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Korea’s 2011 Copyright Act Amendments and Innovation by Online Service Providers

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Abstract

In 2011, Korea amended its Copyright Act to comply with the U.S.-Korea Free Trade Agreement's intellectual property chapter, which included an obligation to enact a safe harbor for secondary copyright infringement in the online environment. Safe harbors protect internet firms from legal liability when their users post infringing content online, on the condition that the firms maintain a system to efficiently remove infringing content when notified of the infringement by rightholders. This paper tests whether the newly established safe harbors had an impact on innovation by Korean internet firms. I hypothesize that the amendments alleviated litigation risks faced by internet firms, incentivizing the development of new products and services. I test this by estimating difference-in-differences regressions on a panel of Korean internet and software producers between 2008 and 2015. Using R&D spending as a share of sales and patent metrics as measures of innovation inputs and outputs, respectively, I find that internet firms increased both R&D/sales and patent applications relative to the control group of software firms after the introduction of safe harbors. I find small changes in the direction of innovation as well: both internet and software firms expanded the set of technologies in which they applied for patents, though this was greater for the internet firms.

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1 Introduction

1.1 Secondary Liability and Safe Harbors

Copyright laws grant creators of new works periods of market exclusivity during which they or their agents have the exclusive right to reproduce and distribute their works. However, they are not absolute. Every copyright law contains exceptions that allow consumers and other users of copyrighted works to make and share copies in limited circumstances, and industries that complement the creation of copyrighted works rely on such exceptions. One type of exception is protection against "secondary liability" for copyright infringement for online service providers.

Secondary liability can be imposed on a firm that does not directly commit copyright infringement itself, but is "found responsible for encouraging, facilitating or profiting" from infringement (Boyle and Jenkins, 2018). In the online environment, a firm that makes a product or service that lets users post infringing content could be subject to secondary liability absent some type of protection from it. Many countries protect internet firms from secondary liability, on the condition that firms take steps to remove infringing content posted by users.

In the United States, the 1998 Digital Millennium Copyright Act (DMCA) protects internet firms from secondary liability for online infringement. To qualify for protection against secondary liability, an online service provider (OSP) must "maintain a 'notice-and-takedown' process whereby the OSP responds expeditiously to remove or disable access to material claimed to be infringing upon receipt of a proper notice from a copyright owner" (United States Copyright Office, 2020)). This protection from secondary liability is commonly referred to as a 'safe harbor.'

U.S. trade policy – guided by a Trade Act requirement that negotiators seek intellectual property obligations that "reflect a standard of protection similar to that found in United States law" – promotes the adoption of this trade-off abroad. The intellectual property chapters of all Free Trade Agreements (FTAs) since the early 2000s have expressly required safe harbors for secondary liability conditioned on the existence of obligations to remove infringing content. The Korea-US Free Trade Agreement was no exception, and Korea amended its law in 2011 to include safe harbors form secondary liability for OSPs.

1.2 The Korean Amendments

Before December 2011, Korea's Copyright Act subjected firms to liability for secondary infringement, even if they had systems in place to remove infringing content. Courts had the discretion to find firms liable if they were negligent in their efforts to monitor user behavior. According to a World Intellectual Property Organization report, the law did not provide a qualifying OSP with a complete indemnity against secondary liability: "the preventive measures undertaken by the OSP only serve to limit or reduce its liability, and only provide a complete indemnity when these measures are 'technically' infeasible or ineffective to prevent or stop the infringing activity" (Seng, 2021).

Rightholders sued OSPs for secondary liability under this regime. For instance, the Korea Music Copyright Association and the Korea Association of Phonogram Producers sued two of Korea's largest internet intermediaries, Naver and Duan, in 2008.

In December 2011, Korea passed Amendment Act No. 11110, which modified its Copyright Act. The amended Copyright Act guarantees safe harbors for secondary liability for online service providers that meet a set of conditions based on those in the U.S. DMCA (Nam, 2018). These conditions include the removal of infringing content at the request of rightholders, and the blocking of users who repeatedly post infringing materials.

The Amendments Act added the safe harbor from secondary liability in order to comply with obligations under the Korea-US Free Trade Agreement, which required Korea to harmonize its law in this area with the U.S. DMCA (Korea Copyright Commission, 2013). It was not added in response to lobbying by domestic stakeholders. Since an external trade obligation caused the legal change, one can view the change as exogenous. This is similar to the justification for exogeniety used by Sakakibara and Branstetter (2001) in their study of a change to Japanese patent law, which had been motivated by U.S. pressure to harmonize its law with American law.

1.3 Overview

This paper evaluates the impact of the Korean Copyright Amendments Act on innovation by online service providers – which I call "internet firms" through the rest of the paper.

I assume that a clear protection from secondary liability lowers or eliminates internet firms' risk of being sued, incentivizing them to conduct further research into areas which – absent this protection – could lead to lawsuits. This further research should ultimately lead to more inventions. For the purposes of this paper, *internet firms are strictly defined as firms whose primary line of business is providing services that allow users to post content online.*

Annual firm-level data on a sample of technology firms is separated into a test group of internet firms and a control group of firms that produce software. R&D spending is used to measure innovative inputs, and patent indicators are used to measure innovative outputs. Econometric tests show that the ratio of internet firms' R&D spending to sales increased approximately 68 - 78 percentage points in the years after Korea passed the copyright amendments, relative the ratio for the control group of software firms.

Internet firms also filed more patent applications, both absolutely and relative to the control group, after acquiring a stock of knowledge through accumulated R&D. The relative change in patent application counts was large. My final model specification estimates that the number of patent applications filed by internet firms relative to the number filed by software firms increased by a factor of up to 4.90 after Korea changed its law.

There was less change than expected in the areas of technology in which innovation occurred. Firms tended to file patents in the same overlapping sets of technology classes before and after the policy change. However, there was movement along the extensive margins of technologies, as firms from both groups moved into new areas and away from others.

Together, the tests on R&D spending and patenting show that protections from copyright liability were associated with more innovation in the internet sector. More broadly, it illustrates how changes to copyright policy may impact industries that complement the publishing industries.

2 Theory and Previous Literature

My theory is based on the assumption that probability-weighted litigation costs factor into decision-making by internet firms.

Internet firms will invest in new products and services that are the most profitable. The most profitable will be those that can generate high revenue (through sales, but also through subscriptions and advertising), and/or be produced at a relatively low cost. For internet firms, lawsuits can be a significant cost. Elimination of legal liability may encourage investments into new media-sharing technologies, driving research into new products and services in these areas. Consider a firm providing a digital product or service that allows users to post content online. Some users will likely post infringing content. This firm operates in a legal environment in which it could be sued for secondary liability. There is no guarantee the firm will face a lawsuit, but if it is sued, the firm will need to pay legal fees and may face a fine or penalty. Therefore, one can express the expense of a lawsuit as a probability weighted cost.

$$E(Cost_{SUED}) = Pr(Lawsuit) \times (LitigationCosts + Penalties)$$

The probability of being sued varies with firm characteristics, including a firm's primary industry and its size, as well as the level of copyright protection available to rightholders. Some industries have been shown to be significantly more litigious than others(Lowry and

Shu, 2002), so firms will face different probability of lawsuits depending on their primary products or services. Larger firms have been shown to face higher litigation risk across all industries (?) (Arena & Ferris, 2018; Kim & Skinner, 2012) and among information and communications technology firm in particular (Cheng et al., 2012). Copyright damages under Korean law can be determined according to the amount of profits illicitly gained through infringement (Korea Copyright Act Sec. 125), which can increase the size of damages for larger internet firms. Since large firms face a higher risk of litigation and may face higher penalties if a successful action is brought against them, the first derivative of $Cost_{SUED}$ with respect to firm size is positive.

$$\frac{d(cost_{SUED})}{d(FirmSize)} > 0$$

Changes to copyright laws that increase damages available to a copyright owner would also have a positive relationship with the probability of legal action (as well as the cost of the damages themselves), so the first derivative of the cost of lawsuits with respect to the strength of copyright is also positive. However, if copyright damages for a specific type of violation are eliminated, then the probability of being sued for this type of violation becomes zero, and $Cost_{SUED}$ becomes zero.

$$\frac{d(Cost_{SUED})}{d(CRStrength)} > 0$$

Finally, a firm planning to invest in research and development must choose which technology to invest in, from a set of technologies with different levels of litigation risk. The firm will conduct research into the technology it believes will lead to the most profitable product or service. If litigation risk due to secondary liability for copyright infringement is one of the costs, as described above, then the technologies that lead to products allowing users to post information online will be potentially less profitable. Removal of this type of liability could alter the relative potential profitability from one technology area to the next. A similar point is made – though not empirically tested – by Legouili and Madio (2022). They argue that strict liability rules for internet platforms can affect and direction of investment, pushing firms away from innovations that lead to new products, and towards smaller, incremental innovations.

