribution assumption. The results are quantitatively similar to the results obtained with the truncated normal distribution assumption. The correlation coefficient between the two value estimates is higher than 99%. More detailed results are shown in Table 3.10 and Figure 3.13.

Table 3. 10 Patent Value at Grant with Exponential Distribution Assumption (million $)

	Published	Unpublished
Median	8.17	7.50
Mean	36.90	32.13
SD	100.92	83.24
Percentiles		
p1	0.10	0.10
p5	0.41	0.39
p10	0.79	0.84
p25	2.44	2.56
p50	8.17	7.50
p75	27.17	24.37
p90	85.40	76.86
p95	165.55	142.73
p99	478.60	413.54
# of Obs.	116573	19125

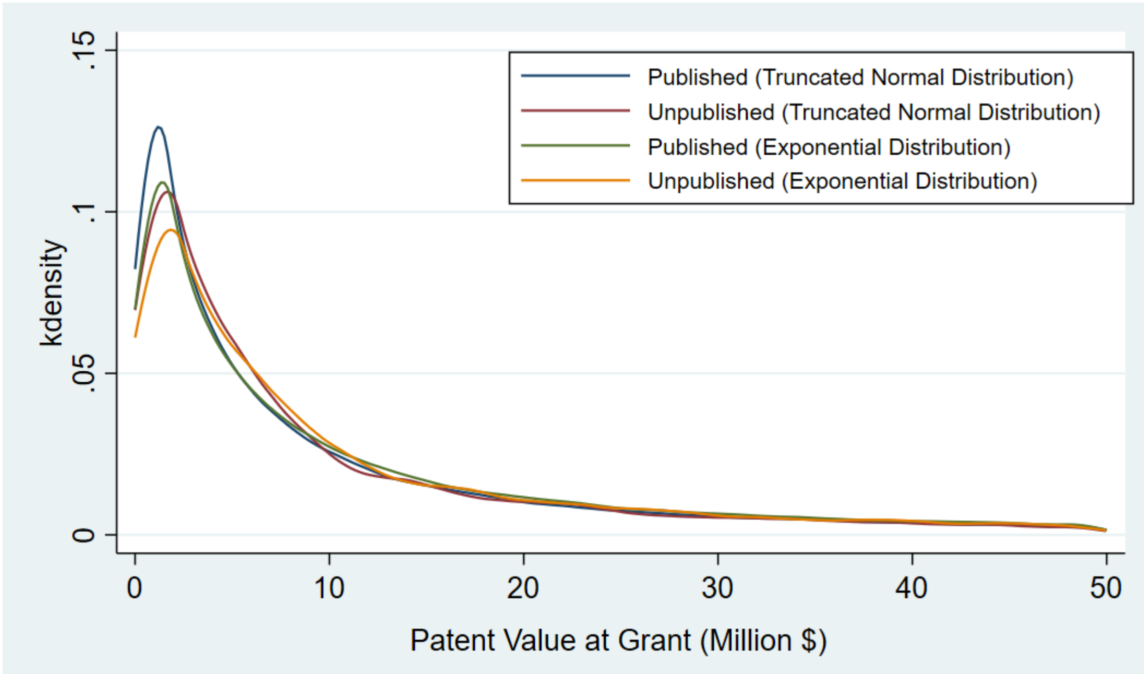

Figure 3. 13 Distribution of Patent Value at Grant with Different Distribution Assumptions

3.5.3 Probability of Grant

In this section, I test how different assumptions on the probability of grant will change the patent value estimations for patents that have been published before grant.

- Case 0: Allow the probability of grant to vary with the time lag between publication and grant. This is the assumption I use in the main results section.
- Case 1: Assume the probability of grant to be a constant for all firms and all patents. This is the assumption that KPSS used in their analysis.
- Case 2: Allow the probability of grant to vary by application year. I match patents with the probability of grant based on the application year. To avoid truncation issues, I only used applications by 2017 to estimate grant rates by year. To obtain an estimate of the probability of grant for years after 2017, I use the average grant rate between 2015-2017.
- Case 3: Allow probability to vary by firm. To do this, I match patents with the probability of grant based on assignee firms.
- Case 4: Allow probability to vary by firms by decade. I match patents with the probability of grant based on the assignee firm and decade of application filing (the 2000s vs. 2010s).
- Case 5: Allow the probability of grant to vary across CPC sections.
- Case 6: Allow the probability of grant to vary across CPC classes.
- Case 7: Allow the probability of grant to vary across CPC subclasses. For Cases 5-7, I match patents with their CPC classification information. When one patent is matched with more than one class, I use the first one.

I estimate patent value with these different assumptions. The results are shown in Table 3.11 and Figure 3.14. All Cases 1-7 give higher estimations than Case 0, indicating that not adjusting for probability dynamics can lead to serious overestimation.

Table 3. 11 Patent Value at Grant in Different Cases (million $)

	Case 0	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7
median	6.60	10.78	10.17	12.96	14.60	10.59	10.81	11.16
mean	29.73	45.62	43.79	56.50	54.68	42.72	43.32	44.17
sd	81.14	112.42	109.41	258.23	125.03	107.59	108.35	112.78
Percentiles								
p1	0.08	0.15	0.15	0.13	0.15	0.14	0.14	0.14
p5	0.33	0.61	0.58	0.50	0.61	0.56	0.55	0.55
p10	0.64	1.17	1.09	1.04	1.21	1.09	1.09	1.08
p25	1.98	3.40	3.15	3.59	3.99	3.20	3.26	3.28
p50	6.60	10.78	10.17	12.96	14.60	10.59	10.81	11.16
p75	21.93	35.97	33.70	44.27	48.97	34.78	35.97	36.71
p90	68.94	111.61	105.10	127.12	136.93	104.22	107.15	107.82
p95	133.74	211.52	201.47	225.30	241.15	191.91	192.63	193.54
p99	382.93	553.83	531.80	574.07	593.35	498.99	492.09	504.23
#of Obs.	118709	118709	109100	115523	102497	118706	118706	118611

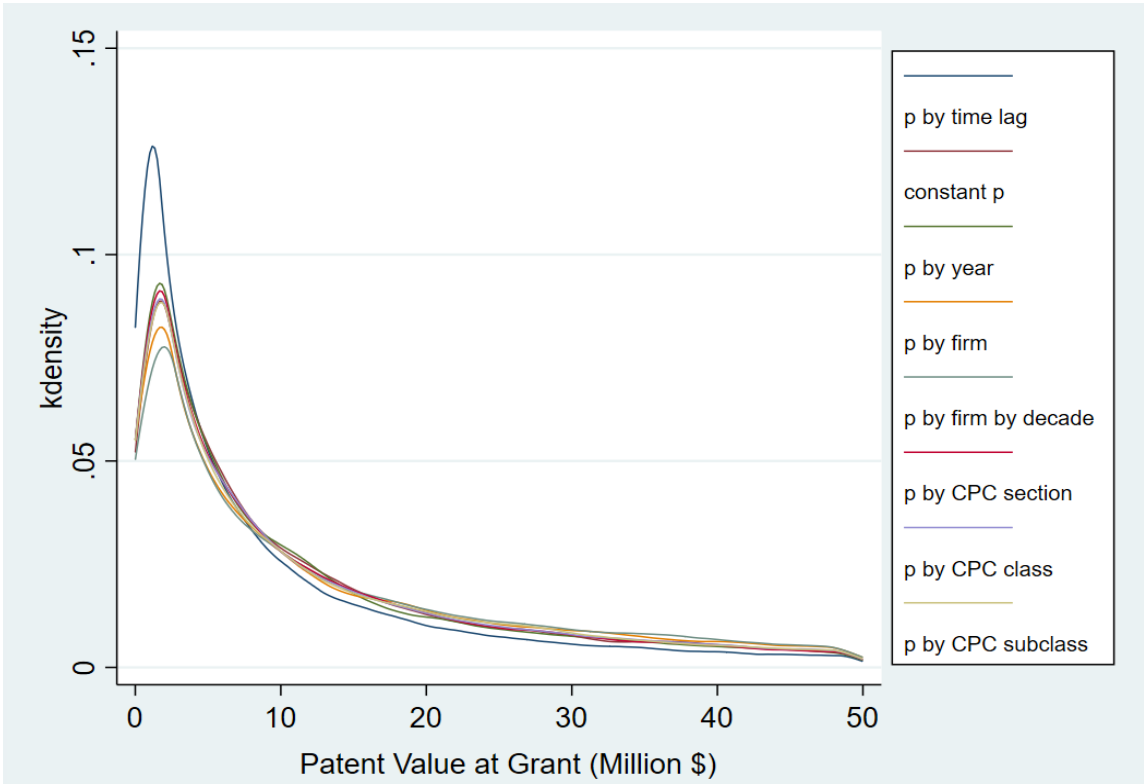

Figure 3. 14 Distribution of Patent Value at Grant in Different Cases

3.5.4 More Analysis of Patent Value and Grant Lag

Theoretically, patent value can either decrease or increase with grant lag. In Section 3.4.6, I explore the relationship between patent value and grant lag using fixed-effect regressions. For robustness check, I redo the analysis using various patent value measures, various grant lag measures, and various fixed effects.

More specifically, for regression of Equation (3.12), I try:

On the LHS, use either

- value at grant adjusted by the unconditional probability of grant,
- value at grant adjusted by the conditional probability of grant,
- log of value at grant adjusted by the unconditional probability of grant, or
- log of value at grant adjusted by the conditional probability of grant.

On the RHS, use either

- grant lag measured by the number of weeks,
- lag categories generated by quantiles of lag in weeks (i.e., 1, 2, 3, 4), or
- a dummy variable (i.e., define long-lag = 1 if the time lag is longer than 75% of all patents and 0 otherwise).

For control variables, use either

- year fixed effects,

- firm fixed effects,
- firm-year fixed effects, or
- CPC class fixed effects.

The results are robust to value or log value, control variables, and the form of the grant lag variable (i.e., number of weeks, categorical, or dummy). Table 3.12 shows the results using log value with firm-year fixed effects.

Table 3. 12 More Regression Results on Log Patent Value and Grant Lag

	$ln(\xi_{jg\_pseudo})$	$ln(\xi_{jg})$
lag weeks	0.00066*** (0.00005)	-0.00409*** (0.00005)
4 categories (category 1 as the control group)	0.01961* (0.00882) 0.03783*** (0.00929) 0.10440*** (0.01004)	-0.19083*** (0.00901) -0.46725*** (0.00949) -0.83138*** (0.01025)
long-lag dummy	0.08176*** (.00806)	-0.56785*** (.00882)

The findings listed in Section 3.4.6 still hold,

- If ignoring the dynamic probability changes, patent value at grant spuriously increases with the time lag.
- If adjusted for the dynamic probability changes, patent value at grant decreases with the time lag.

3.6 Conclusions

The paper extends KPSS and develops a model that involves dynamics in the probability of grant to measure the economic value of patents using stock market response around patent grant. Our sample includes patents of firms listed on NYSE, AMEX, and NASDAQ between Nov 29, 2000, and Mar 31, 2022.

Our measurement assigns a dollar value to each patent of public firms and makes across-firm and across-time comparisons possible. This model builds upon prior work by Austin (1993) and Patel and Ward (2011), as well as KPSS. New methodological contributions of this work include: (1) focusing on sole-grant patents (patents that are granted as the only patent to its assignee firm on its day of grant; (2) using the information on publication dates made available by the American Inventors Protection Act (AIPA) enacted on Nov 29, 2000; (3) developing a dynamic model and replacing the universal unconditional probability of grant with a conditional probability of grant based on grant lag when estimating patent value at grant; (4) addressing the informational effect of grant distinct from the informational effect of publication; (5) coming up with aggregate patent value measure which can be used for R&D accounting. The paper applies the methodology to patents filed between Nov 29, 2000, and March 31, 2022, by public firms and presents economic valuations in dollars for 118,709 published patents and 19,125 unpublished patents.

The results can be used for further studies, for example, studies of factors and policies that influence the economic value of patents.

The findings include:

- In our sample, the probability of grant changes considerably with the time lag between publication and grant. The probability that the application will ever be granted decreases as the time lag increases.

- Our estimates indicate that the average value of patents is overestimated by over 50% if the dynamic decline in grant probability is ignored, as in KPSS. The bias varies with the grant lag.

- Estimation of our model, assuming (as in KPSS) that the probability of grant is independent of the lag to grant, supports the finding of Johnson and Popp (2003), Popp et al. (2004), etc. that the value of patents increases with the lag between application and grant, in other words, more valuable patents take longer to be granted than less valuable ones.

- Estimates using our model with the dynamic probability of grant show that the value of patents does not tend to increase with grant lag, contrary to Johnson and Popp (2003), Popp et al. (2004), etc. Indeed, the value tends to decrease modestly with lag from publication. In other words, more valuable patents are granted earlier than less valuable ones. This finding supports the findings of Regibeau and Rockett (2009), Harhoff and Wagner (2009), etc.

- Grant of published patents reveals information about the issuance of the patent and the changes of the patent between publication and grant, while grant of unpublished patents reveals information about not only the issuance of the patent but also details of the patent at the first time. Thus, different methodologies should be used in the valuation of published and unpublished patents.

- To produce another new result, I compare the value of patents with a pre-grant publication with patents for which the patentee opts to forego foreign applications in exchange for the right to delay publication until grant. Based on grant data, distributions of published and unpublished patent values appear very similar.

- Even if the estimate of value for each patent can have errors, the aggregate value of patents can be quite accurate, according to the Central Limit Theorem. As the number of patents increases, the aggregate value of patents becomes more accurate. This finding has important potential to be used in R&D accounting.

In conclusion, this chapter sets up our dynamic patent valuation framework and estimates the value at grant, producing new results regarding the relation of patent value to grant lag, the distribution of aggregate patent value, and the relative value of patents to patentees who opt to delay publication until grant.

In the following chapters, I estimate the value of patent applications at publication, using the implications of the dynamic probability model at publication. I shall compare value at grant and value at publication and use the values to shed light on the robustness of the dynamic approach used here. I shall also draw inferences on information flow during the patenting process, including before publication, at publication, between publication and grant, and at grant.

4 Valuation of Patents Using Stock Market Response at Publication

4.1 Introduction

In Chapter 3, I extend Kogan, Papanikolaou, Seru, and Stoffman (2017) (hereafter KPSS) and measure patent value at grant using the stock market response in the grant window and dynamics in the probability of grant. In this chapter, I expand my focus beyond patent grant, to another important patent event, patent publication. According to the requirement of the American Inventor's Protection Act (AIPA), most patent applications, with few exceptions, filed on or after Nov 29, 2000, are published by 18 months from filing. At the time of publication, patent application files are made available to the public, so the market can obtain detailed information about a patent application, even before it is granted or abandoned. Thus, patent publication is an important event to study. However, the effects of patent publication have not been studied much in the literature. In this chapter, I examine the information flow around patent publication and develop a second patent value measure based on abnormal stock market response in the publication window. I then combine the results with those in Chapter 3 and compare the two patent value measures: value at grant and value at publication. The results reveal important information about how and when the stock market obtains knowledge about patent value. I also investigate the relationship between the patent value at publication and grant lag (time lag between publication and grant) and find some interesting results.

The remainder of the chapter is structured in the following way. Section 4.2 describes the analytical framework and empirical strategies I use to study the economic value of patents using stock market response at publication. Section 4.3 describes the data I use. Section 4.4 shows the results and discusses some interesting findings. Section 4.5 does robustness checks and Section 4.6 concludes.

4.2 Model and Methodology

I extend the method described in Chapter 3 to measure the stock market value change related to patents in patent publication window. I then develop a new measure of patent value based on the stock market value change in the publication window and the unconditional probability of grant. This methodology to measure patent value at publication is a unique contribution of this chapter. I focus on sole-publication applications that later get granted, i.e., patents that are published as the only patent application for its assignee firm on its day of publication, to avoid mixed signals from multiple patent applications.

4.2.1 Identify Event Window

The first step is to check if publication is an important information event and choose the event window around publication. To guide my decision, I use a similar methodology as described in Section 3.2.2. I examine the pattern of trading volume for the stocks of firms that have published at least one patent application during the examination period (Nov 29, 2000 – March 31, 2022). I focus on the ratio of daily volume to shares outstanding, the share turnover rate, h. I compute the abnormal share turnover around application publication, after adjusting for firm-year and calendar-day fixed effects.

I run the following regression and report the coefficient estimates b_l, l = -3, -2, -1, 0, 1 (and 90 percent intervals) from the following specification:

$$h_{ft} = a_0 + \sum_l b_l I_{ft+l} + cZ_{ft} + u_{ft} \tag{4.1}$$

where

- the indicator variable I_{ft+l} takes the value one if firm f has one or more patent applications published on day $t + l$;
- the vector of controls Z_{ft} includes firm-year and calendar-day fixed effects;
- standard errors are clustered by year.

I select the publication event window as the consecutive days with positive abnormal share turnover around the publication date.

4.2.2 Measure Stock Market Responses

After identifying the publication window, the next step is to measure the stock market responses in the publication window. I use a similar methodology as described in Section 3.2.3. I focus on the sole-publication applications that later get granted, i.e., patents that are published as the only publication for its assignee firm on its day of publication. The reason for focusing on sole-publication applications is the same as that described in Chapter 3, i.e., to avoid mixed signals from multiple publications and avoid assigning the same value to different applications published on the same day. I empirically test for the difference between the signal-to-noise ratio of multiple-publication events and sole-publication events in Section 5.5.1.

The abnormal return *R* of a public firm in a sole-publication event window is comprised of two parts: the part that is related to the patent publication, v, and the part that is unrelated to the patent publication, ε.

$$R_j = v_j + \varepsilon_j \tag{4.2}$$

where v_j is a fraction of the firm's market capitalization. The change in the firm's market capitalization that is related to the patent can be obtained by multiplying v_j with the firm's market capitalization right before the event.

I assume that

- v_j is distributed according to a normal distribution truncated at 0, $v_j \sim N^+(0, \sigma^2_{vfy})$;

- ε_j is normally distributed, $\varepsilon_j \sim N(0, \sigma^2_{\varepsilon fy})$;
- Both σ^2_{vfy} and $\sigma^2_{\varepsilon fy}$ are allowed to vary proportionally across firms and years.

Define the signal-to-noise ratio δ as

$$\delta = \frac{\sigma^2_{vfy}}{\sigma^2_{vfy} + \sigma^2_{\varepsilon fy}} \tag{4.3}$$

Given the above assumptions, the conditional expectation of v_j on R_j is

$$E\left[v_j \mid R_j\right] = \delta R_j + \sqrt{\delta}\sigma_{\varepsilon fy} \frac{\phi\left(-\sqrt{\delta}\,\frac{R_j}{\sigma_{\varepsilon fy}}\right)}{1 - \Phi\left(-\sqrt{\delta}\,\frac{R_j}{\sigma_{\varepsilon fy}}\right)} \tag{4.4}$$

where ϕ and Φ are the standard normal pdf and cdf, respectively.

To estimate the change in the focal firm's market capitalization that is related to patent publication, it is sufficient to estimate δ and $\sigma^2_{\varepsilon fy}$.

To estimate δ, I regressed the log abnormal squared returns on publication-day dummy I_{ft},

$$log\ \left(R_{ft}\right)^{2} = \gamma I_{ft} + cZ_{ft} + u_{ft} \tag{4.5}$$

where Z includes day-of-week and firm-year fixed effects.

