Does Patent Disclosure Dissemination Facilitate Corporate Innovation? Evidence from Patent Classification Harmonization

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Abstract

This study examines whether the broader dissemination of patent disclosures increases corporate innovation. By leveraging the harmonization of patent classification systems between Europe and the US and applying a generalized difference-in-differences approach, I find that patent classification harmonization leads to increased innovation activity and improves the quality and efficiency of innovations for US firms more exposed to European patent disclosure. Enhanced access to richer patent data is the mechanism, as I find that US firms more affected by the harmonization subsequently cite a greater number of European patents. The increase in innovation activity is concentrated among small firms and those without significant subsidiaries in France and Germany, suggesting that entities previously at an information disadvantage benefit most from enhanced patent dissemination. However, there is evidence that harmonization is costly to US firms, as it increases the transparency of their patents to European competitors. US firms facing intense European import competition do not reap similar benefits. In sum, the evidence supports that increased patent disclosure dissemination leads firms to be more innovative.

Keywords: Corporate Innovation, Research and Development, Patents disclosure, Patent Classification Harmonization

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1 Introduction

This study examines the effect of patent disclosure dissemination on corporate innovation. Patent disclosures contain valuable technology information, making them a key source for tracking innovation and technology development. However, barriers such as language differences and variations in national patent systems impede patent disclosure dissemination across national boundaries. Despite the importance of patent disclosure in our economic system, evidence on how patent disclosure dissemination affects corporate innovation is limited.

In this study, I address this gap by investigating the impact of the adoption of the Cooperative Patent Classification (CPC) on corporate innovation. The CPC is a landmark patent classification reform adopted by the United States Patent and Trademark Office (USPTO) and the European Patent Office (EPO) in January 2013, standardizing patent classification codes between the U.S. and Europe. Under this new system, all patent documents filed with either office are classified using language-neutral classification codes, allowing inventors to access relevant documents across different languages easily. Moreover, the CPC is actively maintained and updated by the USPTO and EPO to ensure classification quality and alignment with current technological advancements. As a result, European patents written in non-English languages become more accessible to U.S. inventors after the adoption of CPC[1]. Therefore, the adoption of CPC can be viewed as an exogenous shock to patent disclosure dissemination.

Whether the adoption of CPC increases corporate innovation is ex-ante unclear. On the one hand, the broader dissemination of patent disclosures through the CPC could enable US firms to access existing knowledge more effectively and efficiently, potentially enhancing corporate innovation. New ideas arise by recombining existing goods or concepts, and the technical details in patent disclosures provide valuable insights for subsequent innovators (Kim and Valentine 2021; Hegde, Herkenhoff, and Zhu 2023; Tong 2024). Ultimately, the challenge to innovation growth is

[1]Despite efforts by the World Intellectual Property Organization (WIPO) to create a standardized International Patent Classification (IPC) system in 1971, significant limitations persist. Patent offices in the United States and Europe still prioritize their own classification systems as primary frameworks, using IPC codes only as supplementary references rather than core classification tools.

not generating new ideas but rather processing an abundance of potentially new ideas into usable form (Jones 2023; Weitzman 1998). The broader dissemination of European patent information through the adoption of CPC could enhance US firms' ability to access existing ideas, which increases innovation.

On the other hand, commercial patent databases, experienced patent lawyers, and machine translation technologies may already bridge the information gap between European and U.S. patent systems (Fang and Lin 2025; Singh, Chakraborty, and Vincent 2016). Further, the increasing cost of having European counterparts easily assimilating U.S. patent disclosures may discourage innovation activities among US firms (Verrecchia 1983; Verrecchia and Weber 2006; Glaeser 2018, Dambra, Mihov, and Sanz 2024). Therefore, the innovation consequence of patent disclosure dissemination remain an empirical question.