The Korean Copyright Amendments Act provides an opportunity to test this theory. The change to Korean law in December 2011 made clear that offering certain types of products and services would no longer expose firms to the risk of lawsuits in the event that their customers or users violated copyrights. It alleviated litigation risks faced by internet publishing and web hosting firms.

I hypothesize that the reduction in litigation risk will incentivize research and development of new products and services in this area. It will increase the level of innovative activity by impacted firms, and it will change redirect innovative efforts into impacted areas of technology.

The hypothesis is supported by previous literature. Carrier (2012) shows that copyright litigation risk has reduced investment in internet and communications technology firms – a broad classification of firms that includes both online service providers and other firms. Arena and Julio (2015) find litigation risk to increase cash holdings and decrease investments in a wider set of firms.

One study has shown specifically that removing litigation risk for internet firms increased investment by U.S. firms. Lerner and Rafert (2015) analyze investments in cloud computing firms after the decision in *Cartoon Network v. Cablevision*, which erased secondary liability under U.S. law for online storage services. They found a significant increase in venture capital investment in firms in this industry relative to other industries and relative to European firms in the same industry.

3 Empirical Analysis

3.1 Innovation Inputs: Ratio of R&D Spending to Total Sales

3.1.1 Data

My empirical tests of the copyright law's impact on R&D spending apply a difference in differences methodology to firm-level data. The data is taken from the KIS-Value database published by the National Information and Credit Evaluation (NICE), a Korean credit rating agency.

The database identifies firms with unique stock numbers. It uses a Korean industry classification scheme known as KSIC, which is based on ISIC. The most disaggregated level of classification available in my dataset is KSIC4. I have created a test group and control group of firms, both of which fall under KSIC Section J: Information and Communication. My dataset contains annual data from 2008 through 2015.

Technology firms may be more inclined to expand horizontally into neighboring areas than firms producing physical goods (Libert et al., 2016), which could complicate the division of firms into clear test and control groups. However, the Korean statistical office notes that KSIC identification of a firm engaged in any integrated industrial activity is based on its "principal" output.

Table 1 lists my groups of test and control industries. The test group is comprised of firms that provide internet services allowing their users to post content online, which therefore would have been subject to secondary liability for copyright infringement before the passage of the law in December 2011. These includes internet hosts, web portals, and online database services used to support social media networks.

The control group consists of software manufacturers. These firms are also in Information and Communications category, but their primary products are not used to place content on the internet, so the existence of a safe harbor from secondary liability should not be important to their decisions about where and how much to invest.

Table 1: Disaggregated Industry Groups and Descriptive Statistics for R&D Spending as a Share of Total Sales, Large Firms Only (2008-2015)

Group	KSIC4 Code	Description	Mean R&D/ Sales	St. Dev.	N
Test	J63112	Hosting and Related Service Activities	1.788	0.710	8
	J63120	Portals and Other Internet Information Media Service Activities	1.405	1.654	40
	J63991	Data Base Activities and Online Information Provision Services	1.563	1.969	40
	J63999	Other Information Service Activities n.e.c.	5.288	2.617	8
Control	J58221	System Software Development and Supply	14.381	11.721	16
	J58222	Application Software Development and Supply	2.748	2.861	64

Table 2: Test and Control Descriptive Statistics for R&D Spending as A Share of Total sales, Large Firms Only (2008-2015)

Group	Description	Mean R&D/ Sales	St. Dev.	N
Test	Hosting and Related Service Activities; Portals and Other Internet Information Media Service Activities; Data Base Activities and Online Information Provision Services; Other Information Service Activities n.e.c.	1.827	2.090	96
Control	System Software Development and Supply; Application Software Development and Supply	5.075	7.385	80

The tests exclude firms identified as small and medium enterprises. Korean laws define SMEs as firms with 300 or fewer employees or with a capital stock less than 8 billion won (Yang, 2009). The average annual exchange rate over the period was 1,134 won to 1 U.S. dollar, implying the capital stock cutoff is approximately $6.9 million. An earlier set of tests included firms of all sizes and yielded results with significant coefficients on the difference in differences variable. However, the trends between the treatment and control groups were not parallel. Restricting my tests to the firms not identified as small or medium sized enterprises – "large" firms – produces a set of firms with a test and control group that pass tests for pre-treatment parallel trends, which will be presented in the following subsection on results.

My dependent variable is the ratio of firm-level research and development spending to total sales. Table 1 shows the descriptive statistics for each of the KSIC industry groups, and Table 2 shows the descriptive statistics for the test and control groups as a whole. Among the test group of internet firms, most of the observations come from two of the four industries - J63120 (Portals and Other Internet Information Media Service Activities) and J63991 (Data Base Activities and Online Information Provision Services). R&D spending as a share of sales for internet firms was highest for the firms in J63999 (Other Information Services n.e.c.). There are only two firms in this group. Minwise Co. provides online security services such as mobile phone logins, and Aibit Co. manufactures testing hardware and measuring tools for screen displays. Both Minwise and Aibit reported higher R&D/Sales than the averages for the other industries in the test group.

The control group of software firms can be disaggregated into two KSIC4 classifications: industries J58222 (Application Software) and J58221 (System Software). Industry averages of R&D as a share of sales for both tend to be higher than the figures for the internet firms, and firms in system software are more R&D-intensive than any of the other industries in either group. More observations come from the application software group than the system software group.

3.1.2 Econometric Tests

I run difference in differences panel regressions on logged R&D spending as a share of total sales with separate fixed effects for firm i and year t. The National Science Foundation (2010) identifies this ratio of R&D spending to sales as the most frequently used metric of firm-level research intensity. The econometric model is shown in equation 1.

$$(Log)\frac{R\&D_{i,t}}{Sales_{i,t}} = \alpha + \beta_1 DID_{i,t} + \beta_2 \mathbf{X}_{i,t} + FE_i + FE_t + \epsilon \quad (1)$$

The main independent variable of interest in equation (1) is *DID*, a difference-in-differences variable equal to 1 for observations from internet firms after 2011, and equal to zero for all other observations. The vector $\mathbf{X}$ consists of control variables, which also vary by country i and year t.

(Log) Total Assets and *(Log) Personnel* are indicators of firm size. The unlogged data on total assets are reported in billions of Korean won. Literature on firm size and R&D intensity is mixed. Some find a positive relationship (Mansfield, 1984), but others have found a relatively flat relationship (Coad and Rao, 2010; Cohen et al., 1987). However, Chang-Yang Lee (2002) focuses on industries where "technological competence" determines market share and finds a positive relationship. This may imply a positive relationship for internet and software firms. Studies that focus on sets of Korean firms have been similarly mixed. Min and Smyth (2015) find a positive relationship between firm size and R&D intensity, but Dong-Soo Lee (1999) finds a negative relationship.