I approximate the value of δ, the signal-to-noise ratio, by

$$\hat{\delta} = 1 - e^{-\hat{\gamma}} \tag{4.6}$$

$\sigma^2_{\varepsilon fy}$ can be estimated nonparametrically. I first calculate σ^2_{fy} using the realized mean abnormal squared return, which in turn is a function of σ^2_{vfy} and $\sigma^2_{\varepsilon fy}$. Then I estimate $\sigma^2_{\varepsilon fy}$ using σ^2_{fy}, the fraction of trading days that are sole-publication event days with an application that later gets granted d_{fy}, number of days in a publication event window n, and $\hat{\gamma}$,

$$\sigma^2_{\varepsilon fy} = n\sigma^2_{fy}\left(1 + nd_{fy}\left(e^{\hat{\gamma}} - 1\right)\right)^{-1} \tag{4.7}$$

Then I use the estimated $\hat{\delta}$ and $\sigma^2_{\varepsilon fy}$ to find out the conditional expectation of v_j on R_j. Finally, I multiply this conditional expectation of v_j by the firm's market capitalization right before the patent publication to reveal the changes in the firm's market capitalization ΔV_j that is related to the patent publication.

4.2.3 Estimate Patent Value

I develop a new measure of patent value using stock market response in the publication window and the unconditional probability of grant. The basic equation is:

$$\xi_{jp} = \pi^{-1} * \Delta V_{jp} \tag{4.8}$$

where

- ξ_{jp} is the expected value of patent j conditional on grant at the time of publication,
- π is the unconditional probability of grant,
- ΔV_{jp} is the firm's stock market capitalization change related to the patent j's publication.

The intuition is as follows: assume the market participants know the value of the patent j but they do not know whether the patent will ever be granted or not. The market participants use the universal unconditional probability of a patent grant to approximate the probability patent j will be granted. After the application publication, the stock market price incorporates the expected value of patents: $\pi * \xi_{jp}$. Thus, the stock market value change in the publication window ΔV_{jp} reflects the expected value $\pi * \xi_{jp}$.

4.3 Data

I filter for the data of the patent applications that have a public firm assignee at the time of publication. I match the application data with CRSP data using the publication date and assignee firm at the time of publication. A more detailed description of the data can be found in Chapter 2. The value estimation part focuses on the patent applications that are published alone with no other patent applications from the same firm assignee on its day of publication. Such patent applications only consist of 8.8% of all published patent applications in the data. In other words, more than 90% of patent applications are published with at least one other patent application from the same firm assignee on its day of publication. This chapter focuses on the patent applications that later get granted. The next chapter will investigate the value of patent applications that later get abandoned.

4.4 Results and Discussion

4.4.1 Event Window

As shown in Figure 4.1, there is a moderate and statistically significant increase in share turnover on the day before and the day when a firm has one or more patent applications published. The fact that stock turnover increases around a patent publication implies that a patent publication conveys important information to the market.

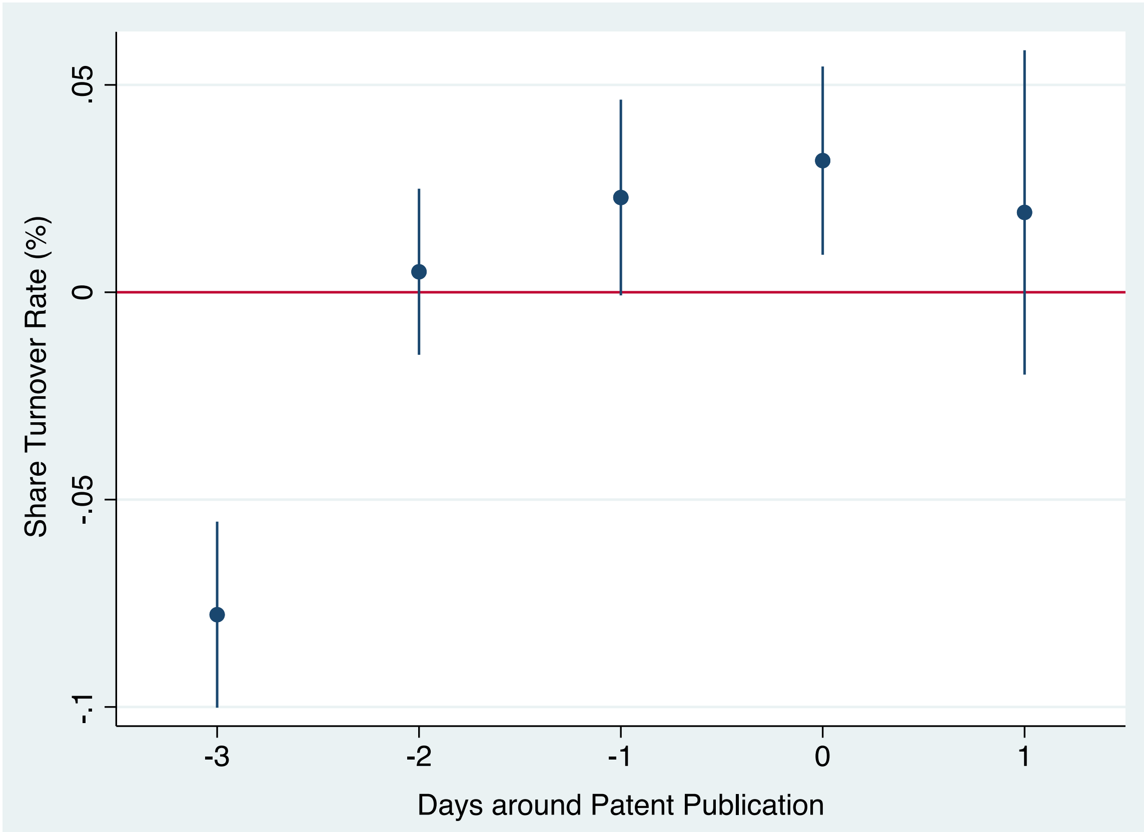

Figure 4. 1 Abnormal Share Turnover around Patent Application Publication

Table 4.1 reports the coefficient estimates b_l, l = -3, -2, -1, 0, 1, (and 90 percent intervals) for specifications as described in Equation (4.1).

Table 4. 1 Coefficient Estimates for Publication Time Window

	Coef.	Std. Err.	90% Conf. Interval	
b-3	-0.078	0.013	-0.100	-0.055
b-2	0.005	0.012	-0.015	0.025
b-1	0.023	0.014	-0.001	0.046
b0	0.032	0.013	0.009	0.054
b1	0.019	0.023	-0.020	0.058
cons	1.105	0.001	1.104	1.106

The classical criteria to choose the event window is to include the day of the event and consecutive days around the day of the event with positive coefficient estimates that are significant. In this case, the publication day itself and the day before publication satisfies the criteria. Therefore, I use a two-day event window over which information about a patent publication is reflected in the stock market.

4.4.2 Stock Market Response

I estimated the stock market value change related to publication, using the two-day event window identified in Section 4.4.1. The results are listed in Table 4.2.

Table 4. 2 Parameter Estimate for Equation (4.5)

	Coef.	Std. Err.	p-value
γ	0.037	0.009	0.000

For publication events, I estimate $\hat{\gamma} = 0.037$ for sole-publication applications that later get granted. Using the estimated coefficient and Equation (4.6), I calculated the signal-to-noise ratio $\hat{\delta}$ for sole-publication applications that later get granted to be 0.037. Table 4.3 shows the stock market value change related to publication. The median value is 7.66 million dollars. The mean is 37.82 million dollars, much higher than the median, indicating high skewness in the distribution. The variance is huge. Figure 4.2 shows the distribution of the market value change related to patent publication.

Table 4. 3 Stock Market Value Change Related to Publication (million $)

	ΔV_{jp}
Median	7.66
Mean	37.82
SD	130.53
Percentiles	
p1	0.11
p5	0.41
p10	0.78
p25	2.33
p50	7.66
p75	27.38
p90	83.01
p95	170.42
p99	441.27
# of Obs.	67817

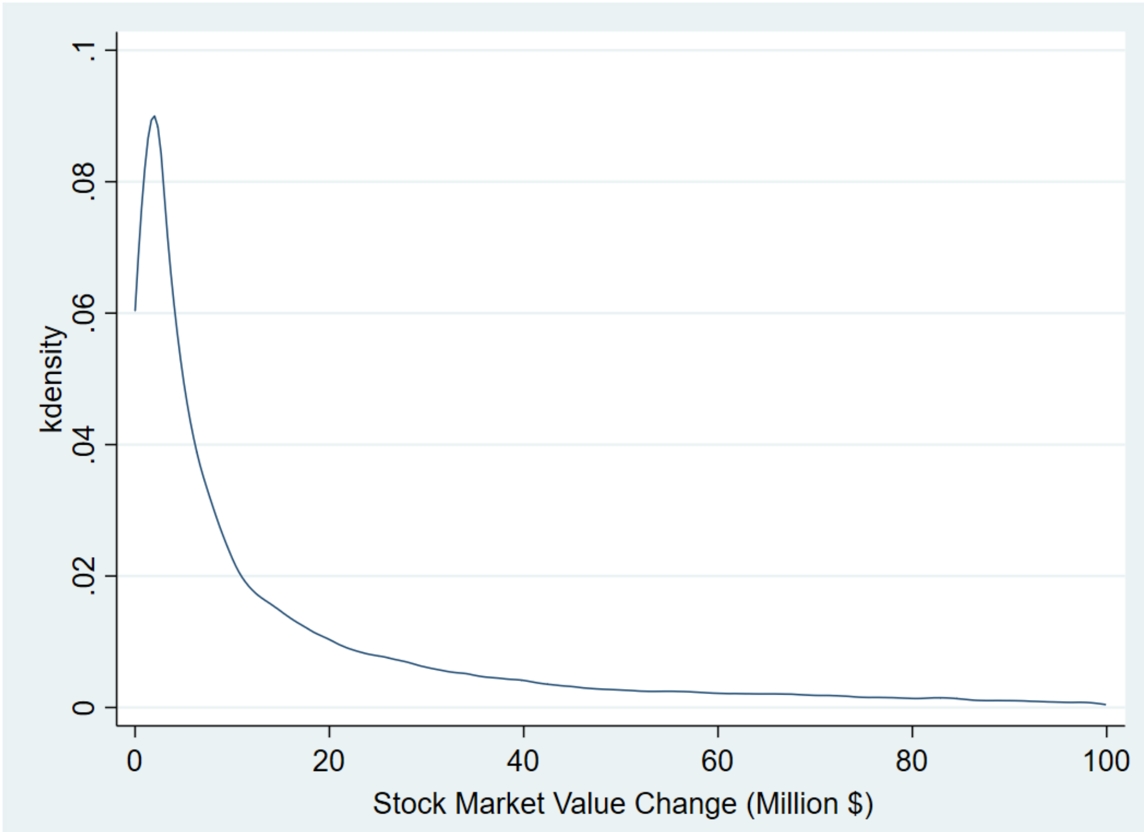

Figure 4. 2 Distribution of Market Value Change Related to Patent Publication

4.4.3 Patent Value

The estimated value at publication is derived according to Equation (4.8), using stock market value change related to publication and the unconditional probability of grant estimated in Section 3.4.1.1. The estimated patent value at publication is shown in Table 4.4. The paper estimated publication value for 67,817 patents. The median patent value at publication is 10.12 million dollars and the mean is 49.96 million dollars. Figure 4.3 shows the distribution of value at publication. The distribution of the value is highly skewed.

Table 4. 4 Patent Value at Publication (million $)

	ξ_{jp}
Median	10.12
Mean	49.96
SD	172.43
Percentiles	
p1	0.15
p5	0.55
p10	1.03
p25	3.07
p50	10.12
p75	36.17
p90	109.65
p95	225.12
p99	582.92
# of Obs.	67817

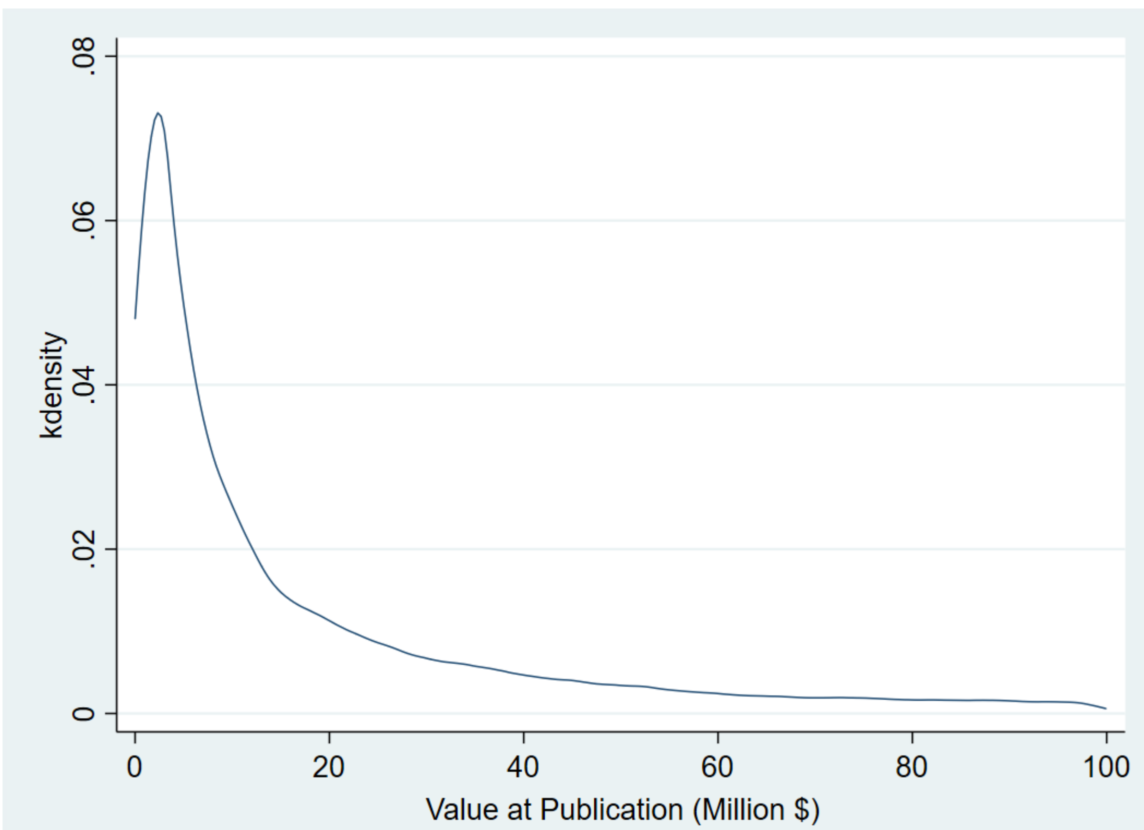

Figure 4. 3 Distribution of Patent Value at Publication

4.4.4 Comparison of Patent Value at Publication and Patent Value at Grant

4.4.4.1 Overall Comparison

To compare patent value at publication and grant, I filter for the patents that have both values estimated at publication and value estimated at grant. These patents need to be published as the only patent for their assignee firm on their publication date and granted as the only patent for their assignee firm on their grant date. I also filter for the patents that have the same assignee firms at publication and at grant[9]. The value estimations are shown in Table 4.5. The median value at publication and the median value at grant are very similar. Figure 4.4 shows the distribution of publication value and grant value. The two distributions are very similar.

Table 4. 5 Patent Value at Publication and Patent Value at Grant: Patents with both Value at Publication Estimate and Value at Grant Estimate (million $)

	Publication	Grant
Median	5.27	5.08
Mean	22.09	21.82
SD	62.53	62.56
Percentiles		
p1	0.13	0.09
p5	0.42	0.30
p10	0.75	0.56
p25	1.92	1.59
p50	5.27	5.08
p75	16.39	16.25
p90	48.32	48.20
p95	94.84	91.53
p99	296.25	289.97
# of Obs.	26085	26085

[9] A small portion of patents, about 1%, have different assignee firms at publication and at grant.

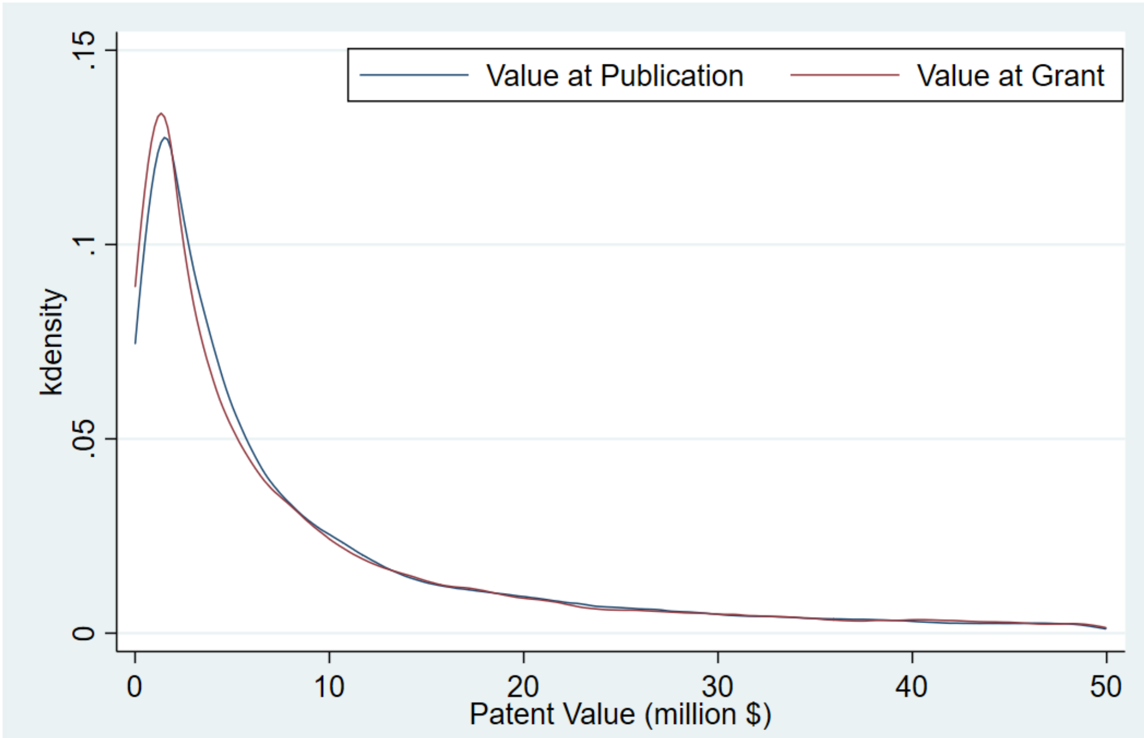

Figure 4. 4 Distribution of Value at Publication and Value at Grant

4.4.4.2 Comparison by Group

I group the patents by CPC Sections and compute the mean and median value of patents, at publication and at grant, in each CPC section. Table 4.6 lists the CPC section names and the number of patents included in this comparison. Figure 4.5 compares the mean value at publication and mean value at grant in each CPC section. Figure 4.6 compares the median value at publication and median value at grant in each CPC section.

Table 4. 6 Number of Patents by CPC Section: Patents with both Value at Publication Estimate and Value at Grant Estimate

CPC Section	# of Obs.
A Human Necessities	4350
B Performing Operations; Transporting	3132
C Chemistry; Metallurgy	4181
D Textiles; Paper	106
E Fixed Construction	616
F Mechanical Engineering; Lighting; Heating; Weapons; Blasting	1512
G Physics	6080
H Electricity	6106

As shown in Figure 4.5, the mean values for different sections vary but the orders of magnitude are the same. Section F, Mechanical Engineering; Lighting; Heating; Weapons; Blasting, has the lowest mean value of patents at publication and at grant, while Section C, Chemistry; Metallurgy, has the highest mean value of patents at publication and grant. The highest mean value is about twice the lowest mean value. Within a CPC section, the mean value at publication and the mean value at grant are very similar. This similarity applies to every CPC section.