The patent classification harmonization between the US and Europe is well-suited for empirical analysis for several reasons. First, the adoption of CPC only changes the way patent regulators classify patent documents without mandating changes in the content, quantity, quality, or timing of patent disclosure. It enhanced the dissemination of existing mandatory patent disclosures to a wider audience of potential innovators by decreasing language barriers. Second, there is a significant variation among US firms in their exposure to this patent classification harmonization shock because there is heterogeneity in a US firm's exposure to European patent disclosure. Therefore, I can test the effect of patent disclosure dissemination on corporate innovation using the generalized difference in difference estimation. Third, the patent classification harmonization shock is exogenous, as U.S. firms are unlikely to preemptively adjust their technological focus based on potential changes in patent classification systems[2]. Finally, the study can directly test whether patent disclosure dissemination is the underlying mechanism by examining whether affected U.S. firms increase their citations of European patents. Together, these factors enable a clear examination of the causal effect

[2]One concern of my setting is that the adoption of the CPC may coincide with other significant shifts in patent information systems, such as the introduction of the Global Dossier initiative. However, the CPC was adopted on January 1, 2013, whereas the Global Dossier was released publicly in November 2015—a gap of nearly three years. As shown in **Figure 2**, the observed effect begins to emerge well before 2016, making it less likely that my findings are confounded by these concurrent changes.

of patent disclosure dissemination on corporate innovation.

In my main analysis, I run a generalized difference-in-difference regression to compare innovation activity between US firms with high exposure to non-English European patent disclosure and those with low exposure. I focus on U.S. firms' exposure to non-English European patent disclosures because the adoption of CPC is expected to have a stronger impact on their access to non-English European patents compared to English-written ones[3]. I find that one standard deviation increase in firm-level exposure to non-English European patent disclosure leads to a 7.54% increase in the firm's innovation output after the adoption of CPC. This finding is compatible with prior literature which finds a 4.3% increase in patenting activity induced by a patent-based regulation (the "AIPA") (Kim and Valentine 2021).

To ensure there is a fundamental shift in U.S. firms' innovation efforts rather than merely a change in patenting strategy or the patent environment, I extend my results by examining firms' real decisions - R&D spending and capital expenditure. R&D spending represents a firm's direct investment in innovation development, while capital expenditure denotes investments in infrastructure and equipment that indirectly support the creation, implementation, and scaling of new innovations. Consistent with my story, I find that US firms with more exposure to non-English European patent disclosures increase their R&D spending and capital expenditure after the adoption of CPC.

Next, I examine the effect of patent disclosure dissemination on innovative efficiency. The adoption of CPC may facilitate innovative efficiency through various channels. First, with improved patent disclosure dissemination, inventors do not need to reinvent the wheel. Further, firms can optimize their R&D investment strategies with information about the success and failure of their peer patents(Krieger 2021; Capkun, Otto, and Wang 2023; Zhang 2023). Consistent with the above argument, I find that firms with more exposure to non-English European patent disclosure increase in innovative efficiency. One standard deviation increase in firm-level exposure to non-English European patent disclosure leads to a 10.85% increase in the firm's innovative efficiency after the adoption of CPC.

[3]The official languages of EPO are English, German and French.

To validate that patent disclosure dissemination is the driver of the increase in corporate innovation, I test and find US firms cite more European patents in their patent filings when they have more exposure to non-English European patent disclosures after the adoption of CPC, suggesting an increase in information transfer between Europe and the US (Jaffe and Fogarty 2000; Jaffe, Trajtenberg, and Henderson 1993). Together, these results are consistent with the story that the broader dissemination of patent disclosures increases innovation activity.

To further corroborate my findings, I conduct several additional cross-sectional tests. Specifically, I find US firms with no significant subsidiaries in France and Germany, which lack localized access to non-English patents, increase their innovation activity following the adoption of CPC, as the adoption of CPC reduce firms' reliance on local expertise[4]. Similarly, I find that small US firms, which are previously constrained by limited resources to navigate foreign patent systems, increase their innovation activities after the adoption of CPC, suggesting the CPC democratizes access to European technical knowledge. Finally, I find that firms in industries with low European import competition see a greater increase in innovation activity than those in high-competition sectors after the adoption of CPC. This evidence suggests that harmonization also comes at a cost for U.S. firms, as it also increases the transparency of their patents to European competitors.

This study make several contribution to the literature. First, I provide novel evidence of the effect of patent disclosure dissemination on corporate innovation. Prior research focuses on how the content or the speed of patent disclosure affects follow-on innovation (Kim and Valentine 2021; Hegde, Herkenhoff, and Zhu 2023; Dyer et al. 2024). Given that innovations are built upon existing ideas and there are functionally infinitely many combinations of existing ideas, a key question emerges: whether disclosure processing costs of patent disclosure deter corporate innovation (Glaeser and Lang 2023; Blankespoor, deHaan, and Marinovic 2020)? This paper addresses this gap by focusing on a regulation shock where only the classification method used by patent regulators changes, while the content, quantity, quality, and timing of patent disclosures remain unchanged. My study shows that the broader dissemination of patent disclosure increases

[4]I focus on France and Germany as the European Patent Office (EPO)'s official languages are English, German and French.

corporate innovation. However, rising proprietary costs from greater transparency may partially mitigate the positive effect of patent disclosure dissemination.