(Log) Intangible to Total Assets is the share of assets held by a firm that are intangible in nature – a measurement of the intellectual property intensity of a firm. This is included to account for previous findings of substantial heterogeneity of R&D intensity between firms within the same industries (Zhu et al., 2021; Coad, 2019).

(Log) Debt Ratio is included as an indicator of a firm's indebtedness, which may be positively associated with investments if it borrows to finance them. Lee & Lee (2019), and Amore et. al. (2013) have found that greater access to banking - observable by greater debt - is associated with more R&D activity. Rao (2016) finds that greater access to capital is a built-in advantage for larger firms in R&D races. Similarly, Dechezleprêtre et. al, (2016) note that financial markets may under-supply credit to smaller firms, which negatively affects research by those firms. However, some authors have found that the link between financing and R&D activities is positive for smaller firms, but disappears for large firms (Hao and

Jaffe, 1993).

(Log) Profits to Sales measures firm profitability. Some have found a positive relationship between firm profitability and R&D spending (Kashi et al., 2015; Bogliacino and Pianta, 2013). Yet others have questioned this link, finding that the relationship with firm size is stronger (Coad and Rao, 2010).

Table 3: Regressions on Logged R&D Spending:
Errors clustered by industry defined by KSCI4
Fixed Effects for Both Firm and Year
DID: Average Treatment Effect on the Treated

	(1)	(2)	(3)
DID	0.675	0.776**	0.728**
	(0.364)	(0.300)	(0.272)
(Log) Total Assets		-0.121	
		(0.164)	
(Log) Personnel			-0.456**
			(0.141)
(Log) Intangible/Total Assets		0.413**	0.379*
		(0.134)	(0.148)
(Log) Profit/Sales		0.745	1.080**
		(0.581)	(0.384)
(Log) Debt Ratio		0.135	0.232
		(0.253)	(0.282)
Constant	0.578**	-2.443	-3.581
	(0.145)	(2.509)	(2.159)
N	170	169	169
Adjusted R^2	0.127	0.334	0.419
Parallel Trends: F statistic	0.19	0.01	0.01
Prob > F	0.681	0.934	0.914

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3 reports the results. Fixed effects control for unobserved differences by year and firm, so stand-alone dummies for the test group and the period after treatment are not included in the table. Standard errors are clustered by KISC4 industry.

The first column includes only the difference in differences variable and the fixed effects, and the results are insignificant. However, coefficient on *DID* is positive and significant across two specifications with control variables, and the value is relatively stable when controls are added. This provides some evidence suggesting that R&D as a share of sales for large internet firms grew approximately 68 - 78 percentage points after the Copyright Amendments Act, relative to software firms.

Column (2) uses the variable *(Log) Total Assets* to control for firm size, but there is no significant relationship between this control and R&D intensity. In this specification, the coefficient on *(Log) Intangible to Total Assets* is positive and significant, indicating the expected relationships, but all other control variables are insignificant. Column (3) measures firm size with *(Log) Personnel*, which enters into the model with negative coefficient. This is likely explained by the correlation between *(Log) Personnel* and total sales, which is the denominator in my dependent variable. Positive significant coefficients on *(Log) Intangible to Total Assets* and *(Log) Profit to Sales* support the expected relationships, though the coefficient on *(Log) Debt Ratio* remains insignificant.

The last two rows of the table report the F test for parallel trends. In columns (2) and (3), the F statistic is not statistically different from zero, so there is no evidence to reject the null hypothesis that pretreatment trends are parallel.

Figure 1 shows the visual diagnostic tests for the parallel trends assumption before the policy change. These are the graphs of the observed means and linear trends of *R&D/Sales* for the test and control groups. The second two panels illustrate that the trends in this variable over the periods up to and including the year of treatment were parallel, and declining. These periods coincide with the 2008 global financial crisis and its immediate aftermath. After treatment, it increased for the test group while continuing to decline for the control, resulting in a large relative change. (The first panel is the visual diagnostic for column one, the specification without control variables that yielded insignificant results.)

In all, the difference in differences regressions demonstrate that the policy change preceded

Figure 1: Visual Diagnostic of Parallel Trends, Pre-Treatment

an increase in the research intensity of the large internet firms, relative to the control group of software firms. Parallel trends test confirm the viability of the difference in differences methodology.

3.2 Innovative Outputs: Patent Applications

To measure innovative output, I use three patent indicators based on patent applications filed per firm per year. Patent data is attractive as an indicator of innovative output for various reasons. Individual patents or patent applications describe inventions that have some level of commercial promise; the patent system records a lot of information, including the fields of technology where inventors are making progress; and there is a long record of data covering many periods.

However, there are well-known criticisms of the use of patents as proxies for innovation. Many patents are linked to inventions that are novel and nonobvious, but lack economic significance (i.e. – a small change to an existing technology). On the other hand, many economically significant new technologies are not patented.

To minimize these problems, it is customary to apply weights to emphasize patent quality in one's dataset. One method is to weight patent applications by the number of citations that a patent (or its family) has received in subsequent filings, on the assumption that more important innovations will be cited more frequently by future applicants. Another method is to weight a patent by the size of its "family" – the set of patent applications filed in different countries protecting the same technology and sharing the same "priority date," the first date an application for a specific invention is filed in any patent office. Firms are likely to seek protection in more markets for commercially valuable inventions, so patents with larger families should be more valuable to patent holders (Kabore and Park, 2019; OECD, 2009).

I use three patent indicators to measure innovative output by my set of firms: the unweighted count of patent applications filed per month by each firm, the count weighted by family size, and the count weighted by forward citations.

My patent data is drawn from the 2018 version of PATSTAT[1], a database published by the European Patent Office that has bibliographic data on patents and patent applications from most of the world's patent offices. I searched for all patent applications since 2008 in the system filed by the firms in the previous section on R&D. To do this, I used an SQL query that searched names "like" each name, and I entered the most basic form of the name. (For instance, I searched for names like "KAKAO" rather than "KAKAO CORP," and my results included patent applications from "KAKAO CORPORATION", "Kakao Corporation", "KAKAO KORP" and others.) This yielded a set of patent applications identified by an application number. I then matched each of the names in the PATSTAT search results back to the unique stock number in the original dataset, allowing me to use its control data.

I use each patent application's "Earliest Filing Date" as the date in which the application occurred. PATSTAT defines the "Earliest Filing Date," as the first date that a patent application was filed anywhere in the world – so it is each patent application's priority date. It is the datum from a patent that is closest to the actual act of innovation.

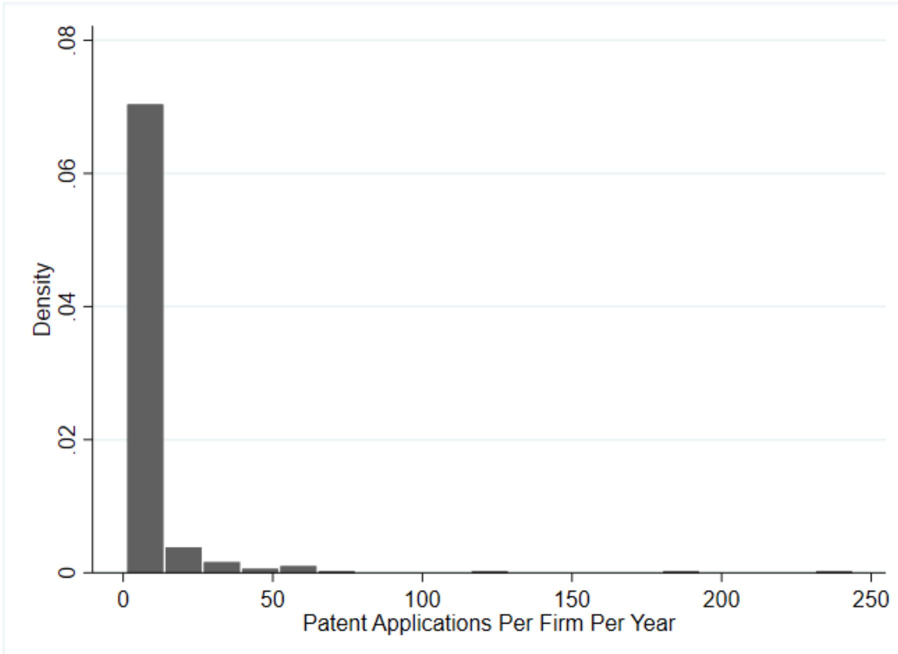
3.2.1 Unweighted counts of patent applications

My unit of analysis is the number of patent applications filed by a firm in a given year. The value of my annual firm patent counts runs from 0 to 244, and the distribution is positively skewed. The unweighted count of applications per firm per year is equal to zero for 72% of the observations.