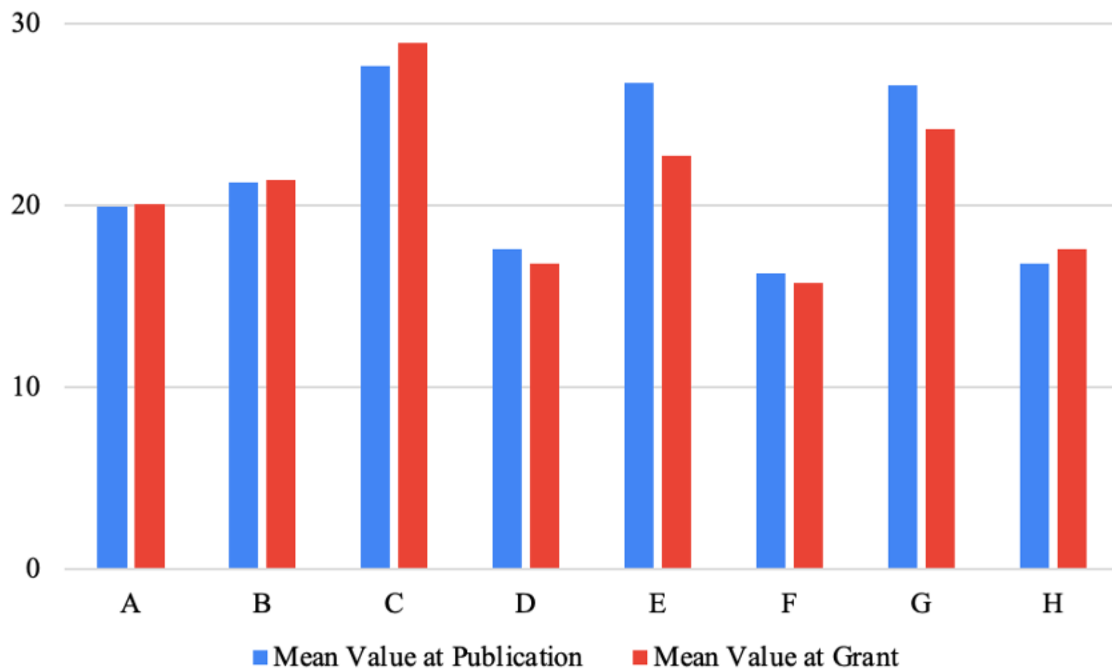

Figure 4. 5 Comparison of Mean Value at Publication and at Grant: by CPC Section

Figure 4.6 shows that the median values for different sections also have the same order of magnitude. Section A, Human Necessities, has the lowest median value, while Section E, Fixed Construction, has the highest median value. The highest median value is about twice the lowest median value. Note that the sections that have the lowest/highest median value are not the sections that have the lowest/highest mean value, suggesting the value distributions in different sections are different. It is also worth noting that within the same section, the median value at publication is very similar to the median value at grant. This similarity applies to every CPC section.

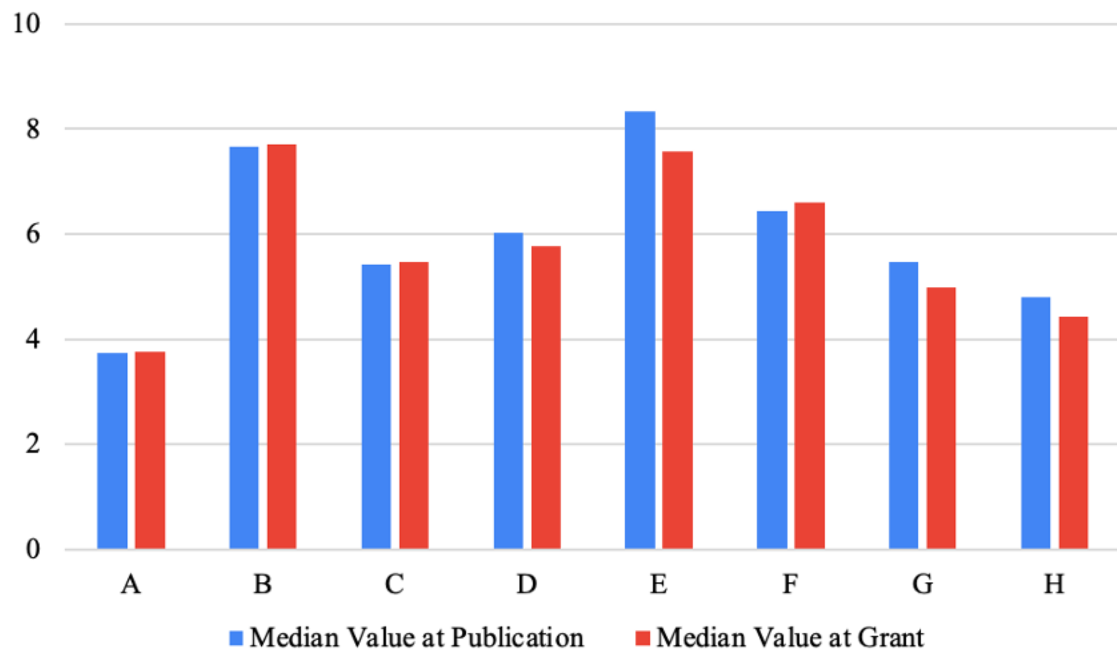

Figure 4. 6 Comparison of Median Value at Publication and at Grant: by CPC Section

I also group the patents by the year of filing and compute the mean and median value of patents filed in different years. To avoid the truncation problem and make sure each year has enough patents for comparison, I only include the years from 2002 to 2016. Figure 4.7 displays the mean patent value at publication and at grant, by the year of filing. Figure 4.8 displays the median patents value at publication and at grant, by the year of filing.

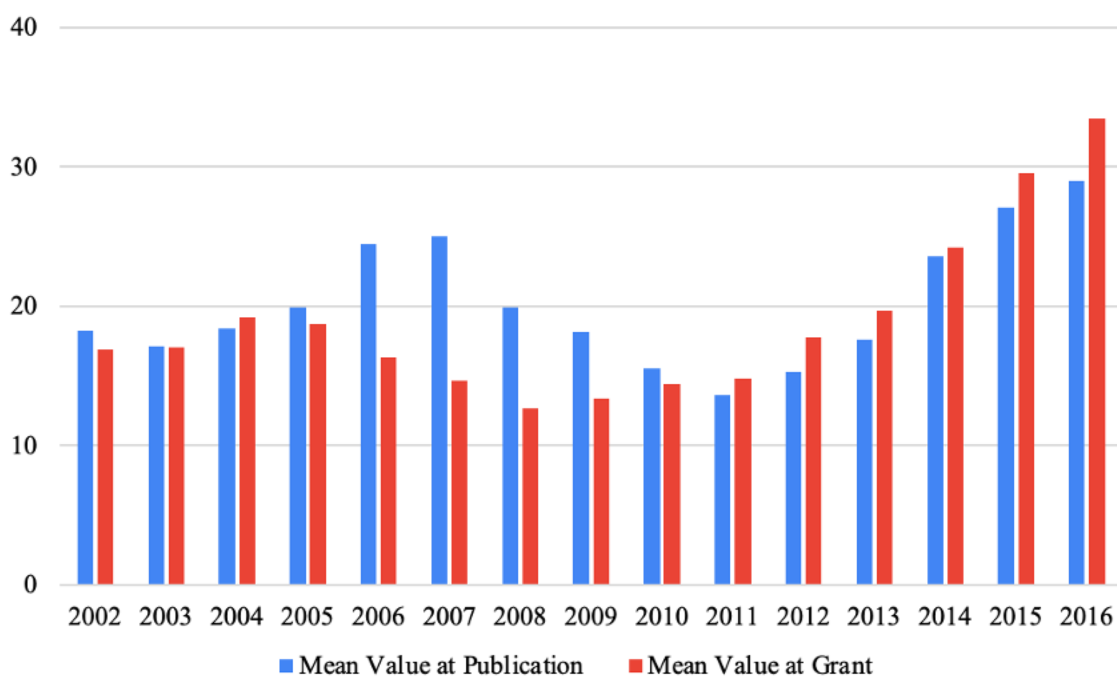

Figure 4. 7 Comparison of Mean Value at Publication and at Grant: by Filing Year

As shown in Figure 4.7, the mean value at publication and at grant are similar for every year except for applications filed in 2006-2009, where the mean value at publication is substantially higher than the mean value at grant. The 2007-2008 financial crisis may play an important role in this difference. I also noticed the mean value of patents, both at publication and at grant, increases considerably between 2011 and 2016.

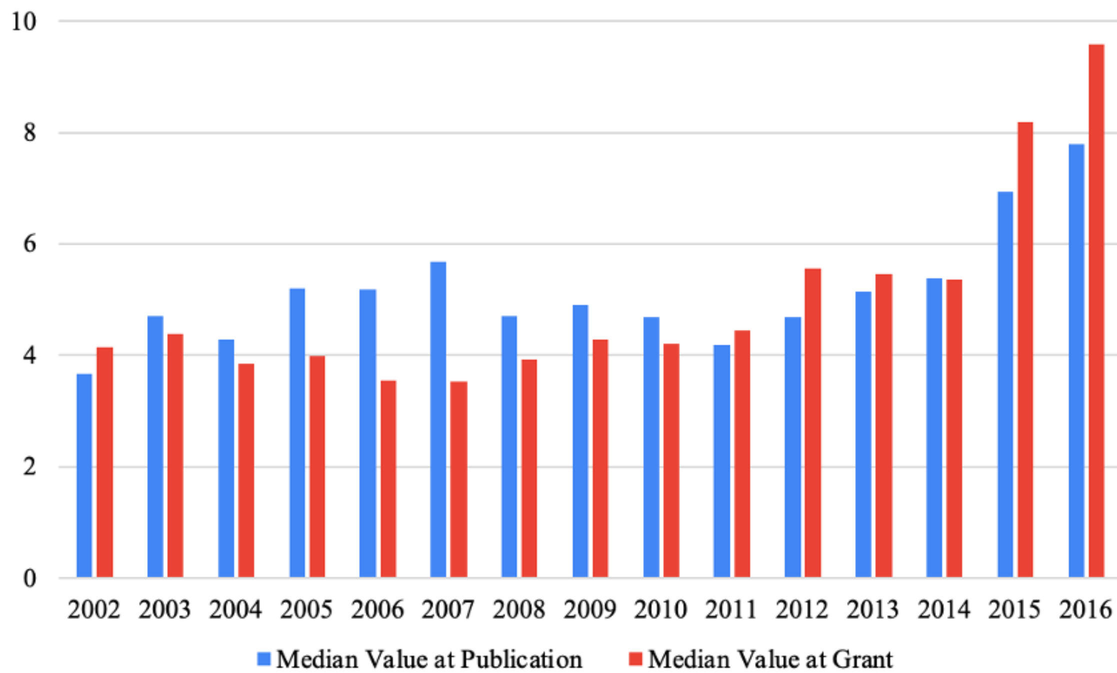

Figure 4. 8 Comparison of Median Value at Publication and at Grant: by Filing Year

Figure 4.8 suggests that the median value at publication and at grant are similar for each year except for applications filed in 2005-2009, where the median value at publication is substantially higher than that at grant. Again, the 2007-2008 financial crisis may play an important role in explaining the difference. Besides, the median value of patents is quite steady across the years, except for a recent increase in 2015-2016.

4.4.5 The Difference between Patent Value at Grant and Patent Value at Publication

For the patents that have both values estimated at publication and at grant, I am interested in exploring the difference in patent values at publication and at grant. Thus, I calculate the difference between grant value and publication value for each of the patents and summarize the distribution of this value difference between publication and grant in Table 4.7. The median of the value differences is 0.03 million dollars, which is very small compared to the value at publication and at grant. Figure 4.9 displays the distribution of the value change between publication and grant. The distribution is roughly symmetric, it centers around 0 and is very concentrated around 0, suggesting that the change in value between publication and grant can be either positive or negative, and the median is close to 0. If the difference is measured in percentage, i.e., $(\xi_{jg} - \xi_{jp})/\xi_{jp}$ *100%, then the median percentage difference is small, only -1.52%, the mean percentage difference is 18.12%. The range of the percentage difference is wide. Figure 4.10 shows the distribution of the percentage difference. As shown in the figure, most patents have a relatively small percentage difference between the value at grant and the value at publication, while some patents can have very large percentage differences.

Table 4. 7 Difference between Patent Value at Grant and Value at Publication: Patent with both Value at Grant Estimate and Value at Publication Estimate

	Difference (million \$) $(\xi_{jg} - \xi_{jp})$	Difference (%) $(\xi_{jg} - \xi_{jp})/\xi_{jp}$
Median	-0.03	-1.52
Mean	-0.27	18.12
SD	36.62	118.24
Percentiles		
p1	-101.35	-89.31
p5	-21.09	-76.74
p10	-8.90	-66.02
p25	-1.98	-40.31
p50	-0.03	-1.52
p75	2.11	45.06
p90	9.55	103.62
p95	22.66	165.18
p99	88.46	412.10
# of Obs.	26085	26085

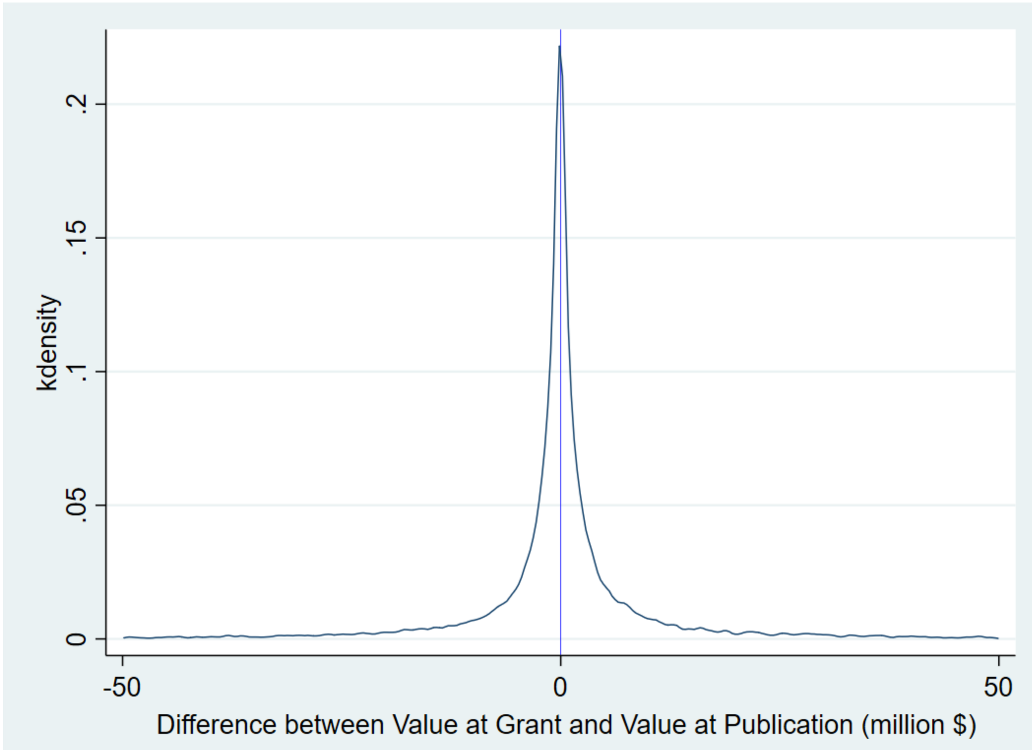

Figure 4. 9 Distribution of the Difference between Patent Value at Grant and Patent Value at Publication (million $)

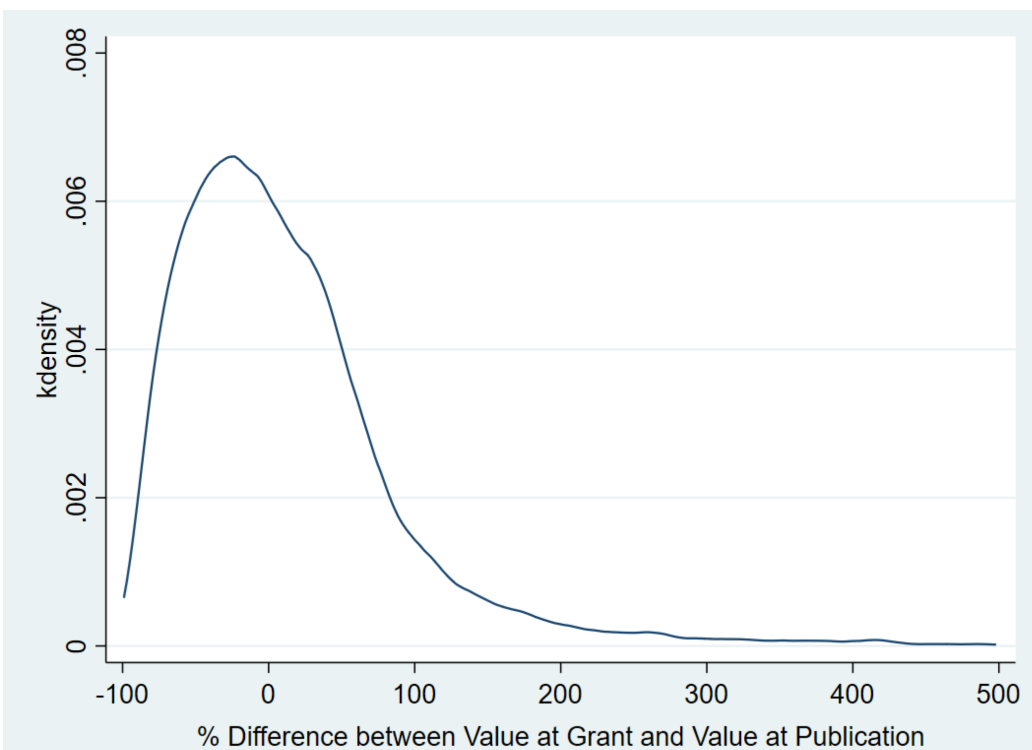

Figure 4. 10 Distribution of the Difference between Patent Value at Grant and Patent Value at Publication (%)

I am interested in where the large percentage differences happen. In other words, do most large percentage differences happen on low-value patents or high-value patents? So, I take a closer look at the percentage differences using the patent value percentile. For each percentile of patent value at publication, I calculated the mean of the percentage differences between the value at grant and the value at publication. Figure 4.11 shows how the mean percentage differences change with patent value at publication. The results suggest that large percentage differences happen mostly on low-value patents. Since the value is low, even a small value difference can become a large percentage difference. In contrast, high-value patents have on average much smaller percentage differences between value at grant and value at publication. For example, the percentage differences in the top 10% most valuable patents are on average only -1.05%. Suggesting that the value estimation methodologies using publication and using grant give very similar results for these high-value patents. Considering that these high-value patents are frequently also the ones that draw the most attention, the findings are especially useful for understanding the patenting process and the value of these patents.