Second, this paper provides timely policy insights into the costs and benefits of a harmonized patent classification system. While the USPTO and EPO advocate for a unified global system, there are worries that significant institutional differences may undermine its benefits—potentially reducing rather than increasing information availability (Stecher and Suijs 2012, Ball, Robin, and Wu 2003). My findings add to this discussion by showing that the patent classification harmonization between the U.S. and Europe, which facilitates patent disclosure dissemination, can increase corporate innovation. However, these results should be interpreted with caution, as the larger institutional differences between the U.S. and other countries might limit the effectiveness of similar harmonization efforts.

2 Hypothesis Development

2.1 Innovation Activity

The development of technology is a complex and challenging process. Economic theory suggests that new ideas often emerge from the combination of existing goods or concepts (Jones 2023; Weitzman 1998). One available source of existing knowledge is patent disclosure, which provides valuable technical information that can facilitate follow-on innovation (Kim and Valentine 2021; Hegde, Herkenhoff, and Zhu 2023; Dyer et al. 2024).

However, accessing an innovating firm's knowledge through patent disclosure is often expensive for external users, especially when it involves foreign patent information. Sophisticated patent lawyers or commercial patent databases can help but are expensive, limiting US firms' ability to leverage international knowledge. The fragmented patent systems in the U.S. and Europe, along with language barriers, created significant search frictions that limited patent dissemination (Hegde, Herkenhoff, and Zhu 2023; Jaffe and Trajtenberg 1999). The adoption of the Cooperative Patent Classification (CPC) system, which classifies both U.S. and European patents using precise

concepts and ensures language neutrality, significantly facilitates patent disclosure dissemination[5]. This harmonized system will be particularly beneficial for US firms with greater exposure to European patents in non-English languages, as language differences amplify information barriers. The broader dissemination of European patent disclosure allow US companies to innovate more, as the barrier to innovation growth often lies in our ability to process existing ideas, not in generating new ones (Jones 2023; Weitzman 1998). This leads to my first hypothesis.

Hypothesis 1. *After the adoption of CPC, US firms with more exposure to non-English European patents increase their innovation activity*

My hypothesis is not without tension. Commercial patent databases, experienced patent lawyers, and machine translation technologies may already mitigate the information barrier between European and U.S. patent systems (Fang and Lin 2025; Singh, Chakraborty, and Vincent 2016). Further, US firms may refrain from innovating as patent disclosure dissemination has a reciprocal effect. After the adoption of CPC, European competitors can also easily assimilate US patents, potentially putting US firms at a competitive disadvantage. The rising proprietary costs of patent disclosure may discourage innovation investment for US firms (Verrecchia 1983; Verrecchia and Weber 2006; Glaeser 2018; Dambra, Mihov, and Sanz 2024). Therefore, the relationship between patent disclosure dissemination and corporate innovation is ex-ante unclear.

2.2 Innovative Efficiency

Further, I examine whether affected US firms increases innovative efficiency after the adoption of CPC. The adoption of CPC may enhance innovative efficiency through several mechanisms. First, by standardizing the patent classification code, the CPC system enables firms to systematically access patent disclosures across industries and national borders. The broader dissemination of patent disclosure reduces redundant research efforts, as companies can directly build on existing knowledge rather than duplicate existing inventions. Second, the CPC system improves transparency in R&D outcomes by facilitating the dissemination of detailed, real-time European patent

[5]See Appendix C for further discussion.

application results. Using this knowledge, firms can strategically allocate R&D resources toward high-potential projects (Krieger 2021; Capkun, Otto, and Wang 2023; Zhang 2023). This helps companies innovate more efficiently. The above arguments lead to my second hypothesis.

Hypothesis 2. *After the adoption of CPC, US firms with more exposure to non-English European patents increase their innovation efficiency*

3 Sample and Research Design

3.1 Sample Selection and Data

My sample includes publicly traded companies from 2009 to 2016. This timeframe was chosen to ensure a balanced representation with four years in the pre-period and four years in the post-period. My sample period starts in 2009 to mitigate any potential influence from the 2008 financial crisis on the observed outcomes.