Figure 2 shows a histogram of nonzero patent applications counts per firm per year. In 29% of these observations, a firm filed just one patent application. In 79% of these, the firm filed 10 or fewer. On the long tail, there are some instances where firms filed a large number of applications. Three observations show that a firm filed more than 100 applications in a

[1]PATSTAT is available from the European Patent Office at https://www.epo.org/searching-for-patents/business/patstat.html

Figure 2: Patent Applications Per Firm Per Year, Observations Equal to Zero Excluded

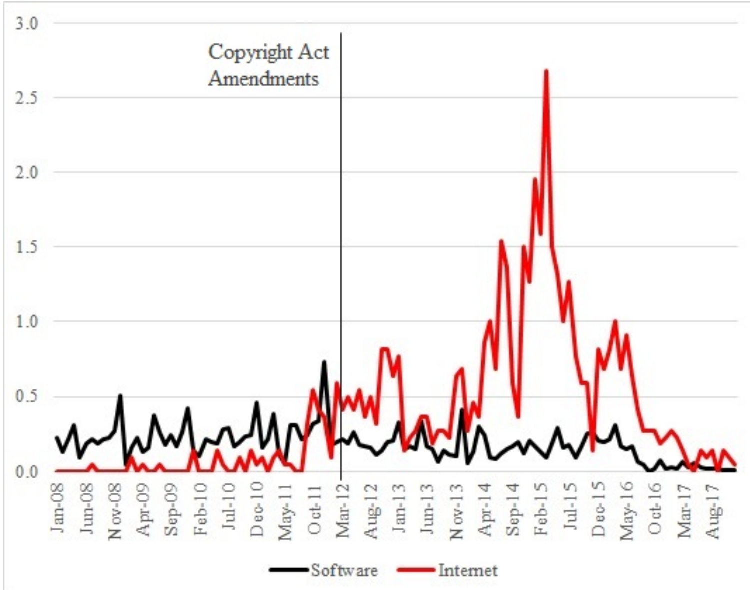


given year.

Table 4 presents the descriptive statistics for annual patent counts by KSIC4 industry classification for each of my three patent indicators. The majority of observations in the test group of large internet firms are from industry J63120 (Portals and Other Internet Information Media Service Activities). Firms in this industry also filed more patent applications than firms in other test group industries. The majority of observations in the control group came from industry J58222 (Application Software Development and Supply). Firms in the two software industries filed patent applications at a similar rate. Table 5 presents the same data with the data summarized at the test- and control group levels.

Figure 3 shows the average count of patent applications per month for internet and software firms. After the Copyright Act's amendments took effect, there was a large increase in monthly patent applications filed by internet firms. Most of the impact comes after a lag, as expected. This reflects the time needed to prepare and file patent applications after a firm has undertaken innovative activities.

Figure 3: Average Count of Patent Applications Per Month



3.2.2 Weighted counts of patent applications

I use the following method to weight the application counts by citations. For each patent application, I collect the number of family-level forward citations from PATSTAT. The inclusion of other patents in the family is important for the inclusion of relevant citations. If a firm applies for patents in numerous jurisdictions, it will have one earliest filing date, but future patent applications by other firms may cite patents filed at a later date for the same invention, which by definition are in the same family.

Values of the patent applications' citation counts range from 0 to 64, though 99% of the values are 10 or less. 45% of the values equal zero, indicating that a patent application, or members of its family, have never been cited. When weighting by citations, I do not want to exclude uncited patent applications altogether – I think an uncited patent application is still an indicator of innovative output, albeit a less commercially significant one. Therefore, I weight using the following formula:

$$AppsCount_{i,t}^{WC} = \delta * AppsCount(\frac{Citations}{64}) + (1 - \delta) * AppsCount \tag{2}$$

Table 4: Industry Groups: Descriptive Statistics for Annual Patent Counts

Group	KSIC4 Code	Description	Mean Patent Count	St. Dev.	N
Test	J63112	Hosting and Related Service Activities - Unweighted - Weighted by Family Size, δ=0.5 - Weighted by Citations, $\delta = 0.5$	0.680 0.385 0.340	1.600 0.926 0.800	25
	J63120	Portals and Other Internet Information Media Service Activities - Unweighted - Weighted by Family Size, $\delta = 0.5$ - Weighted by Citations, $\delta = 0.5$	12.873 7.869 6.504	39.856 24.638 19.993	71
	J63991	Data Base Activities and Online Information Provision Services - Unweighted - Weighted by Family Size, δ= 0.5 - Weighted by Citations, $\delta = 0.5$	0.102 0.055 0.051	0.443 0.242 0.222	59
	J63999	Other Information Service Activities n.e.c. - Unweighted - Weighted by Family Size, $\delta = 0.5$ - Weighted by Citations, $\delta = 0.5$	0.059 0.035 0.030	0.243 0.143 0.123	17
Control	J58221	System Software Development and Supply - Unweighted - Weighted by Family Size, $\delta = 0.5$ - Weighted by Citations, $\delta = 0.5$	2.000 1.109 1.011	4.838 2.665 2.461	126
	J58222	Application Software Development and Supply - Unweighted - Weighted by Family Size, $\delta = 0.5$ - Weighted by Citations, $\delta = 0.5$	2.202 1.263 1.113	6.908 4.011 3.489	357

Table 5: Test and Control Groups: Descriptive Statistics for Annual Patent Counts

Group	Weight	Mean Patent Count	St. Dev.	N
Test	- Unweighted - Weighted by Family Size, $\delta = 0.5$ - Weighted by Citations, $\delta = 0.5$	5.453 3.327 2.755	26.261 16.224 13.179	172
Control	- Unweighted - Weighted by Family Size, $\delta = 0.5$ - Weighted by Citations, $\delta = 0.5$	2.149 1.222 1.087	6.428 3.705 3.251	483

To test variables with different levels of sensitivity to the level of citations, I run tests on variables in which $\delta = 0.25$, 0.50, and 0.75. As stated in the previous subsection, I also run tests on unweighted counts of patent applications, for which $\delta = 0$.

I use the same method to weight the application counts by the size of patent families. For each patent application filed, I collect the size of the family from PATSTAT. I then average these values for each firm i and year t. Values range from 1-8.29, and 63% of the patent applications have a family size of 1. The value of my family-size-weighted counts of patent applications per firm per year is:

$$AppsCount^{WF}_{i,t} = \delta * AppsCount(\frac{FamilySize}{8.291667}) + (1 - \delta) * AppsCount \tag{3}$$

As with the citation-weighted counts, I run tests on variables in which $\delta = 0.25$, 0.50, and 0.75.