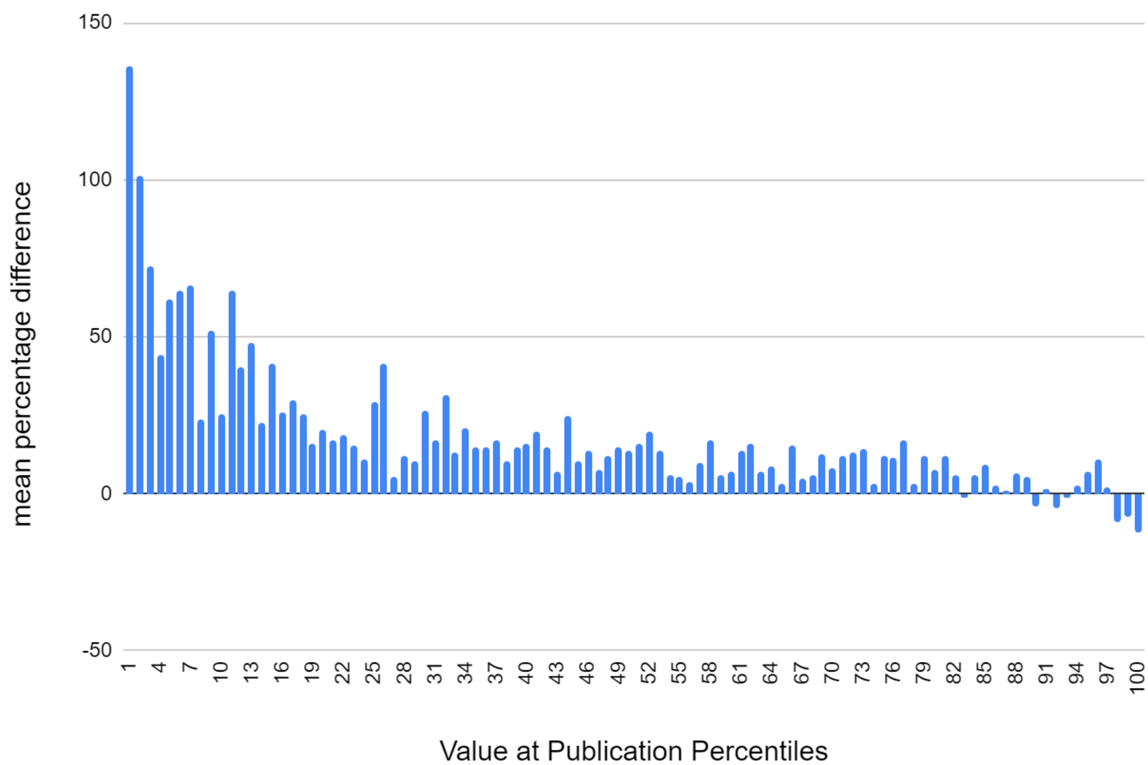

Figure 4. 11 Mean Percentage Differences between Patent Value at Publication and Patent Value at Grant: by Percentile of Patent Value at Publication

4.4.6 Combining the Patent Value at Publication and Patent Value at Grant

Now I have come up with two patent value estimates, one at publication, and the other at grant. I have also made comparisons of the two patent value estimates and find they are similar to each other on the population level (i.e., population mean/median/standard deviation) but can differ at the individual level (i.e., value at publication and at grant for a given patent). If we are willing to assume that patent value remains relatively stable between publication and grant, then it is natural to think about coming up with a new measure, which combines the information from the value at publication and the value at grant, reducing the errors, and is thus more accurate.

One feasible and simple approach to generating the new measure of patent value is to take the average of the patent value estimated at publication and the patent value estimated at grant. This helps reduce the errors and make the estimate more accurate. However, this approach does not consider the patent value change between publication and grant. In practice, patent value can either decrease or increase during the patent examination process.

Another possible approach is to use the weighted average of patent value at publication and patent value at grant. The weights used need to be considered carefully. A potential strategy is to use a higher weight at grant and a lower weight at publication since the value at grant reflects more of the value of the patents at the time of grant, which is more likely to be the actual value of the final approved version of the patent.

There are more possible approaches to generate new measures combining value at publication and value at grant. It is worth further exploring and can be an interesting topic for future studies.

4.4.7 Patent Value at Publication and Grant Lag

Like Section 3.4.6., I would like to explore the relationship between patent value at publication and grant lag, to see if the stock market participants can predict the grant lag from the information revealed in patent publication.

To do this, I regress the log of patent value at publication on grant lag, controlling for firm-year fixed effects.

$$ln\ \xi_{jp} = a + blag_j + cZ_{ft} + u_{ft} \tag{4.9}$$

The results are shown in Table 4.8.

Table 4. 8 Regression Results on Log Patent Value and Grant Lag

	Coef.	Std. Err.	p-value
b	-.00007	.00004	0.066

The results suggest that patent value at publication does not change appreciably with grant lag, indicating that at the time of publication, the market observes the initial value of a patent, which is independent of grant lag. In other words, at the time of publication, the market participants cannot predict with accuracy how long it will take for a patent application to get granted.

4.4.8 Aggregate Patent Value at Publication

I am interested in the distribution of the aggregate patent value at publication. To investigate the distribution, I rank patents by values at publication from low to high and calculate the fraction of aggregate patent value by fraction of patents. The results are shown in Figure 4.12.

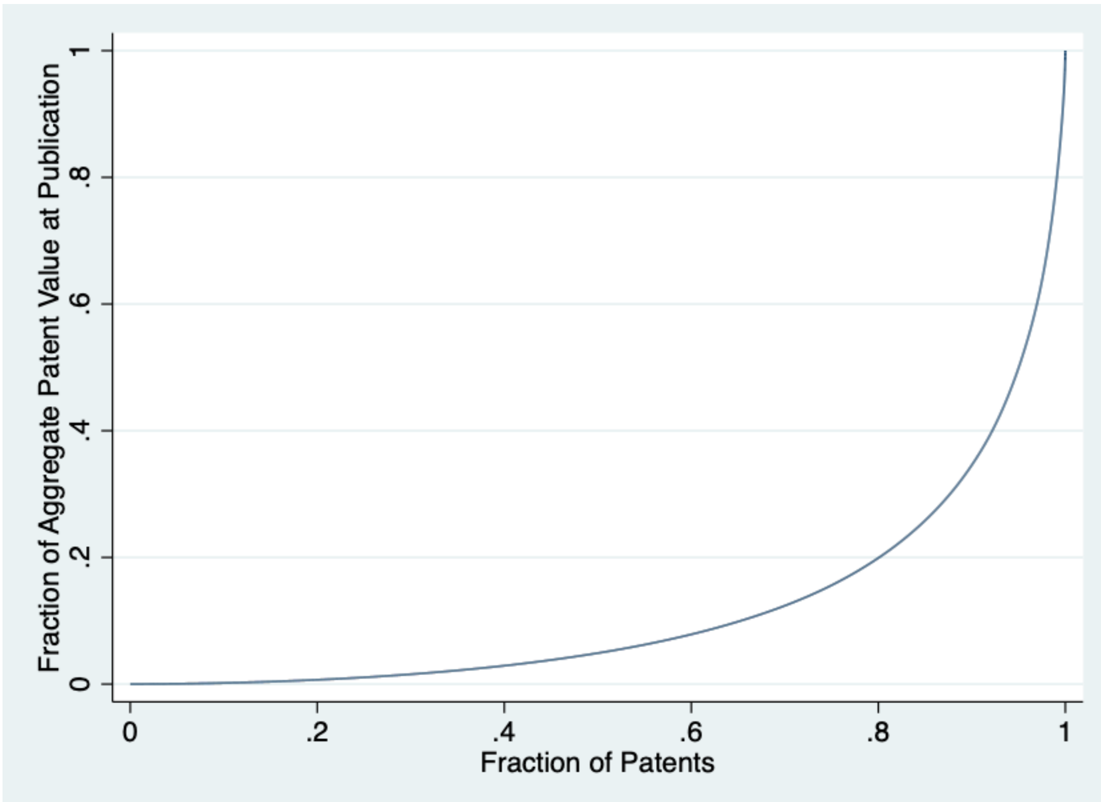

Figure 4. 12 Fraction of Aggregate Patent Value at Publication by Fraction of Patents

Figure 4.12 indicates that most of the aggregate patent value at publication comes from high-value patents. The 20% least valuable patents contribute to less than 1% of the aggregate patent value, while the 20% most valuable patents contribute to over 80% of the aggregate patent value. In other words, most of the aggregate patent value comes from high-value patents. This finding is consistent with the findings about aggregate patent value at grant.

Like Section 3.4.7, the results on patent valuation at publication for each patent can also help with R&D accounting. The total value of the sole-publication patents can be approximated by the product of the mean value and number of patents of interest. By making an additional assumption about identical value distributions in sole-publication patents and multiple-publication patents, the total value estimation can be extended to include all patents with pre-grant publication.

The estimation of the total value can be precise despite the value of any one patent might be with high variance. The reasoning behind this is explained in Section 3.4.7. In short, according to Central Limit Theorem, when the number of patents N is large, the total value is approximately normal. When N is large, the variance of the total value is relatively small compared to the mean, making the estimate of the total value of applications accurate.

For patents that are published before grant, two estimates can be developed for the total value of patents, one using value at publication, and the other using value at grant. In this case, even more information is available on the aggregate patent value, making it possible to generate aggregate value estimates with even higher accuracy.

The findings have important potential to be used in R&D accounting. It has the advantage of high accuracy and high flexibility. For example, it can be used to account for the value of R&D in individual firms, in certain CPC sectors, in certain years, or account for the nationwide aggregate R&D.

4.4.9 Aggregate Patent Value: Back-of-the-Envelope Calculations

4.4.9.1 Aggregate Patent Value: by Year

In this section, I present a back-of-the-envelope calculation of aggregate patent value by year for the patents owned by public firms trading in the U.S. stock market. I make the following simplification assumptions: (1) sole-publication patents have the same value distribution as multiple-publication patents; (2) sole-grant patents have the same value distribution as multi-grant patents; (3) patent value at publication are independent and identically distributed random variables with mean 22.09 million dollars and standard deviation 62.53 million dollars (Table 4.5); (4) patent value at grant are independent and identically distributed random variables with mean 21.82 million dollars and standard deviation 62.56 million dollars (Table 4.5); (5) assume all patents are published before grant (A small portion of patents are not published until granted. The assumption here is for simplification purposes only). I obtain the total number of patents filed each year from the patent application dataset and use CLT to calculate the distribution of the aggregate value at publication and at grant. The results are displayed in Figure 4.13. The error bars represent the 95% confidence intervals. To avoid the truncation problem, I include only the years between 2001 and 2017.

As shown in Figure 4.13, the aggregate value of patents at publication and at grant are very similar to each other every year. Both range from ~1.2 trillion dollars in 2001 to ~1.9 trillion dollars in 2017. The aggregate value of patents at publication is slightly higher than the aggregate value of patents at grant. However, the difference is not statistically significant, as the confidence intervals of aggregate value at publication and aggregate value at grant overlap in each year. It is also worth noting that the confidence interval is relatively small compared with the mean of the aggregate value, suggesting that the aggregate value estimation is of high accuracy, given the assumptions hold.

I note that there is a decline in aggregate patent value in 2009-2011. One possible explanation is that the 2007-2008 financial crisis forced some public firms to invest less in R&D, which then lead to a decline in the number of patents filed in the following years.

2012-2017 have higher aggregate patent value, benefiting from the increased number of patents filed in these years.

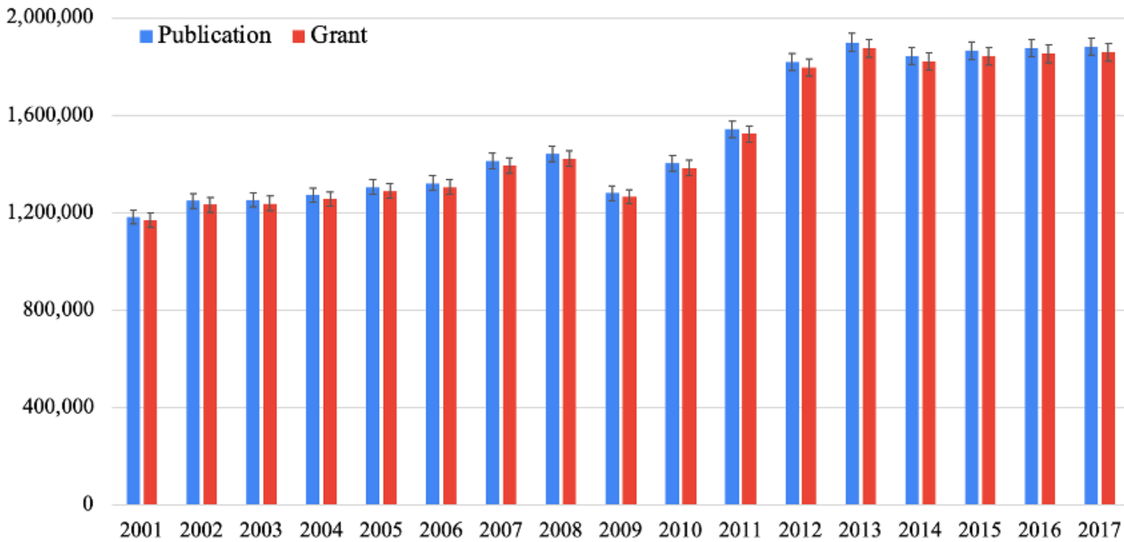

Figure 4. 13 Aggregate Patent Value by Filing Year: at Publication vs. at Grant

4.4.9.2 Aggregate Patent Value: by CPC Section

I do a back-of-the-envelope calculation for the aggregate value of patents by CPC Section for patents owned by public firms trading in the U.S. stock market. I make the following simplifying assumptions: (1) sole-publication patents have the same value distribution as multiple-publication patents; (2) sole-grant patents have the same value distribution as multi-grant patents; (3) patent value at publication, within each CPC section, are independent and identically distributed random variables with mean and standard deviation identified in Section 4.4.4.2 (different CPC sections have different mean and standard deviation); (4) patent value at grant, within each CPC section, are independent and identically distributed random variables with mean and standard deviation identified in Section 4.4.4.2 (different CPC sections have different mean and standard deviation); (5) all patents are published before grant (for simplification purpose only). I obtain the total number of patents in each CPC section from the patent application dataset (Nov 29, 2000, to Mar 31, 2022) and use CLT to calculate the distribution of the aggregate value at publication and aggregate value at grant. The results are displayed in Figure 4.14. The error bars represent the 95% confidence intervals.

Figure 4.14 suggests that differences in the aggregate value of patents in different CPC sections are huge. Section G, Physics, has the highest aggregate value, around 12 trillion dollars, while Section D, Textiles; Paper, has the lowest aggregate value, less than 0.01 trillion. The difference between the highest aggregate value and the lowest aggregate value is over 100 times. This huge difference is mainly driven by the difference in the number of patents in different sections (e.g., ~488 thousand in Section G vs. ~4 thousand in Section D). The differences in average patent value in different sections are relatively small (as shown in Section 4.4.4.2) and only contribute a relatively small share towards the difference in aggregate patent value. It is worth noting that patent values vary substantially within the same CPC section. Each section has high-value patents and low-value patents. Even in sections with high aggregate value, there are still low-value patents; and even in sections with low aggregate value, there are still high-value patents.

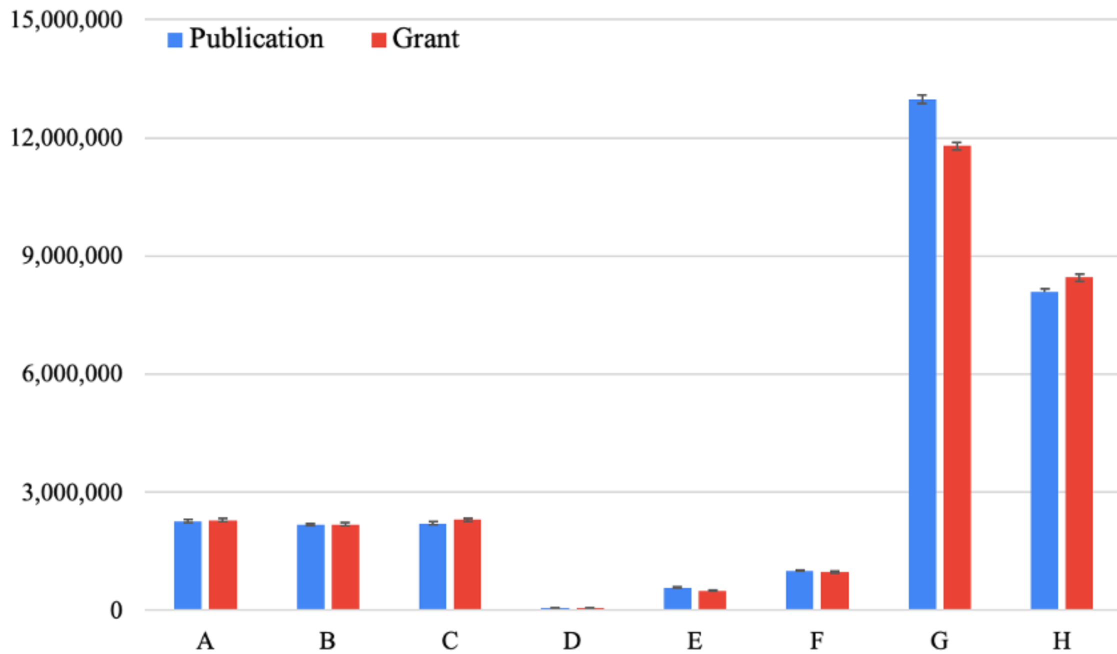

Figure 4. 14 Aggregate Patent Value by CPC Section: at Publication vs. at Grant

Within each section, the aggregate value at publication and at grant are very similar to each other. The confidence intervals of aggregate value at publication and aggregate value at grant for the same section often overlap, suggesting the difference between the two aggregate value measures for the same section are not significantly different. Moreover, the confidence intervals are very small compared with the aggregate value, suggesting the estimation is quite accurate, given the assumptions hold.

4.5 Robustness Checks

4.5.1 Alternative Distribution Assumption

For robustness check, as in Section 3.5.2, instead of assuming v_j follows the truncated normal distribution, I assume that v_j is exponentially distributed with parameter $1/\sigma_v$, keeping all other assumptions unchanged, the conditional expectation of v_j given R_j is

$$E[v|R] = R + \sigma_\varepsilon(\sqrt{\frac{2}{\pi}}\frac{exp(-\tilde{R}^2/2)}{G^c(\tilde{R}/\sqrt{2})} - \frac{\sigma_\varepsilon}{\sigma_v}) \quad (4.10)$$

where G^c is the complementary error function and

$$\tilde{R} = \frac{\sigma_\varepsilon}{\sigma_v} - \frac{R}{\sigma_\varepsilon} \tag{4.11}$$

Using the same signal-to-noise ratio estimated from empirical data in Section 4.4.2, I calculate the value of patents with the exponential distribution assumption. The results are quantitatively similar to the results obtained with the truncated normal distribution assumption. The correlation coefficient between the two value estimates is higher than 99%. More detailed results are shown in Table 4.9 and Figure 4.15.

Table 4. 9 Patent Value at Publication with Exponential Distribution Assumption (million $)

	Publication
Median	12.00
Mean	59.53
SD	206.24
Percentiles	
p1	0.18
p5	0.64
p10	1.22
p25	3.62
p50	12.00
p75	42.99
p90	130.15
p95	268.28
p99	696.64
# of Obs.	67817

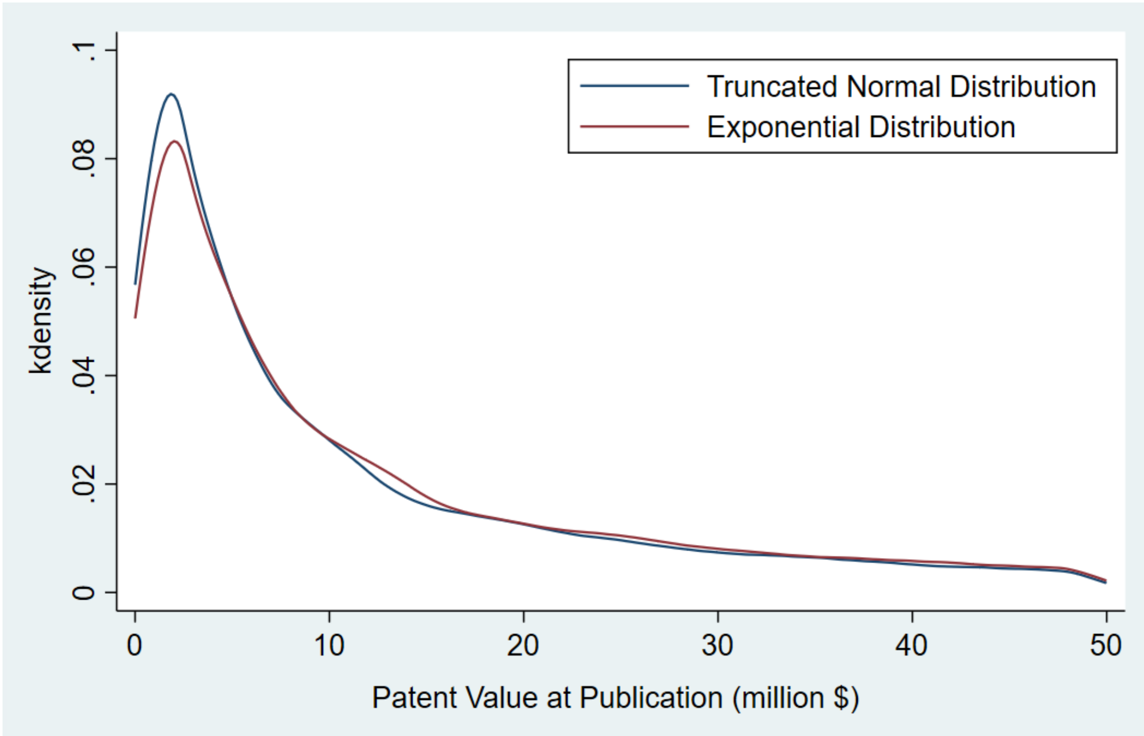

Figure 4. 15 Distribution of Patent Value at Publication with Different Distribution Assumptions

4.5.2 Probability of Grant

Like Section 3.5.3, I test how different assumptions on the probability of grant will change the patent value estimations at publication. I look at the following cases.