To compile the dataset, I integrated financial statement data sourced from Compustat and analyst data from IBES. Additionally, I incorporated patent data initially obtained from (Kogan et al. 2017) and supplemented it with more detailed patent data from PATSTAT and PatentsView.

I retain only firms that have non-missing values of my independent variable of interest. This criterion requires that a firm has filed a granted patent at least once in the twenty years leading to the adoption of the CPC. I also require firms to have relevant CRSP/Compustat variables, such as market capitalization, book assets, and returns[6].

3.2 Variable Measurement

3.2.1 Key Dependent Variable: Innovation Activity

I use several innovation proxies to gauge a firm's innovation activity. Similar to prior literature, I use the number of US patent-generated citations a firm's patents receive over the patents' lifetime

[6]See Appendix B for sample selection procedure

as a proxy for the value of patents (Kim and Valentine 2021; Bernstein 2015; Zhong 2018). I count only US patent-generated citations to make sure that my measurement will not be confounded by the increase in European counterparts' ability to cite US patents after the adoption of CPC. Further, I measure forward citations through 2024 instead of measuring through some constant years because there is an endogenous time lag between when firms file their patents and when the patent applications are available for the public to cite, as my firms may choose to disclose their patent documents earlier to deterring product market competition (Glaeser and Landsman 2021) [7].

Given my focus on firm-level innovation activity, I aggregate US patent-generated forward citations a firm receives for all patents filed for a given firm-filing year, which I refer to as *Forward Citations*. I use *Forward Citation* with inverse hyperbolic sine (IHS) transform, $\sinh^{-1}(\textit{Forward Citation})$, as the primary proxy of innovation. I apply inverse hyperbolic sine (IHS) to the outcome variables to account for their skewed distribution and minimize the impact of outliers in my sample (Glaeser and Omartian 2022)[8].

An issue with my output-based innovation proxy is that it may be affected by a firm's patenting strategy and the patent disclosure environment. For example, the adoption of CPC may facilitate US firms to access and cite US patents. Therefore, I may find an increase in $\sinh^{-1}(\textit{Forward Citation})$ without a genuine increase in innovation activity. I look at *# Claims*, *R&D Intensity*, and *Capex* to alleviate some of these concerns. *# Claims* is the total number of distinct subject matters protected by the patents filed by a firm within a given year. *R&D Intensity* and *Capex* are the ratio of R&D expense or capital expenditure to lagged total assets which reflect the US firm's innovation input[9]. These measures are less likely influenced by a firm's patenting strategy and the patent disclosure environment.

[7] My analysis is run with patent applications made by the end of 2016, and I count forward citations through 2024. Therefore, allowing enough time to eliminate the risk of truncation bias.

[8] As shown in the **Table 12** table, my result is also qualitatively similar and robust when I use fixed effect Poisson regression.

[9] In the robustness check, I also look at the number of patents filed by a firm in a given firm filing year, and the result is consistent.

3.2.2 Key Dependent Variable: Innovative Efficiency

I develop innovative efficiency measurements similar to the approach outlined in the previous literature (Hirshleifer, Hsu, and Li 2013; Chawla 2023). I use *Forward Citation* as a proxy for a firm's innovation output. To proxy a firm's cumulative innovation input, I calculate a firm's cumulative R&D capital, which is defined as the firm's cumulative R&D expense over the last five years, with a depreciation rate of 20%. I use R&D capital instead of current year R&D expense because converting innovation input to output takes time. To calculate *Innovative Efficiency*, I scaled *Forward Citation* by its cumulative R&D capital, which measures how effectively the firm utilizes its resources for innovation[10].

3.2.3 Key Dependent Variable: Patent Disclosure Dissemination

A unique advantage of my setting is that I can directly measure the information transfer between Europe and the US. I use patents' citations as a proxy for patent disclosure dissemination, as prior literature documents that the likelihood of knowledge spillover conditional on the observation of a patent citation is significantly greater than the unconditional likelihood (Jaffe and Fogarty 2000). Given my focus on whether European patent disclosure dissemination promotes US innovation, I count the total number of European patents cited by patent applicants or patent examiners for patent applications filed by a US firm in year t, which I refer to as *EU*. Further, I construct another proxy that counts the total number of European patents solely cited by patent applicants for patent applications filed by a US firm in year t, which I refer to as *EU Appl*.