Table 4 shows the descriptive statistics by industry for the weighted counts in which δ =0.5. The values are less than the unweighted counts, but the ratios between the test and control industries are similar. Table 5 shows the descriptive statistics for the same weighted counts when they are aggregated into the test and control groups.

3.2.3 Empirical Model

This section describes econometric tests of the significance of differences in patenting activity between the test and control groups after the change to Korea's copyright law occurred. The unit of analysis is the number of patent applications filed per firm in a given year.

I estimate the equation using the Poisson Pseudo Maximum Likelihood with High Dimensional Fixed Effects (PPMLHDFE) model introduced by Correia, Guimaranes and Zylkin (2020) (2020). Poisson pseudo maximum likelihood models are well suited for estimating coefficients in models with count data or other discrete dependent variables, for which log-linear models would usually be inconsistent. They are useful for datasets with a large number of zero values (Silva and Tenreyro, 2006). The PPMLHDFE model allows one to use a Poisson pseudo maximum likelihood model in with panel data because it can process multiple fixed effects (Correia et al., 2020).

Equation 4 presents the main model. The independent variable, $AppsCount$ is the patent application count for each firm i in year t. Tests are run on unweighted patent application counts, counts weighted by citations at different levels, and counts weighted by family size at different levels.

$$AppsCount_{i,t} = exp(\alpha + \beta_1 DID_{i,t} + \beta_2 (Log)RDS_{i,t} + \beta_3 \mathbf{X}_{i,t} + FE_i + FE_t)\epsilon \tag{4}$$

The independent variable of interest is DID, the difference-in-differences dummy variable equal to 1 for observations from internet firms after 2011.

The model is based on the idea that patent applications follow the accumulation of an R&D stock. There is a well-established correlation between R&D spending and patenting at the firm level. Much of the literature describes or aims to quantify the relationship in which R&D spending led to subsequent patents (Scherer, 1983; Jaffe, 1986; Griliches, 1990; Baum et al., 2017). Pakes and Griliches (1984) note that the relationship in which causation runs from R&D spending to patenting is stronger when one considers accumulated R&D spending over time. Some papers have provided evidence for the R&D spending-to-patenting relationship for communications technology industries (Kim and Marschke, 2004) as well as the public sector (Link and van Hasselt, 2019). Others have argued that the relationship is one of reverse causality (Baraldi et al., 2014) or two-way causality (Altuzarra, 2019).

To measure R&D stock, I create the variable RDS using the methodology outlined in Park(1991). R&D spending from the current year is added to depreciated R&D spending from prior years. A time trend is used to estimate the depreciated previous-year R&D spending for the observations at the start of the dataset. I apply a 20% rate of depreciation, which is among the higher estimates in the literature, and is consistent with a finding by Li and Hall (2020) that business R&D capital depreciation is higher than 15% and varies by industry. β_2 estimates the relationship between RDS and patent applications.

$\boldsymbol{X}$ is a vector of logged control variables – sales, intangible-to-total assets, debt ratio and profit-to-sales. The rationale for the inclusion of each is described further below. All of the control variables vary by firm i and year t. The equation also includes separate fixed effects for firm i and year t.

(Log)S is the log of each firm's total sales. It is included as an indicator of firm size, which is expected to be positively related to patent applications. Larger firms have more resources to spend on the patent application process, and have the opportunity to benefit from spillover effects between simultaneous projects(Henderson and Cockburn, 1996). A review of historic literature on firm size by Cohen (2010) finds a positive relationship, but the increase of innovative outputs with firm size is less than proportional, owing to factors such as bureaucratic lag. More recently, empirical work by Link and Scott (2018), Balasubramanian and Sivadasan (2011), Scellato (2006), and Chabchoub and Niosi (2005) have confirmed a positive link between firm size and patenting. Arora et. al. (2008) use data from the Carnegie Mellon Survey on Industrial R&D to find a similar positive relationship between firm size and innovative outputs.

(Log)ITA is the logged ratio of intangible to total assets. I include it as a righthand side variable to capture the IP-intensity of each firm. Much as firms within the same industry have different propensities to invest in R&D, firms within the same industries have different propensities to patent (Fink et al., 2021; Blind et al., 2006; Arundel and Kabla, 1998; Mansfield, 1986). The differences in firms' propensity to patent within in my sample can be inferred from the lack of a strong correlation between the *(Log)RDS* and *(Log)ITA* - the raw correlation coefficient is 0.33.

(Log)DR is the firms' logged debt ratio. It is included because debt financing may be used to finance innovation. Various authors have found a positive relationship between debt and innovation measured by patent indicators. Gill and Heller (2000) find that more valuable patent portfolios are associated with higher firm debt ratios. Xin et. al. (2019) find a positive relationship between debt and patent output, though one that was only significant

for the more R&D intensive firms in their sample. Amore et. al. (2013) examine at the relationship from the point of view of the lenders, finding that greater supply of debt by banks is associated with greater output measured by quantitative and qualitative patent indicators.

(Log)PS is the logged ratio of of profit to sales. This measure of profitability is included on the assumption of a positive correlation between profitability and patenting. Various studies have suggested that more profitable firms are more likely to innovate (Cho and Pucik, 2005; Mai et al., 2019). Possible reasons include corporate culture (Minor et al., 2017), and a preference - for large firms in particular - to finance innovation through internal funds rather than borrowing (Hall, 2002). However, much of the literature on profitability and patents examines the relationship from the other direction, finding a positive link between innovations and subsequent profitability (Altuzarra, 2019; Czarnitzki and Kraft, 2010; Huang and Hou, 2019).

Slight adjustments to the model shown in Equation 4 result in the following equations. As before, the key independent variable of interest is the *DID*, which is equal to 1 for observations from internet firms after 2011, and equal to 0 for all other observations.

$$\begin{aligned} AppsCount_{i,t} = exp(&\alpha + \beta_1 DID_{i,t} + \beta_2 (Log)RDS_{i,t} + \beta_3 (Log)RDS_{i,t} * I \\ &+\beta_4 \mathbf{X}_{i,t} + FE_i + FE_t)\epsilon \end{aligned} \tag{5}$$

$$\begin{aligned} AppsCount_{i,t} = exp(&\alpha + \beta_1 DID_{i,t} + \beta_2 (Log)RDS_{i,t-1} + \beta_3 (Log)RDS_{i,t-1} * I \\ &+\beta_4 \mathbf{X}_{i,t} + FE_i + FE_t)\epsilon \end{aligned} \tag{6}$$

Equation 5 addresses the fact that software firms may be less included to patent their innovations. Studies have empirically demonstrated that software firms have a lower propensity to patent than firms in other industries (Bessen and Hunt, 2007; Chabchoub and Niosi, 2005).

This may be due to questions of patentability, though courts have allowed some level of patent protection for software through the patentability of algorithms and business methods since the 1990s (Graham and Mowery, 2003). Software markets are often characterized by network externalities and high switching costs for consumers, leading to a natural first mover advantage (Varadarajan et al., 2008); and patents can be less valuable when first mover advantage protects innovators' market positions (Scherer, 2014). An analysis of IP in the Korean software industry by Suh and Hwang (2010) confirmed the lower propensity to patent in this industry, as Korean software firms relied more on copyright protection than patent protection to protect their work. Equation 3.5 includes the term *(Log)RDS*I* in which the R&D stock variable is interacted with a dummy variable equal to one for observations from internet industry firms. This allows me to capture this difference in the relationship between the R&D stock and the filing of patent applications between the test and control groups. In this specification, β_2 estimates the relationship between R&D stock and patent applications for the software firms, and $\beta_2 + \beta_3$ estimates it for the internet firms.