- Case 0: Allow the probability of grant to vary with the time lag between publication and grant. This is the assumption I use in the main results section.
- Case 1: Assume the probability of grant to be a constant for all firms and all patents. This is the assumption that KPSS used in their analysis.
- Case 2: Allow the probability of grant to vary by application year. I match patents with the probability of grant based on the application year. To avoid truncation issues, I only used applications by 2017 to estimate grant rates by year. To obtain an estimate of the probability of grant for years after 2017, I use the average grant rate between 2015-2017.
- Case 3: Allow probability to vary by firm. To do this, I match patents with the probability of grant based on assignee firms.
- Case 4: Allow probability to vary by firms by decade. I match patents with the probability of grant based on the assignee firm and decade of application filing (the 2000s vs. 2010s).
- Case 5: Allow the probability of grant to vary across CPC sections.
- Case 6: Allow the probability of grant to vary across CPC classes.
- Case 7: Allow the probability of grant to vary across CPC subclasses. For Cases 5-7, I match patents with their CPC classification information. When one patent is matched

with more than one class, I use the first one.

It is worth noting that for patent publication, I only use the unconditional probability of grant, so Case 0 is the same as Case 1. The estimated patent values at publication in different cases are shown in Table 4.10 and Figure 4.16. The distributions are very similar in different cases.

Table 4. 10 Patent Value at Publication in Different Cases (million $)

	Case 0	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7
Median	10.12	10.12	9.12	10.02	10.69	10.18	10.20	10.25
Mean	49.96	49.96	38.15	52.52	54.13	51.22	51.71	52.95
SD	172.43	172.43	98.84	174.31	177.43	172.67	174.72	174.76
Percentiles								
p1	0.15	0.15	0.14	0.16	0.17	0.15	0.15	0.15
p5	0.55	0.55	0.53	0.56	0.62	0.56	0.56	0.56
p10	1.03	1.03	0.99	1.07	1.18	1.06	1.06	1.07
p25	3.07	3.07	2.85	3.14	3.34	3.16	3.15	3.18
p50	10.12	10.12	9.12	10.02	10.69	10.18	10.20	10.25
p75	36.17	36.17	31.16	35.70	37.15	36.71	36.75	36.94
p90	109.65	109.65	89.13	113.34	118.45	113.62	114.84	120.28
p95	225.12	225.12	175.47	236.99	245.00	233.13	236.14	241.86
p99	582.92	582.92	443.39	636.21	661.42	604.45	610.59	637.67
#of Obs.	67817	67817	61321	67776	63792	67814	67814	67812

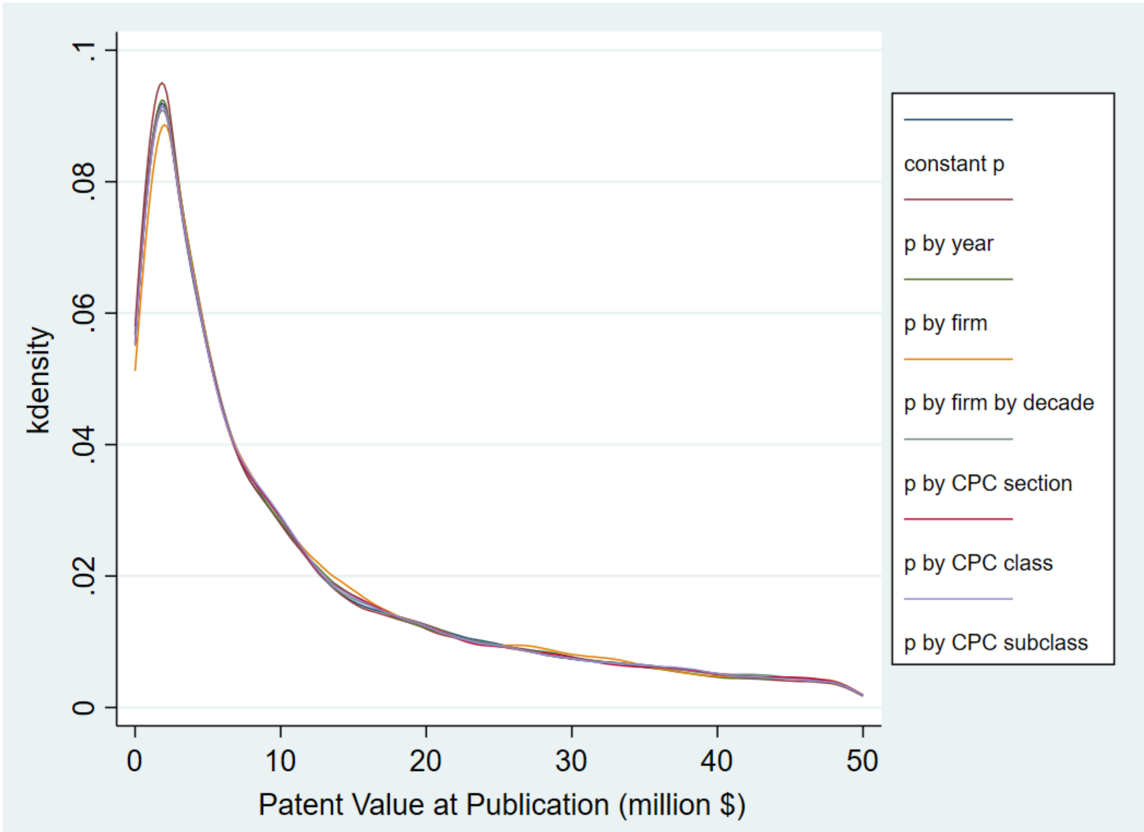

Figure 4. 16 Distribution of Patent Value at Publication in Different Cases

I then calculate the patent value changes between publication and grant using patents that have both publication and grant-based value and have the same assignee firm at publication and at grant. The value of these patents at publication and at grant under different cases are shown in Table 4.11 and Table 4.12, respectively. The difference between publication and grant value of these patents varies in different cases. The differences are shown in Table 4.13. In general, Case 0 has the smallest differences between the value at publication and the value at grant. Figure 4.17 displays the distributions of differences in each case. Distributions of differences in Case 1-7 skew to the right, while the distribution of differences in Case 0 is close to symmetric around 0. Case 0 is where dynamic probability is introduced. The results indicate that including the dynamics of probability is a good idea.

Table 4. 11 Value at Publication in Different Cases: Patents with both Value at Publication Estimate and Value at Grant Estimate (million $)

	Case 0	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7
Median	5.27	5.27	5.08	5.60	5.96	5.44	5.49	5.56
Mean	22.09	22.09	20.68	25.57	26.42	23.13	23.44	24.72
SD	62.53	62.53	59.39	78.33	80.98	65.27	66.19	71.18
Percentiles								
p1	0.13	0.13	0.13	0.15	0.16	0.13	0.13	0.13
p5	0.42	0.42	0.41	0.48	0.53	0.43	0.43	0.43
p10	0.75	0.75	0.74	0.85	0.94	0.77	0.77	0.78
p25	1.92	1.92	1.87	2.12	2.25	2.00	2.01	2.04
p50	5.27	5.27	5.08	5.60	5.96	5.44	5.49	5.56
p75	16.39	16.39	15.23	17.29	18.04	16.69	16.62	16.88
p90	48.32	48.32	45.31	53.76	55.25	49.87	50.65	52.45
p95	94.84	94.84	87.98	103.74	109.40	99.75	101.01	108.08
p99	296.25	296.25	278.44	367.59	360.16	322.36	326.96	357.44
#of Obs.	26085	26085	24364	25594	23263	26083	26083	26049

Table 4. 12 Value at Grant in Different Cases: Patents with both Value at Publication Estimate and Value at Grant Estimate (million $)

	Case 0	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7
Median	5.08	8.16	7.70	9.47	10.69	7.77	7.95	8.18
Mean	21.82	33.50	31.75	38.07	41.81	31.66	32.22	32.39
SD	62.56	86.08	83.49	122.69	98.62	84.67	90.10	91.47
Percentiles								
p1	0.09	0.16	0.16	0.13	0.15	0.15	0.15	0.14
p5	0.30	0.52	0.51	0.44	0.52	0.47	0.47	0.47
p10	0.56	0.97	0.92	0.89	1.04	0.91	0.91	0.89
p25	1.59	2.68	2.52	2.76	3.09	2.51	2.54	2.57
p50	5.08	8.16	7.70	9.47	10.69	7.77	7.95	8.18
p75	16.25	25.91	24.36	32.82	36.68	25.41	26.28	26.61
p90	48.20	75.76	71.79	90.67	101.74	73.02	75.10	75.18
p95	91.53	147.84	136.29	169.88	180.76	135.95	139.54	136.37
p99	289.97	433.03	415.77	430.15	509.44	390.89	391.30	377.01
#of Obs.	26085	26085	24364	25594	23263	26083	26083	26049

Table 4. 13 The Difference between Patent Value at Publication and Patent Value at Grant under Different Cases (million $)

	Case 0	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7
Median	-0.03	1.81	1.57	1.75	2.14	1.33	1.34	1.32
mean	-0.27	11.41	11.07	12.50	15.39	8.52	8.78	7.67
sd	36.62	47.05	52.17	113.29	85.48	50.19	58.36	65.82
Percentiles								
p1	-101.35	-36.09	-47.17	-165.80	-147.75	-78.02	-90.87	-131.88
p5	-21.09	-5.16	-7.17	-23.06	-25.01	-10.85	-13.29	-21.23
p10	-8.90	-1.74	-2.49	-7.48	-8.00	-3.69	-4.44	-6.56
p25	-1.98	0.04	-0.08	-0.79	-0.82	-0.35	-0.46	-0.71
p50	-0.03	1.81	1.57	1.75	2.14	1.33	1.34	1.32
p75	2.11	8.46	8.21	12.46	15.00	7.54	7.95	8.40
p90	9.55	29.46	29.10	43.37	52.73	25.62	27.43	29.36
p95	22.66	60.52	58.78	84.83	99.44	51.21	56.62	60.67
p99	88.46	200.55	219.23	268.07	332.58	179.90	182.16	189.34
#of Obs.	26085	26085	24364	25594	23263	26083	26083	26049

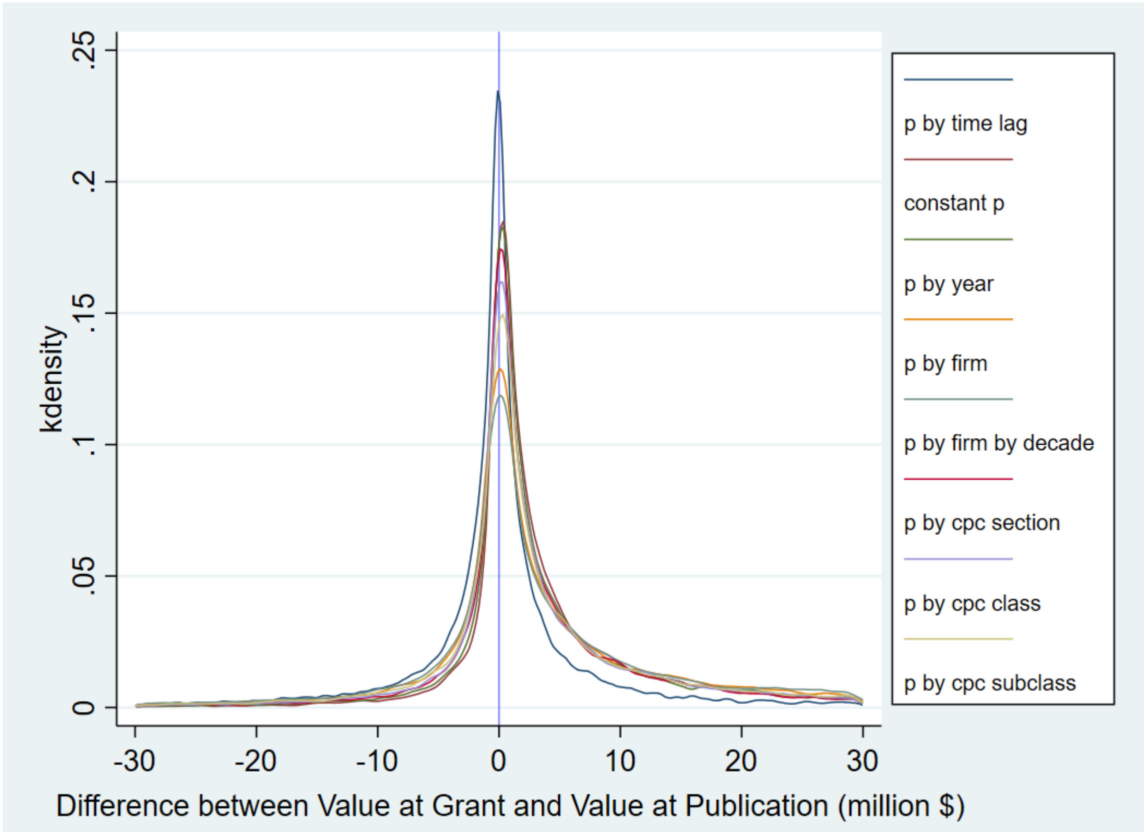

Figure 4. 17 Distribution of the Difference between Patent Value at Publication and Patent Value at Grant under Different Cases

4.5.3 More Analysis of Patent Value at Publication and Grant Lag

In Section 4.4.6, I explored the relationship between the patent value at publication and grant lag. Like Section 3.5.4, for robustness check, I redo the analysis using various patent value measures, various grant lag measures, and various fixed effects.

More specifically, for regression of Equation (4.9), I try:

On the LHS, use either

- value at publication, or
- log of value at publication.

On the RHS, use either

- grant lag measured by the number of weeks,
- lag categories generated by quantiles of lag in weeks (i.e., 1, 2, 3, 4), or
- a dummy variable (i.e., define long-lag = 1 if the time lag is longer than 75% of all patents and 0 otherwise).

For control variables, use either

- year fixed effects,
- firm fixed effects,

- firm-year fixed effects, or
- CPC class fixed effects.

The results are robust to value or log value, control variables, and the form of the grant lag variable (i.e., the number of weeks, categorical, or dummy). Table 4.14 shows the results using log value with firm-year fixed effects.

Table 4. 14 More Regression Results on Log Patent Value at Publication and Grant Lag

Grant Lag Measures	Coef.
lag weeks	-0.00007 (.00004)
4 categories (category 1 as the control group)	-0.00120 (0.00745) -0.01308 (0.00778) -0.01795* (0.00829)
Long-lag dummy	-0.01200 (.00661)

The findings listed in Section 4.4.6 still hold, patent value at publication doesn't change with grant lag.

4.6 Conclusions

The chapter focuses on patent publication events and develops a new patent value measure based on the abnormal stock market value change in the patent publication window and the unconditional probability of grant. The chapter then compares the value at publication with the value at grant estimated in Chapter 3. The two value measures give very similar results. The chapter then explores the relationship between patent value and grant lag and finds some interesting results. The chapter also does back-of-the-envelope calculations of aggregate patent value, by patent filing year, and by CPC section.

Some important findings include:

- The patent publication event is of vital importance. The patent publication is the time point when the public gain accurate information about the patent and generate their initial estimate of patent value.

- After correcting for changes in the probability of grant, patent value at publication and value at grant are similar. This implies that the market is risk-neutral and rational, and on average makes good patent value estimations at publication and grant.

- Patent value at publication is not affected by grant lag, indicating that the market participants cannot predict how long it will take for a patent application to get granted given the information available at the time of publication.

- The aggregate value at publication and at grant are very similar to each other. The confidence intervals of aggregate value at publication and aggregate value at grant often overlap, suggesting the difference between the two aggregate value measures are not significantly different.

In the next chapter, I focus on the published patent applications that later get abandoned. This group of patent applications has received little attention in literature but can play an important role in understanding the patent decision-making process. I estimate the value at publication of these later-abandoned applications and then compare the value with the value estimated in this chapter of later-granted applications, to investigate if there are any significant differences between application value and their probability of grant.

5 Valuation of Abandoned Patent Applications Using Stock Market Response at Publication

5.1 Introduction

In Chapter 3 and Chapter 4, I focus on patents and developed two measures for patent value using stock market response at grant and at publication, respectively. However, not all published patent applications later get granted. Many of the published applications later get abandoned for various reasons at various stages of the patent application. For example, some applications are abandoned implicitly as their patent applicants didn't respond to the examiner's notice in the given period (usually 6 months), while some others are explicitly requested by their applicants for abandonment. These abandoned applications have received little attention in the literature, especially in the literature on patent valuation. The questions, of whether abandoned patent applications have value, and if yes, what is the value, have not been thoroughly studied.

Using the methodology developed in Chapter 4, this chapter looks at these abandoned patent applications and measures their value for their assignee firm conditional on grant at the time of publication. This chapter also compares the value at publication of applications that later get abandoned with that of applications that later get granted, to see if there is a significant difference between the value at publication of these two groups of applications.

I find that at the time of publication, these patent applications that later get abandoned have similar economic value to those patent applications that later get granted. The results suggest that the underlying value of patent applications conditional on grant does not depend on whether they are later granted or not. In other words, the value of patent applications at publication is not correlated with the probability of grant. This indicates the stock market participants cannot predict with accuracy at the time of publication whether a patent application will be granted or not. It also implies that when making decisions on patent grants, the USPTO focuses on patent validity, instead of patent value conditional on grant. I also develop a simplified model and use empirical data to test if the applications, after abandoned, have any private value to the firm that owns them. The findings have important implications for patent-relevant studies and policy analysis.

The remainder of the chapter is structured in the following way. Section 5.2 describe the analytical framework and empirical strategies I use to study the economic value of abandoned patent applications using stock market response at publication. Section 5.3 describes the data I use. Section 5.4 shows results and briefly discusses some important findings. Section 5.5 provides robustness checks and Section 5.6 concludes.

5.2 Model and Methodology

In Chapters 3 and 4, I investigate the publication and grant of patents. Since abandoned patent applications are never granted, they do not have value at grant. But they can still have value at publication. So, I study their publication event. I use the method developed in Chapter 4 to measure the stock market value change related to abandoned patent applications in the publication window. Then I inflate the stock market value change by the unconditional probability of grant to generate the value of the abandoned applications. The methodology follows Chapter 4 but instead of focusing on patents, this chapter focuses on patent applications that are published and then abandoned sometime later. I focus on sole-publication applications that later get abandoned, i.e., applications that are published as the only patent application of its assignee firm on its day of publication and later get abandoned, to avoid mixed signals from multiple publications. I also empirically test if there are significant differences in signal-to-noise ratios on multiple-publication events, sole-publication events with an application that later gets granted, and sole-publication events with an application that later gets abandoned.