One key point is that PatentsView, the database I use to generate patent disclosure dissemination proxies, classifies references cited by the examiner as "cited by the examiner," regardless of whether the applicant also cites them or not. Therefore, my *EU Appl* proxy will inherently underestimate the number of European patent citations added by the applicant for patents filed by a firm in year t.

[10] In the untabulated table, my result is robust when my innovative efficiency is measured by scaling the number of granted patent filed by a firm in a given firm-filing year by its R&D capital

3.2.4 Key Independent Variable: Firm-level Exposure to CPC Adoption

My analysis involves quantifying U.S. firms' exposure to both English and non-English European patent disclosures to proxy the impact of patent classification harmonization. Intuitively, firms operating in technology fields where there is more non-English European patent disclosure will benefit more from the adoption of CPC than those in other fields, as language barriers limit their access to relevant technological knowledge. My approach measures a firm's exposure to CPC adoption by examining its level of exposure to English and non-English European patent disclosures within the technology fields where it conducts R&D. These technology fields are categorized by the CPC. I follow and modify the measurement methods used in (Mezzanotti 2021). My method capitalizes on two key features of the setting. First, there is a lot of variation across the technology fields in the prevalence of European patent disclosure. Second, many companies operate across different technology fields.

I express an individual firm *i* exposures to the adoption of CPC as a function of two quantities. (1) the technology fields *j* in which the firm *i* operates, and (2) the prevalence of European patent disclosure across technology fields *j*. Specifically, I define σ_j^i as the share of firm *i* patents across the different technology fields *j* and $\rho_{l,j}$ as the prevalence of European patent disclosure in technology fields *j*, where *l* indicate language (English vs. Non-English). Therefore, firm *i* exposure to English or non-English European patent disclosure can be constructed by weighting the prevalence of European patent disclosure in each technology field by the share of activity that firm *i* has in each of these fields, which is:

$$Exposure_{i,l} = \sum_{j=1}^{T} \sigma_j^i \rho_{l,j}$$

To proxy for a firm i 's exposure in each technology field j, σ_j^i, I compute the ratio of US patents filed by firm i within each technology field j from 1993 to 2012 to the total number of US patents filed by firm i during the same period. Here, the technology fields are defined by CPC, which classifies patents into over 600 distinct subclasses.

To estimate the prevalence of the European patent disclosure across technology fields j, I use

patent data from PATSTAT, a comprehensive patent database provided by EPO. PATSTAT provides detailed information on the language in which these European patents are written, enabling me to categorize them into English-written and non-English-written patents (Patents that are written in French and German – the other two official languages of EPO). Using patent filing data from 1993 to 2012, I calculate the prevalence of the European patent disclosure across technology subclass j by dividing the number of English/non-English European patents by the number of US patents within each specific technology subclass. I present the prevalence of European patent disclosure across technology sections (not subclasses) in **Figure 1** for demonstration.

I estimate $Exposure_{i,l}$ by combining the two measurements I mentioned above. I separately estimate two kinds of exposure based on the language written in the European Patent, $Exposure_En$ and $Exposure_Other$.

I acknowledge that a firm may file multiple patent documents in different countries (Fink, Khan, and Zhou 2016). A lot of patents are filed in both the United States and Europe. When computing firm-level exposure to CPC adoption, I determine whether a patent is a US or European patent based on the location of its initial filing. This approach assumes that the initial filing location reflects the patent's origin and where its disclosure is first made available. I still find that US firms with more exposure to non-English European patents increase their innovation activity after the adoption of CPC if I define a European Patent as a patent that is only filed in Europe, not subsequently filed in the US.

I acknowledge that while an EPO patent may not be written in English when the EPO grants it, the patent applicants need to translate the granted patent's claims into two other languages and publish them in the European Patent Bulletin in English, German, and French. However, European patent applications shall be published in the language of the proceedings well before the patents receive approval. In addition, European patents disclose their specifications only in the language of the proceedings when they get granted. Therefore, my measurements $Exposure_En$ and $Exposure_Other$ will correctly document two different kinds of exposure.

3.2.5 Control Variable

I add a set of firm-level controls that may influence a firm's innovation activities in my regression based on prior literature (Kim and Valentine 2021). More specifically, to control for financial friction, agency conflict, and investment opportunity that may influence a firm's innovation activities, I include *Age*, *Firm Size*, *Cash*, *Return on Assets*, *Book to Market*, *Number of Analysts*, and *Leverage* as a set of controls. I winsorize all continuous variables at the 1% and 99% to prevent the influence of outliers. Detailed definitions of all variables are in the Appendix.