Equation 6 lags the variables *(Log) RDS* and *(Log) RDS* I* one year. In the first two specifications of the model, the unlagged version of these variables include both knowledge from current R&D spending, and discounted knowledge accumulated in previous years. However, current-year R&D may be so closely timed with the filing of a patent application that it lacks relevance. Thus, I introduce a one year lag in the final specification.

3.2.4 Results

Table 6 reports the regression results of the basic model expressed in Equation 3. The coefficients presented are unexponentiated. Column (1) reports the results when I regress the count of unweighted patent applications. Columns (2) through (4) report the results when δ – the citation-weighted portion of the count indicator – is equal to 25%, 50%, and 75% of the total, respectively. Columns (5) through (7) report the family size-weighted counts of patent applications, with the corresponding values of δ. The results from the weighted regressions are similar to the results from the unweighted patent applications counts reported in column (1).

Table 6: P.P.M.L. Regressions on Counts of Patent Applications
Errors clustered by industry defined by KSCI4, Fixed Effects for Firm and Year

	(1) Not Weighted $\delta = 0$	(2) Citation Weighted $\delta = 25$	(3) Citation Weighted $\delta = 50$	(4) Citation Weighted $\delta = 75$	(5) Family Weighted $\delta = 25$	(6) Family Weighted $\delta = 50$	(7) Family Weighted $\delta = 75$
DID	2.922***	2.891***	2.832***	2.684***	2.813***	2.647***	2.363***
	(0.198)	(0.199)	(0.200)	(0.204)	(0.207)	(0.223)	(0.249)
(Log)RDS	-0.327***	-0.325***	-0.322***	-0.314***	-0.319***	-0.305**	-0.275*
	(0.104)	(0.106)	(0.108)	(0.114)	(0.110)	(0.121)	(0.149)
(Log) S	0.741*	0.741*	0.743*	0.748*	0.750*	0.766*	0.805**
	(0.436)	(0.432)	(0.422)	(0.397)	(0.424)	(0.402)	(0.361)
(Log)ITA	-0.196**	-0.198**	-0.201**	-0.211**	-0.208**	-0.229**	-0.272***
	(0.0898)	(0.0903)	(0.0914)	(0.0947)	(0.0903)	(0.0917)	(0.0967)
(Log)DR	0.115	0.113	0.107	0.0924	0.118	0.124	0.136
	(0.0981)	(0.0981)	(0.0981)	(0.0981)	(0.0968)	(0.0945)	(0.0886)
(Log)PS	-0.455	-0.455	-0.456	-0.461	-0.443	-0.426	-0.405
	(1.446)	(1.445)	(1.443)	(1.435)	(1.451)	(1.458)	(1.463)
Const.	0.182	-0.0812	-0.438	-0.996	-0.116	-0.534	-1.210
	(3.455)	(3.457)	(3.462)	(3.478)	(3.510)	(3.611)	(3.838)
N	270	270	270	270	270	270	270
Pseudo R^2	0.779	0.766	0.743	0.694	0.771	0.759	0.743

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The coefficients on *DID* are significant at the 99% level of confidence in each of the specifications. They confirm the large increase in patent applications by internet firms after the policy change shown graphically in Figure 3. In column (1), the unexponentiated coefficient of 2.922 implies that after the new law took effect, the number of patent applications filed by internet firms relative to the number filed by software firms increased by a factor of $e^{2.922} = 18.58$. The coefficients the next six columns indicate the similar relationship with the patent application counts weighted by either family size or citations. Unexponentiated coefficients on *DID* from 2.363 to 2.891 relative increases in citation- or family size-weighted patent counts of factors between $e^{2.363} = 10.62$ and $e^{2.891} = 18.01$.

The control variables behave the same across all seven tests. In column (1), the coefficient on *(Log)RDS* implies that a 1% increase in the R&D stock from the mean would be associated with a change of $e^{-0.327} = 0.72$ unweighted patent applications - or a decrease of 28%. The coefficient on *(Log)S* implies a 1% increase in sales is associated with an increase of applications with a factor of $e^{0.741} = 2.10$, or 1.10 additional applications; and the coefficient on *(Log)ITA* implies that a 1% increase in the share of a firm's intangible assets in total assets is associated with a change in patent applications of a factor of $e^{-0.196} = 0.82$, or an 18% decrease patent applications. The coefficients on these terms in the subsequent columns are similar in size and significance. The controls for firms' debt ratio and profitability are insignificant. The McFaden Pseudo R2 runs from 0.69 to 0.78 across specifications, suggesting an acceptable overall fit.

Next, I run tests using Equation 5, which includes the interaction term *(Log)RDS*I*. The results are reported in Table 7. According to this model, the relationship between R&D stock and patenting activity is stronger for the internet firms than the software firms in my sample. In column (1), the coefficient on *(Log)RDS*I* implies that a 1% increase in the R&D stock from the mean for software firms is associated with a $e^{-0.428} = 0.65$ factor change in the number of patent applications filed, or a 35% decrease. However, the coefficient on *(Log)RDS*I* implies that the same increase in R&D stock for internet firms is associated with an $e^{0.620-0.428} = 1.21$ factor increase (or a 21% increase) in patent applications, though it is only significant at the 90% level of confidence. This increase is estimated to be larger in the equations with citation- and family size weights, especially when $\delta = 75$, implying that the relationship is stronger for more economically significant inventions.

Adding this interaction variable does not otherwise alter the overall results of the equation. The coefficients on *DID* and the other control variables are similar to those in the previous specification of the model. Coefficients remain significant when various weights based on citation or family size are applied.

Finally, I run tests using Equation 6 that apply a one-year lag to my two R&D stock

Table 7: P.P.M.L. Regressions on Counts of Patent Applications
Interaction Term (Log) R&D*Internet Added
Errors clustered by industry defined by KSCI4, Fixed Effects for Firm and Year

	(1) Not Weighted $\delta = 0$	(2) Citation Weighted $\delta = 25$	(3) Citation Weighted $\delta = 50$	(4) Citation Weighted $\delta = 75$	(5) Family Weighted $\delta = 25$	(6) Family Weighted $\delta = 50$	(7) Family Weighted $\delta = 75$
DID	2.398***	2.356***	2.276***	2.075***	2.239***	2.003***	1.607***
	(0.341)	(0.334)	(0.319)	(0.280)	(0.315)	(0.274)	(0.205)
(Log)RDS	-0.428***	-0.430**	-0.433**	-0.441**	-0.436**	-0.448**	-0.471**
	(0.166)	(0.168)	(0.171)	(0.181)	(0.170)	(0.176)	(0.188)
(Log)RDS*I	0.620*	0.637*	0.668**	0.751**	0.695**	0.810***	1.016***
	(0.337)	(0.333)	(0.326)	(0.308)	(0.321)	(0.295)	(0.244)
(Log)S	0.671*	0.669*	0.667*	0.662*	0.672*	0.676*	0.694**
	(0.407)	(0.401)	(0.389)	(0.357)	(0.386)	(0.353)	(0.294)
(Log)ITA	-0.267***	-0.270***	-0.277***	-0.295***	-0.287***	-0.321***	-0.386***
	(0.101)	(0.102)	(0.104)	(0.109)	(0.104)	(0.108)	(0.116)
(Log)DR	0.0968	0.0944	0.0898	0.0773	0.101	0.108	0.129
	(0.111)	(0.111)	(0.111)	(0.110)	(0.109)	(0.105)	(0.0970)
(Log)PS	-0.490	-0.492	-0.496	-0.510	-0.486	-0.484	-0.495
	(1.441)	(1.440)	(1.438)	(1.429)	(1.447)	(1.456)	(1.470)
Const.	0.458	0.202	-0.142	-0.665	0.187	-0.190	-0.796
	(3.517)	(3.523)	(3.536)	(3.570)	(3.598)	(3.740)	(4.033)
N	270	270	270	270	270	270	270
Pseudo R^2	0.781	0.768	0.745	0.697	0.773	0.763	0.749

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

variables and report the results in Table 8. The coefficients on *DID* remain highly significant, but their value falls. In column (1), the coefficient on *DID* implies that after the law was in force, the number of patent applications filed by internet firms relative to the number filed by software firms increased by a factor of $e^{1.590} = 4.90$. Applying citation weights or family-size weights yields estimates of $e^{0.722} = 2.06$ to $e^{1.545} = 4.69$.