5.2.1 Measure Stock Market Response

Using the publication window identified in Section 4.4.1, I apply a similar methodology as described in Section 4.2.2 to measure the stock market responses in the publication window of applications that later get abandoned. I focus on the sole-publication applications that later get abandoned, i.e., applications that are published as the only publication for its assignee firm on its day of publication and later get abandoned. The reason for focusing on sole-publication applications is the same as that described in Chapter 4, i.e., to avoid mixed signals from multiple publications and avoid assigning the same value to different applications published on the same day. I empirically test for the difference between the signal-to-noise ratios of multiple-publication events and sole-publication events in Section 5.5.1.

The abnormal return *R* of a public firm in a sole-publication event window is comprised of two parts: the part that is related to the publication of the patent application that later get abandoned, v, and the part that is unrelated to the publication of the patent application that later get abandoned, ε.

$$R_j = v_j + \varepsilon_j \tag{5.1}$$

where v_j is a fraction of the firm's market capitalization. The change in the firm's market capitalization that is related to the application that later gets abandoned can be obtained by multiplying v_j with the firm's market capitalization right before the event.

I assume that

- v_j is distributed according to a normal distribution truncated at 0, $v_j \sim N^+(0, \sigma_{vfy}^2)$;
- ε_j is normally distributed, $\varepsilon_j \sim N(0, \sigma_{\varepsilon fy}^2)$;
- Both σ_{vfy}^2 and $\sigma_{\varepsilon fy}^2$ are allowed to vary proportionally across firms and years.

Define the signal-to-noise ratio δ as

$$\delta = \frac{\sigma_{vfy}^2}{\sigma_{vfy}^2 + \sigma_{\varepsilon fy}^2} \tag{5.2}$$

Given the above assumptions, the conditional expectation of v_j on R_j is

$$E[v_j \mid R_j] = \delta R_j + \sqrt{\delta}\sigma_{\varepsilon fy} \frac{\phi\left(-\sqrt{\delta}\frac{R_j}{\sigma_{\varepsilon fy}}\right)}{1 - \Phi\left(-\sqrt{\delta}\frac{R_j}{\sigma_{\varepsilon fy}}\right)} \tag{5.3}$$

where ϕ and Φ are the standard normal pdf and cdf, respectively.

To estimate the change in the focal firm's market capitalization that is related to publication of the application that later get abandoned, it is sufficient to estimate δ and $\sigma_{\varepsilon fy}^2$.

To estimate δ, I regressed the log abnormal squared returns on a publication-day dummy I_{ft},

$$log\ (R_{ft})^{\,2} = \gamma I_{ft} + cZ_{ft} + u_{ft} \tag{5.4}$$

where Z_{ft} includes day-of-week and firm-year fixed effects.

I approximate the value of δ, the signal-to-noise ratio, by

$$\hat{\delta} = 1 - e^{-\hat{\gamma}} \tag{5.5}$$

$\sigma_{\varepsilon fy}^2$ can be estimated nonparametrically. I first calculate σ_{fy}^2 using the realized mean abnormal squared return, which in turn is a function of σ_{vfy}^2 and $\sigma_{\varepsilon fy}^2$. Then I estimate $\sigma_{\varepsilon fy}^2$ using σ_{fy}^2, the fraction of trading days that are sole-publication event days with an application that later get abandoned d_{fy}, number of days in a publication event window n, and $\hat{\gamma}$,

$$\sigma_{\varepsilon fy}^2 = n\sigma_{fy}^2\left(1 + nd_{fy}\left(e^{\hat{\gamma}} - 1\right)\right)^{-1} \tag{5.6}$$

Then I use the estimated $\hat{\delta}$ and $\sigma_{\varepsilon fy}^2$ to find out the conditional expectation of v_j on R_j. Finally, I multiply this conditional expectation of v_j by the firm's market capitalization right before the application publication to reveal the changes in the firm's market capitalization ΔV_j that is related to the publication of the application that later get abandoned.

5.2.2 Estimate Abandoned Application Value

I use a similar methodology as described in Section 4.2.3 to estimate the value of abandoned applications.

I estimate the value at publication of an application that later gets abandoned using the stock market response in the publication window and the unconditional probability of grant. The basic equation is:

$$\xi_{jp} = \pi^{-1} * \Delta V_{jp} \tag{5.7}$$

where
ξ_{jp} is the expected value of application j conditional on grant at the time of publication,
π is the unconditional probability of grant,
ΔV_{jp} is the firm's stock market capitalization change related to the application j's publication.

The intuition is as follows: assume the market participants know the value of the application j but they do not know whether the application will ever be granted or not. The market participants use the unconditional probability of a patent grant to approximate the probability application j will be granted. After the application publication, the stock market price incorporates the expected value of the application: $\pi * \xi_{jp}$. Thus, the stock market value change in the publication window ΔV_{jp} reflects the expected value $\pi * \xi_{jp}$.

5.3 Data

I filter for the data of the patent applications that have a public firm assignee at the time of publication and later get abandoned. I match the application data with CRSP data using the publication date and assignee firm at the time of publication. A more detailed description of the data can be found in Chapter 2.

5.4 Results and Discussion

5.4.1 Stock Market Response

I estimated the stock market value changes related to publication of an abandoned application, using the two-day event window identified in Section 4.4.1. The results are listed in Table 5.1.

Table 5. 1 Parameter Estimate for Equations (5.4)

	Coef.	Std. Err.	p-value
γ	0.031	0.016	0.048

For publication events of applications that later get abandoned, I estimate $\hat{\gamma} = 0.031$ for sole-publication applications that later get abandoned. This is close to the $\hat{\gamma} = 0.037$ estimated for sole-publication applications that later get granted, in Chapter 4. I test if there is a significant difference between these two parameters in Section 5.5.1. The results show that the difference is not significantly different from zero (with p-value = 0.661), so I cannot reject the null hypothesis. In other words, a publication that later gets abandoned and a publication that later gets a patent granted share the same signal-to-noise ratio. Using the estimated coefficient and Equation (5.5), I calculated the signal-to-noise ratio $\hat{\delta}$ for sole-publication applications that later get abandoned to be 0.030.

Table 5.2 shows the stock market value change related to publication of sole-publication applications that later get abandoned. The median value is 5.19 million dollars. The mean is much higher, 28.05 million dollars. Figure 5.1 show the distribution of the market value change related to sole-publication applications that later get abandoned.

Table 5. 2 Stock Market Value Change Related to Publication of Abandoned Applications (million $)

	ΔV_{jp}
Median	5.19
Mean	28.05
SD	73.35
Percentiles	
p1	0.08
p5	0.26
p10	0.50
p25	1.44
p50	5.19
p75	20.80
p90	70.09
p95	140.49
p99	338.41
# of Obs.	23906

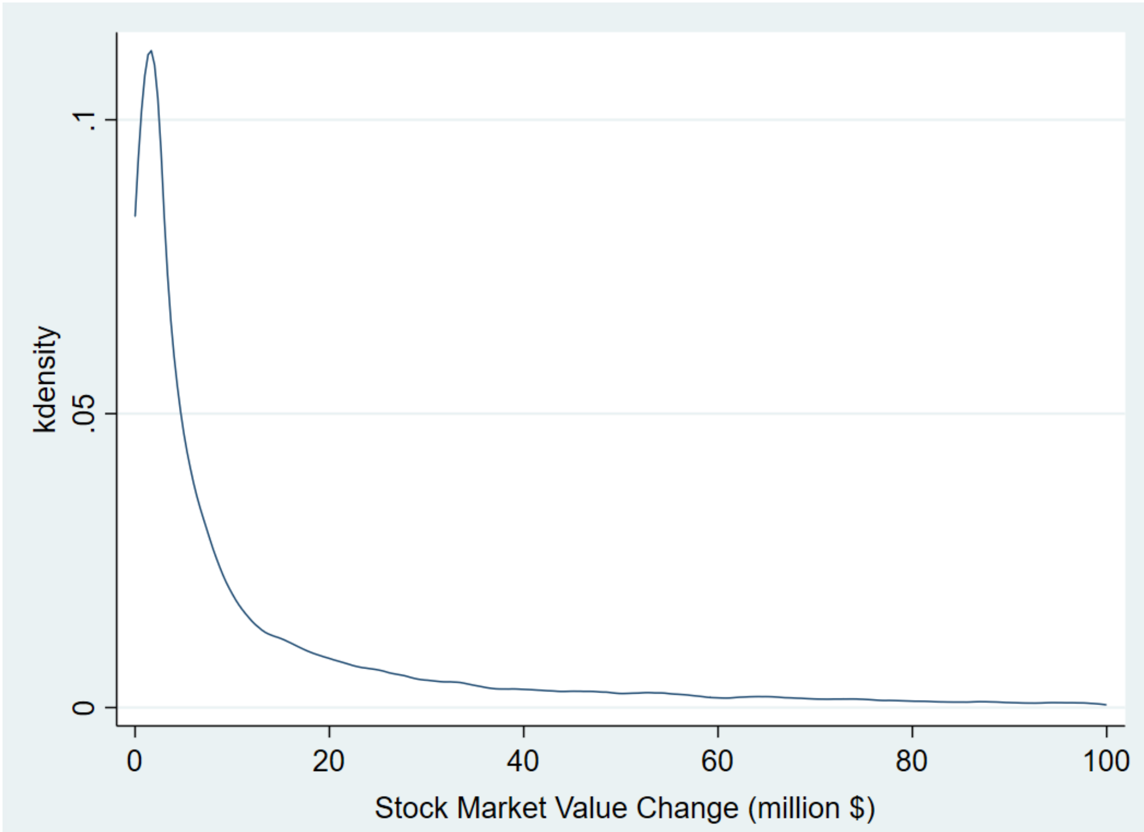

Figure 5. 1 Distribution of Market Value Changes Related to the Publication of Patent Applications that Later get Abandoned

5.4.2 Abandoned Application Value

The estimated value of abandoned applications at publication is derived according to Equation (5.7), using stock market value change related to publication and the unconditional probability of grant. The estimated abandoned application values at publication are shown in Table 5.3. The paper estimated publication value for 23,906 abandoned applications. The median abandoned application value at publication is 6.85 million dollars and the mean is 37.05 million dollars. Figure 5.2 shows the distribution of value at publication. The distribution of the value is highly skewed.

Table 5. 3 Abandoned Application Value at Publication (million $)

	ξ_{jp}
Median	6.85
Mean	37.05
SD	96.90
Percentiles	
p1	0.11
p5	0.34
p10	0.66
p25	1.90
p50	6.85
p75	27.48
p90	92.59
p95	185.59
p99	447.04
# of Obs.	23906

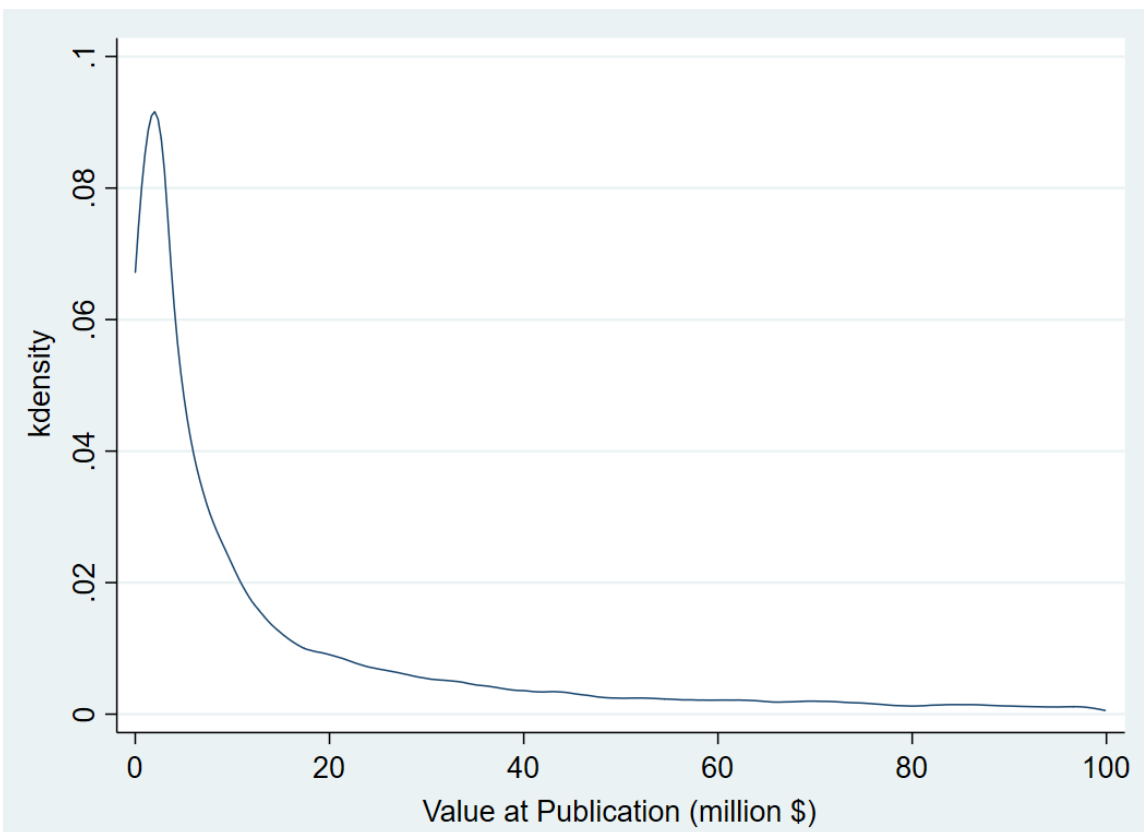

Figure 5. 2 Distribution of Abandoned Application Value at Publication

5.4.3 Comparison of Abandoned Applications and Patented Applications

5.4.3.1 Overall Comparison

To have a better comparison of applications that later get granted and applications that later get abandoned, I summarized the information on stock market value changes and values at publication of the two types of applications in Table 5.4 and Table 5.5, respectively. The comparisons of distributions of stock market value change and values at publication of the two groups of applications are displayed in Figure 5.3 and Figure 5.4.

The results show that the median market value change related to the publication of an application that later gets granted is slightly higher than that of an application that later gets abandoned. However, considering the huge variance, this difference may not be significant. The distribution of the value of applications that later get abandoned and the value of applications that later get granted are very close to each other except that the abandoned applications have a slightly higher value concentration near 0, suggesting that some abandoned applications could have very low value. However, the distributions on the tails are very similar to each other, suggesting the distributions of high-value applications are similar in applications that later get granted and applications that later get abandoned.

Table 5. 4 Stock Market Value Change Related to Publication: Abandoned vs. Granted (million $)

	Granted	Abandoned
Median	7.66	5.19
Mean	37.82	28.05
SD	130.53	73.35
Percentiles		
p1	0.11	0.08
p5	0.41	0.26
p10	0.78	0.50
p25	2.33	1.44
p50	7.66	5.19
p75	27.38	20.80
p90	83.01	70.09
p95	170.42	140.49
p99	441.27	338.41
# of Obs.	67817	23906

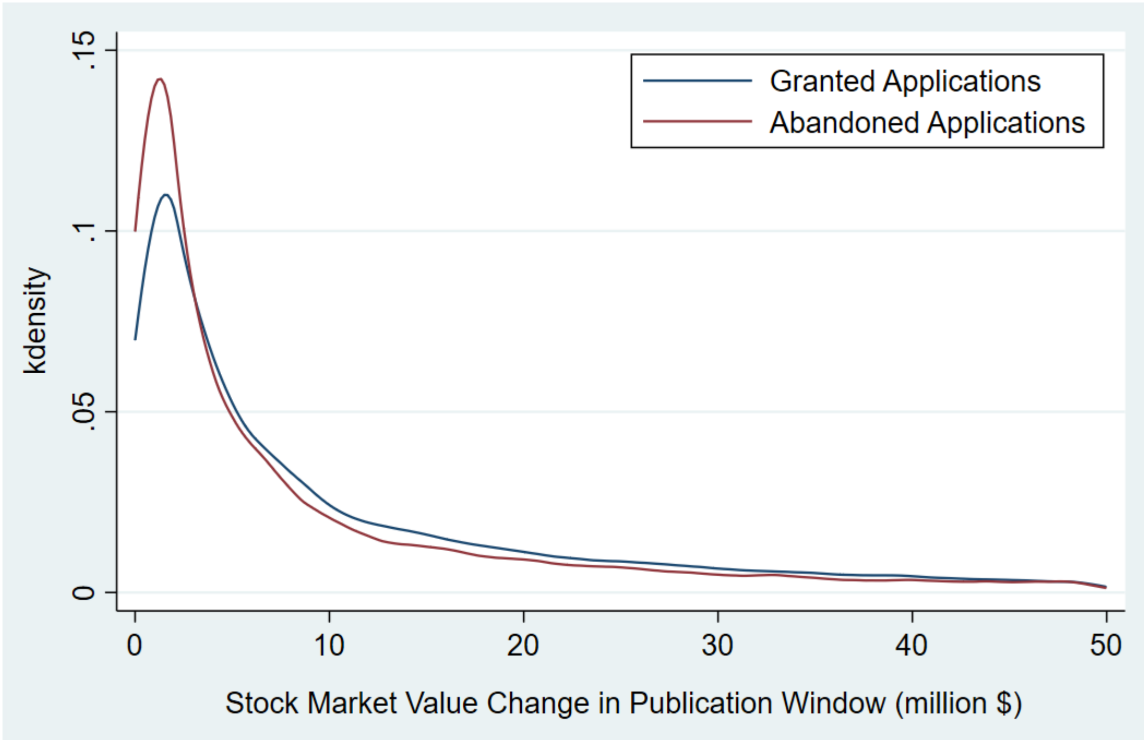

Figure 5. 3 Distribution of Stock Market Value Change Related to Publication: Abandoned vs. Granted

Table 5. 5 Value at Publication: Abandoned vs. Granted (million $)

	Granted	Abandoned
Median	10.12	6.85
Mean	49.96	37.05
SD	172.43	96.90
Percentiles		
p1	0.15	0.11
p5	0.55	0.34
p10	1.03	0.66
p25	3.07	1.90
p50	10.12	6.85
p75	36.17	27.48
p90	109.65	92.59
p95	225.12	185.59
p99	582.92	447.04
# of Obs.	67817	23906

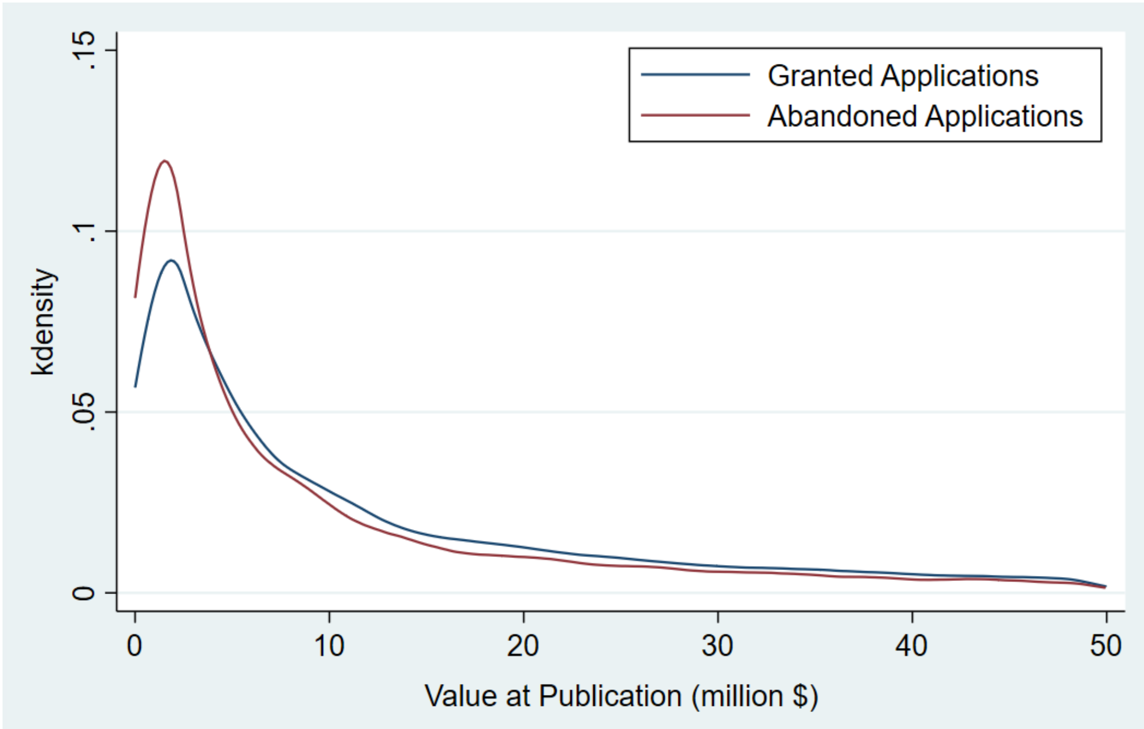

Figure 5. 4 Distribution of Value at Publication: Abandoned vs. Granted

5.4.3.2 Comparison by Groups

The overall comparison suggests that the abandoned applications have similar value distributions to patented applications except for a higher concentration at low values. I would like to check if this similarity still holds in smaller groups, for example, applications filed in the same year, applications in the same CPC section, and applications with the same firm assignee. To do this, I group the applications by year of filing, CPC section, and firm assignee, respectively, and generate summary statistics (e.g., mean, median) that compare the value of abandoned and granted applications. In general, the similarity between the value at publication of abandoned and granted applications still holds in these smaller groups.