3.3 Research Design

My primary empirical analyses employ a difference-in-difference design around the implementation of the CPC. For my first hypothesis, the model I use is the following:

$$Innovation\,proxy_{i,t} = \beta_1 Exposure_Other \times Post + \beta_2 Exposure_En \times Post + \beta_3 Controls_{i,t} + \delta_i + \pi_t + \mu_{i,t}$$

The unit of observation is at the firm *i* and year *t* level. Innovation proxy is one of the proxies for innovation. The coefficients on the interaction terms *Exposure_Other* $\times$ *Post* and *Exposure_En* $\times$ *Post* capture the impact of the CPC. I predict β_1 to be positive since I expect firms with more exposure to non-English European patent disclosure to increase their innovation activity after the adoption of CPC. I have no prediction on β_2. I define the firm and year fixed effects as δ_i and π_t, and I cluster standard errors at the firm levels.

For my second hypothesis, I replace the dependent variable with my variable of interest, which is the innovative efficiency proxy. I predict β_1 to be positive since I expect the adoption of CPC to improve innovative efficiency for firms with more exposure to non-English European patent disclosure.

4 Empirical Results

4.1 Descriptive Statistics

Table 1 presents descriptive statistics for the main independent variable of interest. On average, firms in my sample receive 189 forward citations across their patents filed in a year. Firms in the sample are about 23 years old.

4.2 Evidence of CPC's Effect on Innovation Output

My hypothesis predicts that US firms operating in technology fields with more non-English European patent disclosure will increase innovation activity after the adoption of CPC. **Table 2** regresses $\sinh^{-1}(\textit{Forward Citation})$ on *Exposure_Other* $\times$ *Post* and *Exposure_En* $\times$ *Post*. Column (1) contains results without control variables but with firm and year-fixed effects. Column (2) adds a host of control variables discussed in section 5.1. The significant and positive coefficient on *Exposure_Other* $\times$ *Post* in Column (2) (coef. = 1.14; t-stat = 2.69) indicates that patent disclosure dissemination increases corporate innovation. The coefficient implies that after the adoption of CPC, with one standard deviation increase in firm-level exposure to non-English European patent disclosure, firms file patents that receive on average 7.54% more *Forward Citation* relative to the pre-CPC average. This effect is statistically and economically significant as prior literature finds a 4.3% increase in patenting activity induced by a patent-based regulation (the "AIPA") (Kim and Valentine 2021).

4.3 Dynamics for Innovation output

The casual interpretation of a generalized difference-in-difference model depends on the validity of the parallel trend assumption. The dynamic analysis enables me to investigate whether my results are influenced by reverse causality or dissimilar trends between the treatment and control groups. To provide suggestive evidence of this, I reestimate a dynamic model by including a set of

dummy variables that represent each year before and after the adoption of CPC (i.e., 2013):

$$Innovation\ proxy_{i,t} = \beta_1 Exposure_Other \times Year_t + \beta_2 Exposure_En \times Year_t + \beta_3 Controls_{i,t} + \delta_i + \pi_t + \mu_{i,t}$$

The results of the dynamic model are reported in **Table 3**. *Year*$_{2012}$ × *Exposure_Other* is omitted as the baseline result. In both column (1) and column (2), none of the coefficient estimates on *Year*$_{2009}$ × *Exposure_Other*, *Year*$_{2010}$ × *Exposure_Other*, or *Year*$_{2011}$ × *Exposure_Other* are statistically significant, suggesting the satisfaction of the parallel assumption of the difference-in-difference approach and hence no evidence of reverse causality. In contrast, the coefficient estimates on *Year*$_{2014}$ × *Exposure_Other*, *Year*$_{2015}$ × *Exposure_Other*, or *Year*$_{2016}$ × *Exposure_Other* are positive and significant at the 5% or 1% level, indicating that the adoption of CPC spurs innovation output one year after the adoption of CPC.

To visualize the parallel trends, I plot the coefficient estimates obtained from the dynamic model in **Figure 2**. The X-axis represents the year relative to the adoption of CPC year. The Y-axis represents the coefficient estimates on the time indicator variables surrounding the adoption of CPC. Vertical bars represent 90% confidence intervals. **Figure 2** shows that the coefficient estimates for the pre-event years are virtually indifferent from zero, hence validating the parallel trends assumption. However, innovation output significantly rises starting in the second year following the adoption of CPC.