The coefficients on the lagged variables measuring R&D stock have similar values, but a slightly higher level of significance. The coefficient on $(Log)RDS_{i,t\text{-}1}$ is significant at the 99% level in 6 of the 7 specifications, and the one on $(Log)RDS_{i,t\text{-}1} * I$ is significant at the 95% level of confidence or higher in each. The coefficient on this variable in Column (1)

Table 8: P.P.M.L. Regressions on Counts of Patent Applications
Interaction Term (Log) R&D*Internet Added and R&D Stock Variables Lagged
Errors clustered by industry defined by KSCI4, Fixed Effects for Firm and Year

	(1) Not Weighted $\delta = 0$	(2) Citation Weighted $\delta = 25$	(3) Citation Weighted $\delta = 50$	(4) Citation Weighted $\delta = 75$	(5) Family Weighted $\delta = 25$	(6) Family Weighted $\delta = 50$	(7) Family Weighted $\delta = 75$
DID	1.590***	1.545***	1.461***	1.244***	1.424***	1.169***	0.722***
	(0.280)	(0.278)	(0.273)	(0.262)	(0.271)	(0.255)	(0.223)
$(Log)RDS_{t-1}$	-0.148***	-0.149***	-0.151***	-0.155**	-0.153***	-0.160***	-0.169***
	(0.0534)	(0.0545)	(0.0565)	(0.0616)	(0.0560)	(0.0592)	(0.0622)
$(Log)RDS_{t-1} * I$	0.595**	0.610**	0.641**	0.722**	0.664**	0.776***	0.988***
	(0.298)	(0.299)	(0.299)	(0.301)	(0.295)	(0.289)	(0.274)
(Log)S	0.741*	0.740*	0.739*	0.736**	0.746*	0.754**	0.775**
	(0.406)	(0.401)	(0.390)	(0.362)	(0.388)	(0.359)	(0.304)
(Log)ITA	-0.302***	-0.304***	-0.307***	-0.314***	-0.314***	-0.333***	-0.370***
	(0.0699)	(0.0698)	(0.0698)	(0.0700)	(0.0680)	(0.0649)	(0.0593)
(Log)DR	0.167	0.165	0.160	0.147	0.169	0.173	0.185
	(0.126)	(0.127)	(0.127)	(0.128)	(0.125)	(0.122)	(0.115)
(Log)PS	0.489	0.489	0.489	0.487	0.501	0.518	0.541
	(1.093)	(1.088)	(1.079)	(1.052)	(1.088)	(1.080)	(1.059)
Const.	-4.550*	-4.820**	-5.191**	-5.786**	-4.879**	-5.352**	-6.153**
	(2.372)	(2.361)	(2.342)	(2.295)	(2.396)	(2.454)	(2.607)
N	253	253	253	253	253	253	253
Pseudo R^2	0.793	0.779	0.756	0.706	0.785	0.775	0.761

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

implies a 1% increase in the lagged knowledge stock from its mean would be associated with an increase of the factor $e^{0.595\text{-}0.148} = 1.56$ in additional unweighted patent applications for the internet firms in my sample.

The coefficients on *(Log)S* are higher in this version of the model, suggesting a stronger relationship between firm size and the number of patent applications filed. The coefficients on *(Log)ITA* are similar to the corresponding coefficients in Equation 4, and the other two controls remain insignificant. A slight increase in the Pseudo R squared indicates that adding the lag to the R&D stock variables improves the overall model.

In sum, empirical tests on patent applications after Korea's policy change support the hypothesis that large internet firms engaged in more innovative activity after the country's passage of safe harbors from secondary liability for copyright infringement. Results remain stable when citation and family-size weights are added to patent count indicators as quality controls. Adjusting the model to allow for a different relationship between R&D stock and patent applications for the test and control groups does not change the outcome of the tests. Applying lags to the knowledge stock decreased the size of the estimated difference in differences, while increasing the overall fit of the model. The next section will delve deeper into the patent data, examining the technologies covered by the patents in the set to see if firms redirected the direction of their innovation after the policy change.

3.3 Firm- and Industry-Level Changes in Technologies Patented

This section examines differences in the 'direction' of innovative outputs using the areas of technology indicated on each patent application.

3.3.1 Technology classes cited in patent applications

Patent applicants indicate the technological area of their claimed inventions by assigning one or more International Patent Classification (IPC) subclasses. The IPC scheme was established in 1974 to allow for internationally comparable searches of patents and patent applications. It is a hierarchical organization structure in which broadly based "titles" are divided into "classes" and "subclasses," and then into more precise groups. I use the four-digit subclass as my unit of measurement. Figure 4 provides an example, which breaks down the subclass G06F, the most commonly included IPC subclasses in my dataset.

Figure 4: Example of an IPC Subclass

G	06	F
Title G: Physics	*Class* 06: Computing, Calculating or Counting	*Subclass* F: Electric Digital Data Processing

Table 9 shows the 24 most commonly used IPC subclasses in my set of patent applications filed by firms from 2008 through 2017. They are concentrated in Titles G: Physics, and H: Electricity. The table also shows the share of patent applications by each group of firms that

Table 9: Industry Groups: Descriptive Statistics for Annual Patent Counts

IPC Subclass	Definition	Internet	Software
G06F	Electric Digital Data Processing	0.392 (0.367)	0.359 (0.392)
G06Q	Data Processing Systems or Methods, Specially Adapted for Administrative, Commercial, Financial, Managerial, Supervisory or Forecasting Purposes; Systems or Methods Specially Adapted for Administrative, Commercial, Financial, Managerial, Supervisory or Forecasting Purposes, Not Otherwise Provided For	0.549 (0.051)	0.269 (0.364)
H04L	Transmission of Digital Information, e.g. Telegraphic Communication	0.127 (0.241)	0.209 (0.296)
H04N	Pictorial Communication, e.g. Television	0.107 (0.225)	0.095 (0.240)
H04W	Wireless Communication Networks	0.118 (0.222)	0.122 (0.237)
G06K	Recognition of Data; Presentation of Data; Record Carriers; Handling Record Carriers	0.066 (0.243)	0.047 (0.159)
G06T	Image Data Processing or Generation, in General	0.041 (0.160)	0.012 (0.077)
H04M	Telephonic Communication	0.016 (0.056)	0.022 (0.080)
H04B	Transmission	0.004 (0.025)	0.024 (0.093)
A61B	Diagnosis; Surgery; Identification	0	0.030 (0.139)
H04H	Broadcast Communications	0.0002 (0.001)	0.005 (0.027)
G01C	Measuring Distances, Levels or Bearings; Surveying; Navigation; Gyroscopic Instruments; Photogrammetry or Videogrammetry	0.006 (0.018)	0.001 (0.007)
G09B	Educational or Demonstration Appliances; Appliances for Teaching, or Communicating with, The Blind, Deaf or Mute; Models; Planetaria; Globes; Maps; Diagrams	0.009 (0.038)	0.004 (0.039)
G10L	Speech Analysis or Synthesis; Speech Recognition; Speech or Voice Processing; Speech or Audio Coding or Decoding	0.022 (0.144)	0.004 (0.044)
G01R	Measuring Electric Variables; Measuring Magnetic Variables	0	0.013 (0.080)
G08G	Traffic Control Systems	0.001 (0.005)	0.007 (0.068)
H04Q	Selecting	0	0.031 (0.170)