Figure 5.5 and Figure 5.6 shows the median and mean value of applications by year of filing, respectively. To avoid truncation issues, I only used applications filed on or before 2017. As shown in Figure 5.5, each year, the median value of applications that later get abandoned is similar to the median value of the applications that later get granted, while abandoned applications have a smaller median value each year. In Figure 5.6, The distribution of the mean value by year suggests that, except for the year 2001, when the publication policy just started to enact and the year 2017, which may be subject to truncation problem, all the rest of the years (2002-2016), the mean value of applications that later get abandoned are very similar to the mean value of applications that later get granted. In some years, e.g., 2008, 2009, 2010, 2013, 2014, and 2015, the mean value of applications that later get abandoned is slightly higher than the mean value of applications that later get granted. Since the mean value is more sensitive to high patent value than the median. The comparisons between the mean value in different years support the claim that the difference between the value of applications that later get abandoned and the value of applications that later get granted concentrates on the low-value part, i.e., the proportion of low-value applications are relatively bigger in applications that later get abandoned. On the high-value part (the tails), however, the value distribution of applications that later get abandoned is very similar to the value distribution of applications that later get granted. This is to say, even very high-value applications can get abandoned.

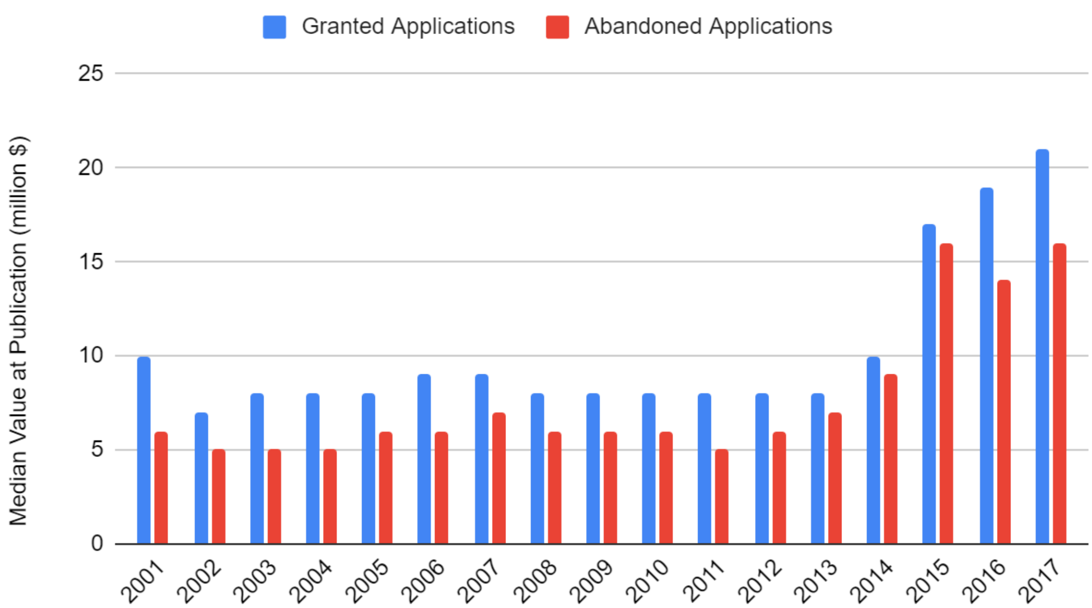

Figure 5. 5 Median Value at Publication by Year: Abandoned vs. Granted

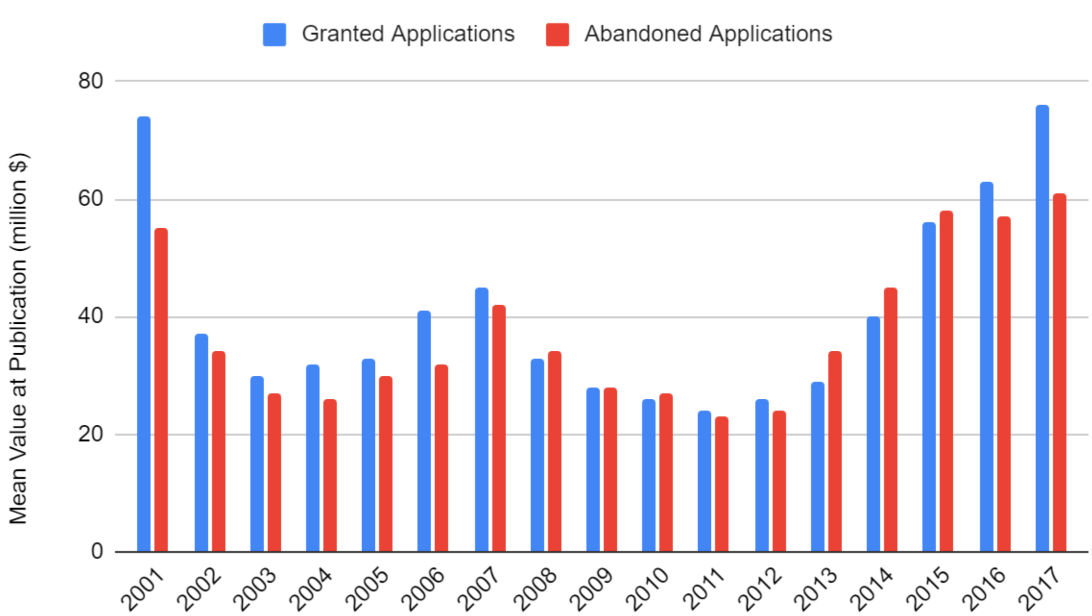

Figure 5. 6 Mean Value at Publication by Year: Abandoned vs. Granted

Figure 5.7 and Figure 5.8 shows the median and mean value of applications by CPC section, respectively.

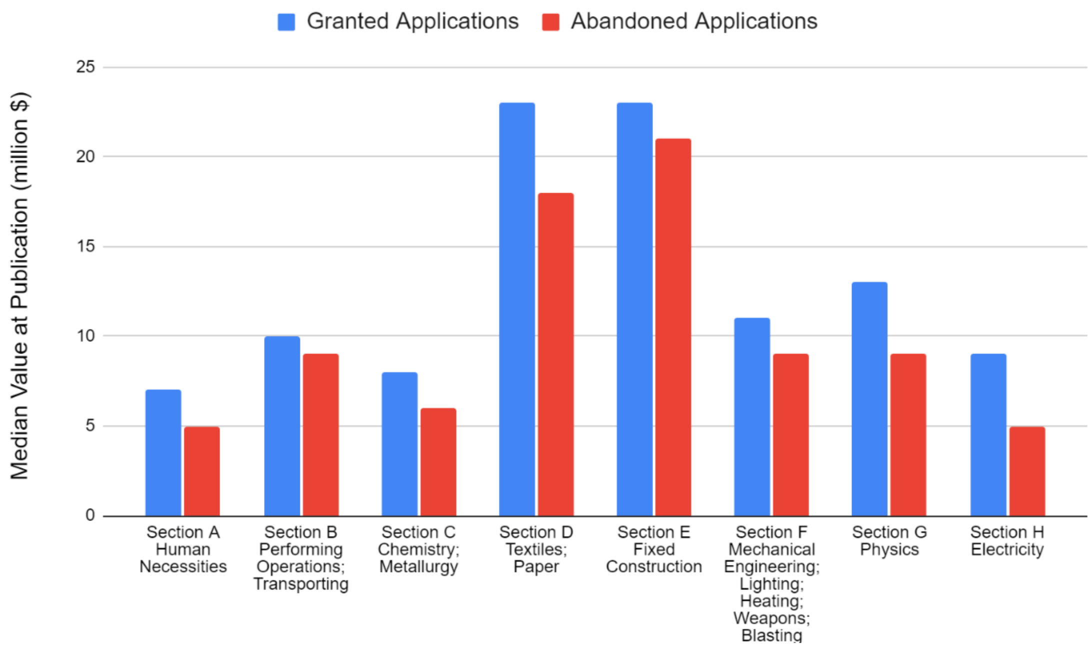

Figure 5. 7 Median Value at Publication by CPC Section: Abandoned vs. Granted

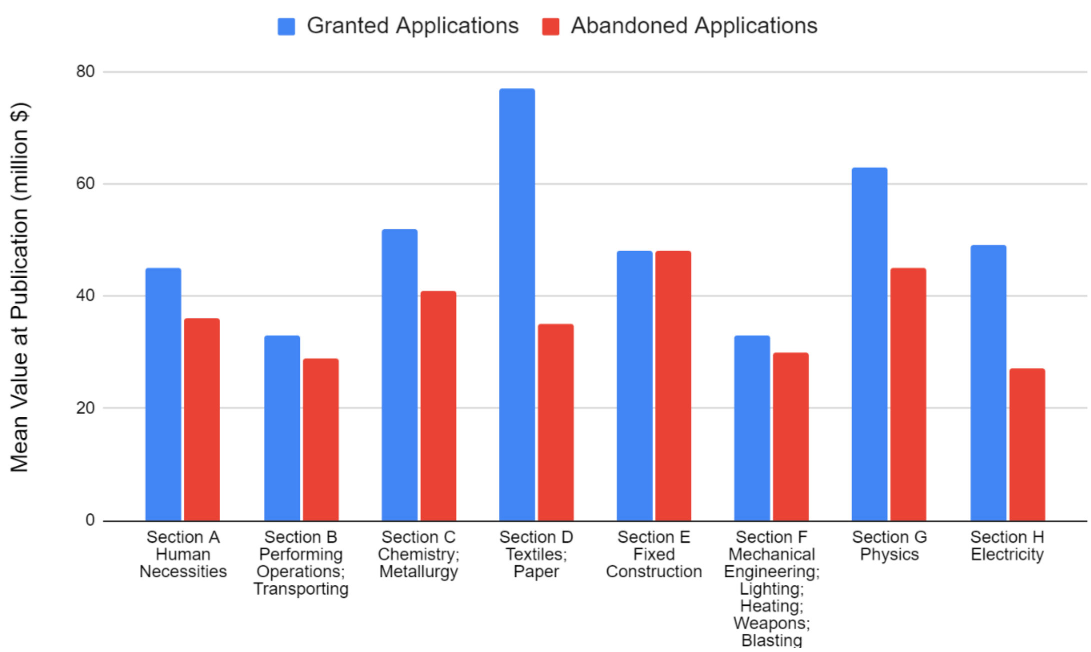

Figure 5. 8 Mean Value at Publication by CPC Section: Abandoned vs. Granted

Within each section, the median values of granted and abandoned applications are similar while the median value of abandoned applications is slightly lower. The mean value follows similar patterns except for Section D, where the mean value of granted applications is much higher than that of abandoned applications. There are two possible factors contributing to the difference: (1) Section D has some extremely-high-value patents that drive up the mean value of the granted applications, and (2) Section D has a small number of applications (424 applications in Section D vs. at least 1800 applications in other sections), making the mean value more sensitive to extremely-high-value applications.

Figure 5.9 and Figure 5.10 shows the median and mean value of applications by assignee firm, respectively. I included 10 big firms that are active in patenting.

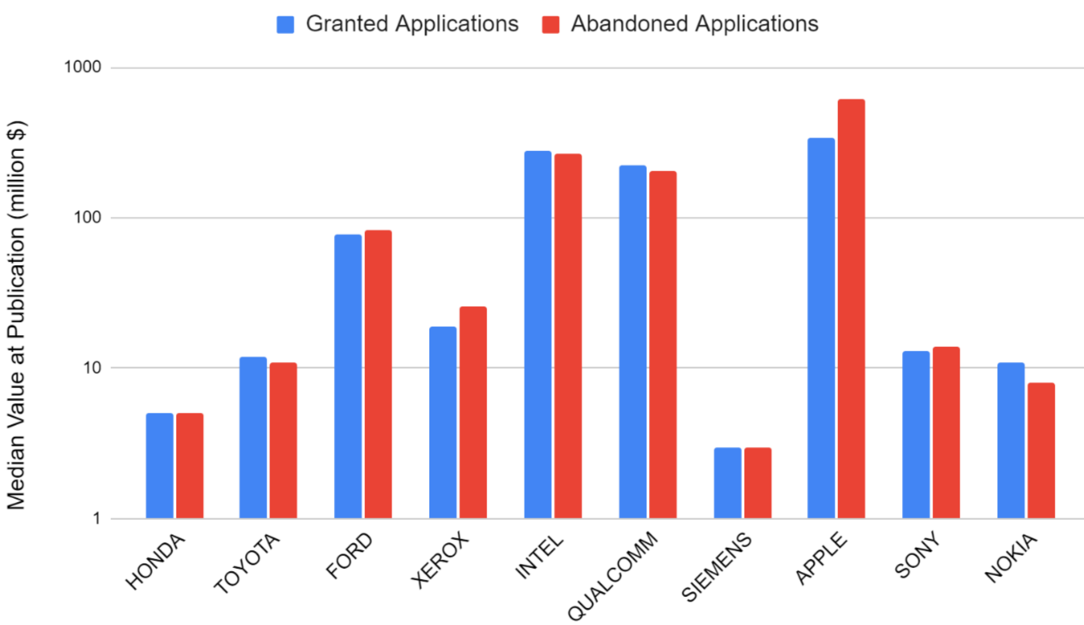

Figure 5. 9 Median Value at Publication by Firm: Abandoned vs. Granted

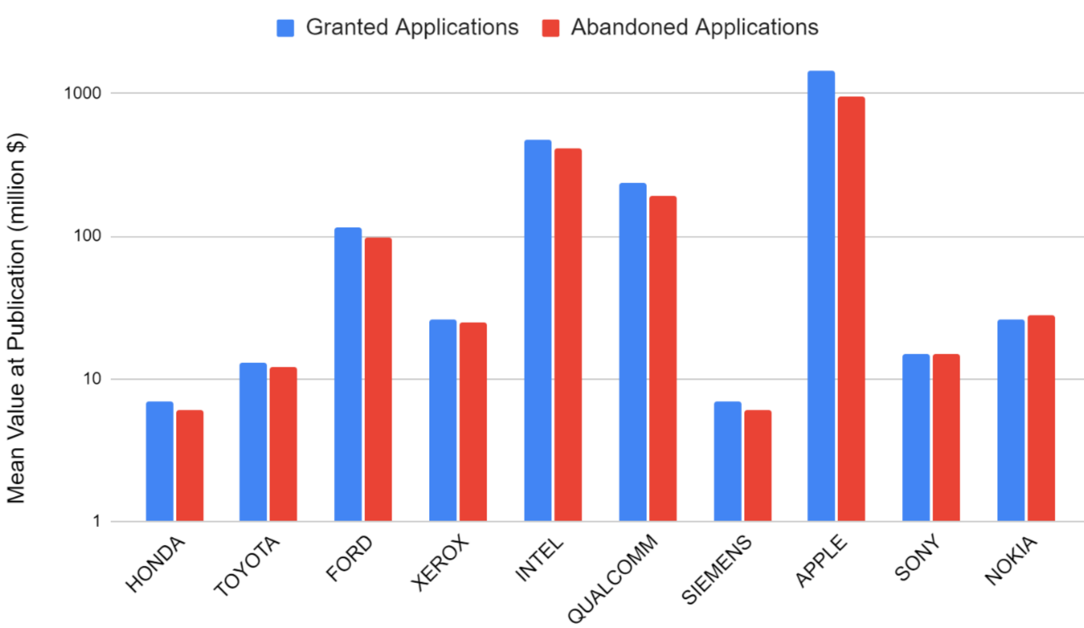

Figure 5. 10 Mean Value at Publication by Firm: Abandoned vs. Granted

The figures show that the median values of granted and abandoned applications are similar within the same firm and vary a lot across different firms. The mean value displays similar patterns. The results imply that within a firm, there are on average no significant differences between the values of patent applications that are later granted and that are later abandoned, suggesting that even the firms who apply for patents cannot accurately predict whether a patent application will be approved or not.

In the overall comparison and comparison by year of filing, and comparison by section, a slightly lower value is observed for abandoned applications. However, after controlling for big active-patenting firms, the value of abandoned applications is on average quite close to that of granted applications, indicating that many low-value abandoned applications could come from firms that are weak at patenting or innovating.

5.4.4 Do Applications Have Private Value after Abandoned?

In this chapter, I measured the value at publication of the sole-publication applications that later get abandoned. These abandoned applications have expected value at the time of publication because the market participants cannot predict with accuracy if a patent application will be granted or not. I am interested in the question, of whether an abandoned application, after it is abandoned, has any private value for the firm that owns it or not. To answer this question, I develop a simple model and test it with empirical data.

Consider a representative patent application. Assume at the time of publication, the application has a probability p to get granted and a probability $(1-p)$ to get abandoned. Assume the private value of the application, if granted, is V_g, and the private value of the application, if abandoned, is V_a. So, the stock market value change related to application publication is the weighted average of the two values, i.e., $p * V_g + (1-p) * V_a$.

The stock market value change, $p * V_g + (1-p) * V_a$, can be empirically measured, and the value if granted, V_g, can also be empirically measured for applications that later get granted. If I assume that there is no significant difference between the V_g of applications that later get granted and the V_g of applications that later get abandoned, then we can use the V_g for patents to approximate the V_g of a representative patent application. Then, using empirical data on the probability of grant p, value if granted V_g, and stock market value change at publication $p * V_g + (1-p) * V_a$, I can then solve for the private value of an application if abandoned, V_a.

The empirical results in this chapter and Chapters 3 and 4 suggest that $p = 75.7\%$, $V_g =$ 21.75 million dollars (the mean value), and $p * V_g + (1-p) * V_a = 16.78$ million dollars (the mean value change). In this case, V_a is 1.29 million dollars. While this is a rough estimation with several simplification assumptions, it sheds some light on the private value of a patent application if abandoned. An abandoned application may have some positive value, but it is much smaller than the value of a granted application (1.29 million dollars vs. 21.75 million dollars). Moreover, since the value estimation has a high variance, the estimated private value of an abandoned application may not be statistically different from zero.

5.5 Robustness Checks

5.5.1 Alternative Signal-to-Noise Ratio

I would like to test if the signal-to-noise ratio is the same for multiple-publication events and sole-publication events, so I added an indicator variable I_{mft}, which equals 1 if there are multiple publications of firm *f* on date *t*.