Continuation of Table 9			
IPC Subclass	Definition	Internet	Software
B60R	Vehicles, Vehicle Fittings, or Vehicle Parts, Not Otherwise Provided For	0.001 (0.010)	0.025 (0.146)
G08B	Signaling or Calling Systems; Order Telegraphs; Alarm Systems	0	0.010 (0.073)
G09G	Arrangements of Circuits for Control of Indicating Devices Using Static Means to Present Variable Information	0.012 (0.054)	0.016 (0.108)
G01S	Radio Direction-Finding; Radio Navigation; Determining Distance or Velocity by Use of Radio Waves; Locating or Presence-Detecting by Use of the Reflection or Reradiation of Radio Waves; Analogous Arrangements Using Other Waves	0.003 (0.023)	0.030 (0.221)
G05D	Systems for Controlling or Regulating Non-Electric Variables	0	0.017 (0.218)
G06N	Computer Systems Based on Specific Computational Models	0.053 (0.253)	0.013 (0.185)
G08C	Transmission Systems for Measured Values, Control or Similar Signals	0	0.019 (0.136)

included each of the IPC subclasses. Patent applications often include multiple IPCs, so the IPC subclass shares of the most heavily used classes sum to a value greater than one.

There is considerable overlap between the IPC subclasses included in patents filed by each group of firms. The distribution of IPC subclasses is strongly skewed. The top two IPC subclasses each appear on 27% or more of patent applications filed by both groups of firms. After the top 10 IPCs, the share of IPCs included on patent applications does not exceed 0.031.

Table 10 presents the mean shares of IPC subclasses in patent applications before and after the policy change, as well as the significance of the change (based on simple T-test). There was little significant change in the direction of innovation apparent from IPC subclasses included in patent applications. There was a significant decrease in the share of IPCs filed by internet firms in two of the 24 top subclasses. There was a slightly higher shift in the direction of patenting among the software firms as indicated by significant changes in five out of 24 IPC shares. Software firms increased the share of patent applications citing H04L (Transmission of Digital Information, e.g. Telegraphic Communication) and G06K

(Recognition of Data; Presentation of Data; Record Carriers; Handling Record Carriers); but they filed a smaller share of patents citing H04W (Wireless Communication Networks), H04H (Broadcast Communications), and H04Q (Selecting).

If one looks at the most frequently cited subclasses, there were few significant changes in the share of patents citing particular technological areas. However, the tail of less frequently cited IPCs shows that internet firms were patenting in new areas of technology. In 11 of the top 24 areas of technology, internet firms filed zero patents before the law was passed, but a non-zero number ≤ 0.086 after the law was passed. This implies growth along the extensive margins of the set of technologies, which is the subject of the next subsection.

3.3.2 Changes at the extensive and intensive margins

This subsection borrows from trade literature, which examines the changes to trade flows on extensive and intensive margins. Specific definitions vary from one study to next, but the extensive margin generally refers to the creation of new trading relationships and/or dissolution of existing ones, while the intensive margin refers to changes in the volume of trade within existing relationships. I apply this concept to the areas of technology in which firms sought to patent their inventions. Table 11 shows one measure of change along the extensive and intensive margins.

Change on the extensive margin represents changes in the areas of technologies in which each group of firms is applying for patents. The increase on the extensive margin is the number of IPC subclasses that appeared in patent applications in 2013-17, which had not appeared in patent applications by that group in 2008-2012. Conversely, the decrease on the external margin is shown by the number of IPC subclasses that each group included on patents in 2008-2012, but not in 2013-2017.

By this measure of the extensive margin, there was net growth for both software and internet firms, though net growth was higher for the internet firms (despite the number of patenting firms being lower).

Table 10: Share of Patent Applications Including Each IPC Subclass Before and After the Policy Change in 2012

IPC	Internet Firms			Software Firms		
	Before	After	Sig.	Before	After	Sig.
G06F	0.516	0.355	0	0.351	0.364	0
G06Q	0.580	0.539	0	0.277	0.264	0
H04L	0.327	0.094	- - -	0.162	0.237	+
H04N	0.072	0.117	0	0.114	0.084	0
H04W	0.128	0.115	0	0.156	0.102	-
G06K	0	0.086	0	0.014	0.067	+ +
G06T	0	0.053	0	0.003	0.027	0
H04M	0.022	0.014	0	0.023	0.021	0
H04B	0.008	0.004	0	0.032	0.019	0
A61B	0	0	0	0.024	0.034	0
H04H	0	0.0003	0	0.012	0.002	- - -
G01C	0	0.008	0	0.0002	0.0007	0
G09B	0.030	0.003	-	0.002	0.006	0
G10L	0	0.029	0	0.001	0.006	0
G01R	0	0	0	0.018	0.011	0
G08G	0	0.002	0	0.012	0.004	0
H04Q	0	0	0	0.071	0.008	- - -
B60R	0	0.002	0	0.027	0.025	0
G08B	0	0	0	0.001	0.015	0
G09G	0	0.016	0	0.018	0.015	0
G01S	0	0.004	0	0.021	0.036	0
G05D	0	0	0	0	0.027	0
G06N	0.154	0.023	0	0	0.022	0
G08C	0	0	0	0.023	0.017	0

Table 11 also shows change on the intensive margins as measured by the number of IPC subclasses that appeared on patent applications in both before (and through) 2012, and after 2012. An increase (decrease) on the intensive margin occurs when more (less) applications cited a particular IPC subclass. Overall, there is less change on the intensive margins. There was an increase of 10 IPC subclasses on the intensive margin for internet firms, and there was a net decrease of 3 on the intensive margins by software firms. Internet firms filed more applications in areas of technology where they had filed applications before, while software firms were withdrawing, though the magnitude of change along the intensive margin is small.

Table 11: Changes on the Extensive and Intensive Margins of Technology
Number of IPC Subclasses Cited in At Least One Patent Application

Change	Internet	Software
# Increase on extensive margin	28	39
# Decrease on extensive margin	2	24
Net change	*26*	*15*
# Increase on intensive margin	10	13
# Decrease on intensive margin	0	16
Net change	*10*	*-3*

4 Conclusion

Safe harbors from secondary liability for copyright infringement eliminate the chance that Online Service Providers (OSPs) will face expensive litigation and penalties if their users post infringing content online. If one considers such litigation fees and penalties as probability-weighted cost associated with OSPs' products and services, then eliminating these costs can increase the potential profitability of new products and services in this sector. Higher potential profits in this sector should lead to further investment in R&D, and subsequently to new products and services.

This paper has used Korea's exogenous introduction of safe harbors in 2011 to test the hypothesis that safe harbors would lead to an increase in innovative inputs and outputs. It finds that a sample of OSPs spent a greater share of their sales on R&D after the law took effect, relative to a control group of software firms. They subsequently filed more patent applications, both absolutely and relative to the control group. Both OSPs and software firms expanded the set of technologies in which they applied for patents, though this expansion along the extensive margin of technology was greater for the OSPs.

The results provide one example where safe harbors promoted innovation among OSPs. It suggests that countries legislating secondary infringement for OSPs can benefit this sector by creating clear, effective safe harbors. It further suggests that American legislators considering changes to the DMCA (for instance, through the "discussion draft" of the Digital Copyright

Act of 2021) should be careful when altering the balance between protecting copyright owners and online intermediaries. However, the analysis is narrowly focused on OSPs that complement the creative industries that produce new works. Future studies could compare the benefits to OSPs to potential harms posed to creators by safe harbors for secondary copyright liability.

More generally, the results illustrate that changes to laws governing copyright exceptions can influence firms in industries that depend on them. The empirical literature on the impact of copyright exceptions is thin, so further work in this area could improve the evidence base for policymaking.

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