For sole-publication events, I am also interested in testing if the signal-to-noise ratio is the same for publications that later get granted and publications that later get abandoned. So, I include another indicator variable I_{aft}, which equals 1 if the sole publication for firm *f* on date *t* later gets abandoned. Thus, for publication events, I regress the log abnormal squared returns on three dummies: publication-day dummy I_{ft}, multiple-publication-day dummy I_{mft}, and sole-abandoned-publication-day dummy I_{aft}.

$$log\left(R_{ft}\right)^{2} = \gamma I_{ft} + \gamma_m I_{mft} + \gamma_{abn} I_{aft} + cZ_{ft} + u_{ft} \tag{5.8}$$

If γ_m is significantly different from zero, it indicates that the signal-to-noise ratio of multiple-publication events is different from that of sole-publication events. If γ_{abn} is significantly different from zero, it implies that a publication that later gets abandoned leads to a signal-to-noise ratio that is significantly different from that caused by a publication that later gets a patent granted.

I estimate $\hat{\gamma}$ to be 0.039 for sole-publication applications that later get granted. γ_{abn} is estimated to be -0.008, small and not significantly different from zero (p-value = 0.661), so I cannot reject the null hypothesis. In other words, a publication that later gets abandoned and a publication that later gets a patent granted share the same signal-to-noise ratio. I also observe that γ_m is not significantly different from zero, thus, there is no sufficient evidence to reject the null hypothesis, i.e., the signal-to-noise ratio of multiple-publication events is the same as that of sole-publication events. The estimation results are shown in Table 5.6.

Table 5. 6 Parameter Estimates for Equation (5.8)

	Coef.	Std. Err.	p-value
γ	0.039	0.009	0.000
γ_{abn}	-0.008	0.018	0.661
γ_m	0.012	0.013	0.349

5.5.2 Alternative Distribution Assumption

For robustness check, like Section 4.5.1, instead of assuming v_j follows the truncated normal distribution, I assume that v_j is exponentially distributed with parameter $1/\sigma_v$, keeping all other assumptions unchanged, the conditional expectation of v_j given R_j is

$$E[v|R] = R + \sigma_\varepsilon\left(\sqrt{\frac{2}{\pi}}\frac{exp(-\tilde{R}^2/2)}{G^c(\tilde{R}/\sqrt{2})} - \frac{\sigma_\varepsilon}{\sigma_v}\right) \tag{5.9}$$

where G^c is the complementary error function and

$$\tilde{R} = \frac{\sigma_\varepsilon}{\sigma_v} - \frac{R}{\sigma_\varepsilon} \tag{5.10}$$

Using the same signal-to-noise ratio estimated from empirical data in Section 5.4.1, I calculate the value at publication of patent applications that later get abandoned with the exponential distribution assumption. The results are quantitatively similar to the results obtained with the truncated normal distribution assumption. The correlation coefficient between the two value estimates is higher than 99%. More detailed results are shown in Table 5.7 and Figure 5.11.

Table 5. 7 Abandoned Applications Value at Publication with Exponential Distribution Assumption (million $)

	Publication
Median	8.20
Mean	44.57
SD	117.09
Percentiles	
p1	0.13
p5	0.41
p10	0.79
p25	2.25
p50	8.20
p75	32.95
p90	110.12
p95	221.24
p99	544.49
# of Obs.	23906

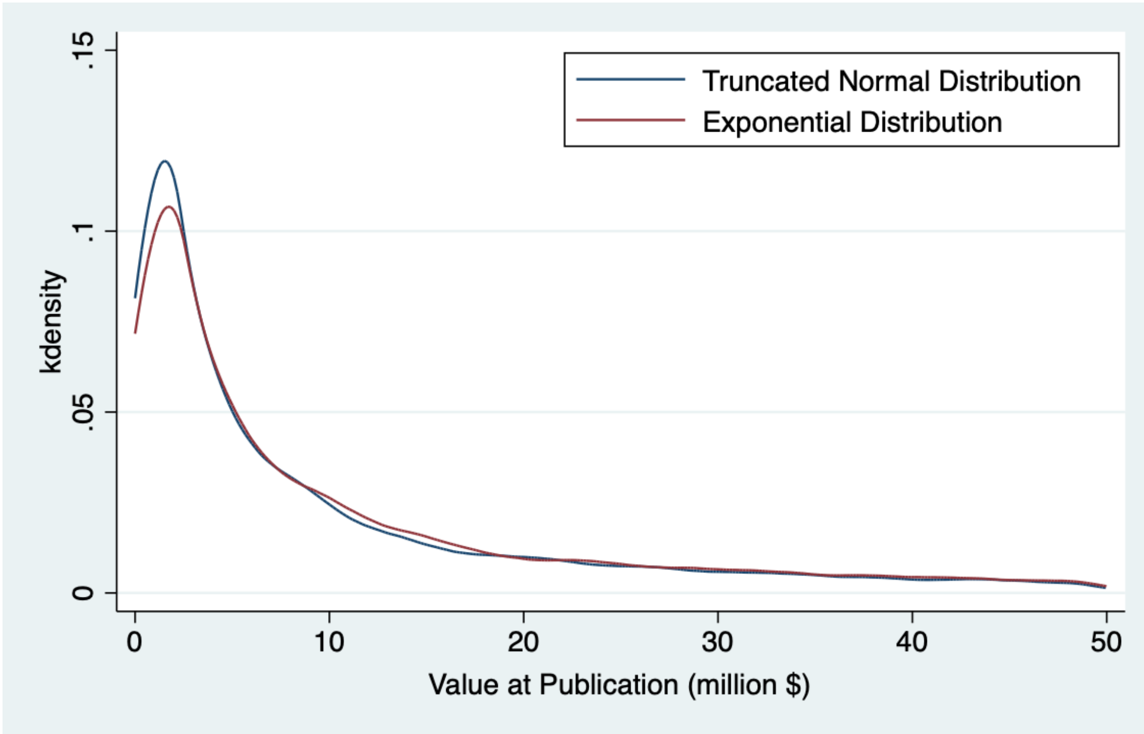

Figure 5. 11 Distribution of Abandoned Applications Value at Publication with Different Distribution Assumptions

5.5.3 Different Probability of Grant

Like Section 4.5.2, I test how different assumptions on the probability of grant will change the abandoned applications value estimation at publication. I look at the following cases.

- Case 0: Allow the probability of grant to vary with the time lag between publication and grant.
- Case 1: Assume the probability of grant to be a constant for all firms and all patent applications.
- Case 2: Allow the probability of grant to vary by application year. I match patent applications with the probability of grant based on the application year. To avoid truncation issues, I only used applications by 2017 to estimate grant rates by year. To obtain an estimate of the probability of grant for years after 2017, I use the average grant rate between 2015-2017.
- Case 3: Allow probability to vary by firm. To do this, I match patent applications with the probability of grant based on assignee firms.
- Case 4: Allow probability to vary by firms by decade. I match patent applications with the probability of grant based on the assignee firm and decade of application filing (the 2000s vs. 2010s).
- Case 5: Allow the probability of grant to vary across CPC sections.
- Case 6: Allow the probability of grant to vary across CPC classes.
- Case 7: Allow the probability of grant to vary across CPC subclasses. For Cases 5-7, I match patent applications with their CPC classification information. When one

application is matched with more than one class, I use the first one.

Like Section 4.5.2, since I only use the unconditional probability of grant for applications valuation at publication, Case 0 is the same as Case 1. The estimated abandoned applications values at publication in different cases are shown in Table 5.8 and Figure 5.12. The distributions in different cases vary in the low-value part but are similar in the high-value part (the tail).

Table 5. 8 Abandoned Application Value at Publication in Different Cases (million $)

	Case 0	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7
Median	6.85	6.85	6.69	8.34	9.63	7.15	7.26	7.68
Mean	37.05	37.05	35.26	46.43	49.63	39.53	40.56	45.39
SD	96.90	96.90	90.65	125.98	131.92	102.39	104.92	120.03
Percentiles								
p1	0.11	0.11	0.11	0.13	0.14	0.11	0.12	0.12
p5	0.34	0.34	0.35	0.50	0.57	0.37	0.38	0.40
p10	0.66	0.66	0.67	0.92	1.04	0.70	0.71	0.75
p25	1.90	1.90	1.90	2.45	2.83	2.02	2.06	2.18
p50	6.85	6.85	6.69	8.34	9.63	7.15	7.26	7.68
p75	27.48	27.48	26.26	32.58	36.22	28.71	29.43	31.70
p90	92.59	92.59	88.13	112.80	121.94	98.66	102.25	115.54
p95	185.59	185.59	175.08	230.63	241.96	204.02	208.83	228.41
p99	447.04	447.04	431.09	573.54	602.61	481.57	501.31	578.47
#of Obs.	23906	23906	22902	23725	21392	23906	23906	23904

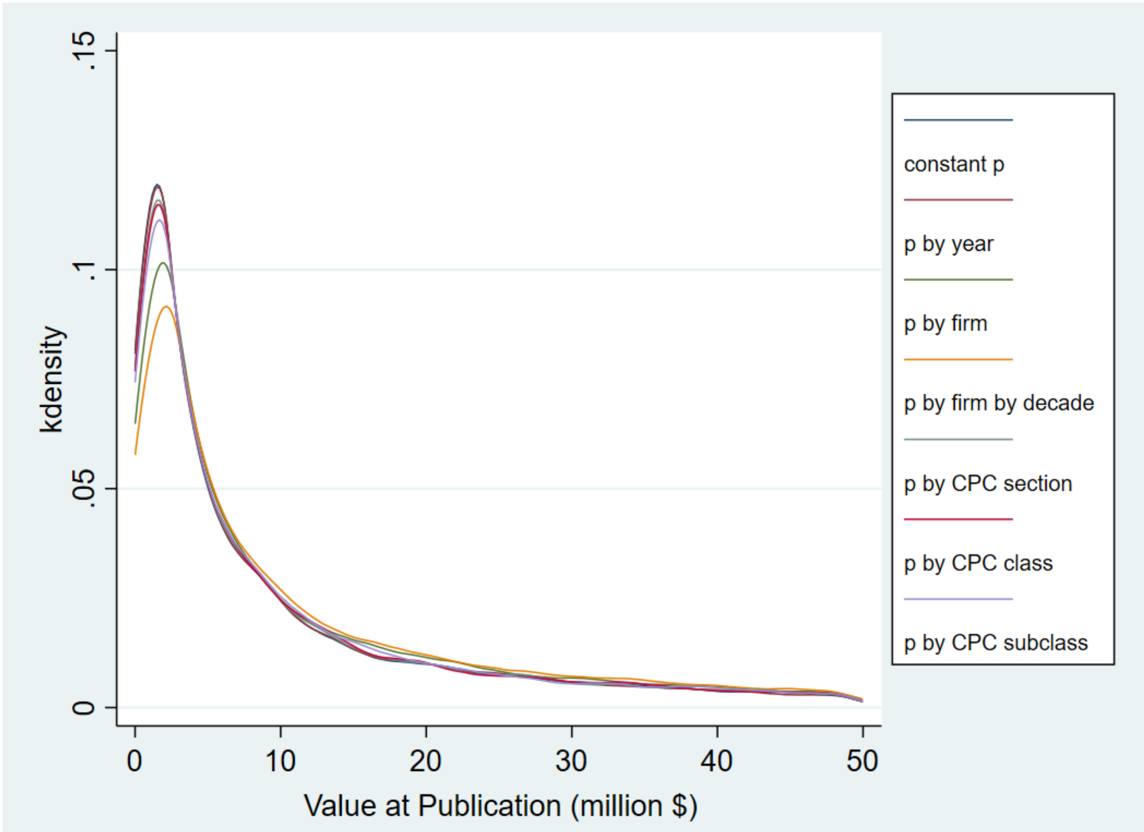

Figure 5. 12 Distribution of Abandoned Application Value at Publication in Different Cases

5.6 Conclusions

The chapter extends the focus from successful patent applications, i.e., patents, to failed patent applications, i.e., abandoned applications. I use the methodology developed in Chapter 4 to estimate the value at publication of the patent applications that later get abandoned. I estimate values for 23,906 abandoned applications. The median value is 6.85 million dollars, and the mean value is 37.05 million dollars. Like the distribution of the value of patents, the distribution of the value of abandoned applications is also highly skewed. I then make detailed comparisons between the value of patents and the value of abandoned applications at publication.

Some important findings are:

- Abandoned applications have value and introduce significant stock market value change for their assignee firms at publication.

- In general, the distribution of the value of patents and the value of abandoned applications at publication are similar, while the value of abandoned applications tends to be slightly smaller than the value of patents.

- The similarity between the value of patents and the value of abandoned applications still holds when controlling for the year of filing, section, and assignee firm.

- The differences in the value of patents and the value of abandoned applications happen mostly on the low-value part, the high-value part (the tails) has very similar distribution.

- The stock market participants, in general, cannot predict with accuracy at the time of publication whether a patent application will be approved or not.

- The value of patent applications at publication is not correlated with their probability of grant, indicating that the USPTO, when making decisions on patent applications, focuses on the validity of the applications, instead of the applications' value if granted.

- Patent applications, after being abandoned, have only very low, if any, private value for the firms that own them.

6 Inferences on Information Flow in the Patent Application Process at the USPTO

6.1 Introduction

Chapters 3, 4, and 5 come up with patent value estimates at publication and at grant, as well as abandoned application value estimates at publication. Besides the value estimates, the results in Chapters 3 to 5 also have important implications for the information flow during the patent application process at the USPTO. This chapter explores these inferences on information flow in more detail.

The structure of the remainder of the chapter is as follows: Section 6.2 summarizes the findings of the inferences on information flow in each stage of the patent application process at the USPTO. Section 6.3 explains the reasoning and the evidence supporting the inferences on information flow. Section 6.4 concludes.

6.2 Inferences on Information Flow

6.2.1 Information Flow Before Publication

This stage includes the period from the filing of a patent application to right before the publication of the application. During this pre-publication period, the analysis implies that there is only negligible information flow related to patents. In this stage, the market participants know little about the patent application (e.g., title, claims, class, firm assignee, novelty, etc.) since the patent information is not available to the public. Due to the lack of information, the market participants cannot form predictions on either the value of the patent application if granted or the probability of the patent application being granted in the future.

6.2.2 Information Flow at Publication

At this stage, the patent application is published. The market participants now have access to detailed information about the patent application (title, claims, inventor, firm, invention details, etc.). Using the detailed information, the market participants form an estimate of patent value if granted, but they still cannot predict whether a patent application will be granted or not.

6.2.3 Information Flow After Publication and Before Grant

In the period between publication and grant, there is little information flow on the patent value. The market participants do not get real-time information on the details in the patent examination process (e.g., changes in claims, pre-grant citations, etc.) and thus cannot update their value estimate accordingly. The expected probability of grant decreases as the lag from publication increases.

6.2.4 Information Flow at Grant

At the time of grant, the market participants obtain two kinds of important information: first, the patent is approved; second, the final version of the granted patent is made easily available to the public. At this stage, the market participants update both the value estimation and the probability of grant expectation. The value estimation is updated based on the information revealed in the final version of the patent, and the probability of grant jumps to 100%.

6.2.5 Summary

Publication and grant are the two events with important information flow on patent value and probability of grant, while the other stages of the patent application process (i.e., before publication and between publication and grant) only exhibit little information flow due to the lack of real-time information updates. At the time of publication, market participants form an initial estimate of patent value if granted but cannot predict whether a patent application will be granted or not in the future. Between publication and grant, the expected probability of grant declines as the lag from publication increases. At the time of grant, the market participants update their expected probability of grant to 100% and update their patent value estimation based on the final version of the approved patent as well as other information available at the time of grant.

6.3 Reasoning and Supporting Evidence

The information flow during the patent application process has two important elements: information flow on probability of grant, and information flow on patent value. Section 6.2 summarizes the inferences on the information flow in each stage of the patent application process. This section discusses the reasoning and supporting evidence for inferences on information flow to investors and market participants.

6.3.1 Probability of Grant

The inference on the probability of grant is that the market participants (including firms that apply for patents) cannot predict with accuracy whether a patent application will be granted until it is granted. At the time of publication, the market participants receive information about a patent application and set the expected probability of grant as the unconditional probability of grant. The expected probability of grant then declines with the time lag from publication. At grant, the probability of grant jumps to 100%.

Two important inferences that require further explanations are: first, the market participants cannot predict with accuracy whether a patent application will be granted, and second, the expected probability of grant declines with time lag from publication.

The first inference is drawn from the finding in Chapter 5 that at the time of publication, the stock market value changes related to applications that are later abandoned are not significantly different from those related to applications that later get granted. This finding suggests that the market participants, at the time of publication, cannot predict whether a patent application will later get granted.

The second inference comes from the dynamic probability model developed in Chapter 3 and the supporting evidence that the empirical approximation of the conditional probability of grant decreases with time lag from publication. Indirect supporting evidence for this is the similarity between the publication value distribution and grant value distribution as established in Chapter 4. If the probability estimation is wrong, it is very unlikely to see such similar estimates using two different methods and stock market data observed at different times and using two different functions of the probability of grant in the value calculations.

6.3.2 Patent Value

One inference on patent value is that market participants generate their initial estimate of patent value if granted at the time of publication and update the estimation at the time of grant. There is little information flow on the patent value before publication or after publication and before grant.

There is little information flow before publication because the existence of the patent application and the details about the patent application is not known until publication. This is supported by the empirical evidence in Chapter 4 that there is a large and significant stock market value increase related to the patent application at the time of publication. If a substantial part of the information on patent value were obtained before publication, the value change at publication would not increase as much and would not be an accurate estimate of the expectation of the value at grant.

Publication is the time when market participants first form an estimate of patent value if granted. This is supported by the stock market value change around the publication window as identified in Chapter 4.

Little information flow on patent value happens after publication and before grant. This inference is supported by the fact that in practice, market participants cannot easily obtain real-time updates on the patent application details (e.g., change in claims, pre-grant citations, interactions with USPTO patent examiner). Thus, there is little information available to update the estimate of patent value.

Grant is an important event when the market participants update their estimation of patent value. At the time of grant, market participants obtain access to the final approved version of the patent so that they can update the estimation of patent value to reflect the changes in the patent details and the reduction in the effective patent lifetime. Supporting evidence for this is offered in Chapter 4 where the value at grant is compared to the value at publication for each patent. The results suggest that the value of a patent at grant can be quite different from the value of the same patent at publication, suggesting the value estimation is updated at grant. However, the evidence is that the value estimate at publication is an unbiased estimate of the value estimated at grant. If there were significant value adjustments between publication and grant in the market estimate of the value at grant, then the estimate of value based on the effects of grant would not be consistent with the expectation of value based on stock value change at the time of publication. The results also reveal a negative relationship between patent grant lag and patent value at grant, suggesting patent value at granted has been adjusted to reflect the reduction in effective patent life.

6.4 Conclusions

This chapter summarizes the inference on information flow during the patent application process using the findings in Chapters 3, 4, and 5. This chapter also provides explanations for the reasonings behind the inferences and supporting evidence for the inferences.

In conclusion, publication and grant are the two important events with information flow on patent value and probability of grant. At the time of publication, market participants form an initial estimation of patent value but cannot predict whether a patent application will be granted or not. At the time of grant, the market participants update the probability of grant to 100% and update their patent value estimation based on the final version of the patent and other available information (e.g., remaining patent life, pre-grant citations, etc.). Before publication, there is little information flow because of the lack of information on the existence and the details of patent applications. Between publication and grant, the conditional probability of grant decreases with the time lag from publication but there is little information flow about patent value since the market participants cannot conveniently obtain access to real-time updates on patent application details (e.g., changes in claims, interactions with the USTPO examiner, etc.) without significant extra efforts or private information sources.

The inferences discussed in this chapter are important for understanding the information flow during the patent application process at the USPTO. They have a high potential for future use in many patent-related studies. This chapter provides a brief discussion of the information flow and there is more to explore in future work.

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