The dynamic model suggests that the innovative output gradually increases and becomes economically and statistically significant one year after the implementation of the CPC, which alleviates some of the concerns that changes in patenting strategies or patent disclosure environment drive my results.

4.4 Placebo test

To alleviate the concern that my main findings may be spurious, I conduct a falsification test by randomly shuffling *Exposure_Other* to each firm and reestimating the regression equation. I repeat

this process 500 times. **Figure 3** and **Figure 4** shows the distribution of estimated coefficients and t-stats of $\sinh^{-1}(\textit{Forward Citation})$ on *Post* $\times$ *Exposure_Other* based on placebo regression using randomized *Exposure_Other*. The distributions for DiD estimates and t-statics, based on placebo regressions, are centred around zero, which contrasts starkly with the estimated effects of **Table 2**, shown by the red line in **Figure 3**. Therefore, my documented effect is unlikely to be spurious.

4.5 Evidence of CPC's Effect on Number of Patent Claims

One concern for my previous results is that the adoption of CPC may facilitate US firms to access and cite US patents. Further, firms may be motivated to subdivide their inventions across multiple patents to reduce their foreign competitors' ability to expropriate useful signals from their patent disclosure. With more patents filed by US firms, one may find an increase in *Forward Citation*, where there is no genuine increase in innovation activities.

To address these concerns, I examined the number of patent claims a firm filed in a given year, which I refer to as *#Claims*. This proxy captures the number of distinct components of an invention that are covered and protected by the patent, making it less susceptible to the concern mentioned above.

Table 4 shows results from regression $\sinh^{-1}(\textit{\#Claims})$ on *Exposure_Other* $\times$ *Post*. The coefficient on *Exposure_Other* $\times$ *Post*. One can find that firms who are more exposed to non-English European patent presence increase *#Claims* they file after the adoption of CPC, which alleviates some concerns that my results are driven by the change in patenting strategy or patent disclosure environment rather than a genuine increase in innovation activity.

4.6 Evidence of CPC's Effect on Innovation Input

Previous results illustrate that the adoption of CPC leads to a rise in innovation output and my result is less likely driven by patenting strategy or patent disclosure environment. To further solidify the argument, I next examine *R&D Intensity* and *Capex* as input-based proxies for innovation activity. *R&D intensity* reflects the proportion of resources a firm dedicates directly to

developing innovation, while *Capex* represents the resources allocated to indirectly support innovation by providing the infrastructure and equipment required to invent, implement and scale a new innovation[11].

Table 5 presents results from regressing *R&D Intensity* on *Exposure_Other* $\times$ *Post*. From Column (2) and Column (4) of **Table 5**, one can find that firms who are exposed to non-English European patent presence increase their R&D spending and capital expenditure after the adoption of CPC. Taken together, it is unlikely that the documented change in innovation activity is driven by the change in patenting strategy or patent disclosure environment.

4.7 Evidence of CPC's Effect on Patent Quality

Building on the evidence that the adoption of CPC encourages more innovation activity, I now investigate whether it also leads to higher-quality innovation output. To do so, I calculate the average forward citations for the portfolio of patents filed in a given firm-year, *#Forward Citations/Patent*. One concern is that the increase in $\sinh^{-1}$(*#Forward Citation/Patent*) could simply reflect an easier environment for citing relevant patents in the post-adoption period. To address this issue, I also examine whether firms file more claims per patent, *#Claims/Patent*.

Table 6 presents the results. The positive and significant coefficients of *Exposure_Other* in Column (2) and Column (4) demonstrate that patent quality increases for firms more exposed to non-English European patent presence after the adoption of CPC. Combined with my main result in **Table 2**, these findings suggest that the quality and quantity of innovation output increase after the adoption of CPC.

4.8 Evidence of CPC's Effect on Innovative Efficiency

Next, I examine the effect of patent disclosure dissemination on innovative efficiency. I scaled *Forward Citation* by its cumulative R&D capital to calculate the variable of interest, *Innovative*

[11] An example of capital expenditure facilitating innovation is when large tech corporations, like Amazon, invest in data centers or cloud computing.

Efficiency. I expect and find that affected US firms' innovative efficiency increases after the adoption of CPC. **Table 7** reports the results from regressing $\sinh^{-1}(\textit{Innovative Efficiency})$ on *Exposure_Other* × *Post* and *Exposure_En* × *Post*. In both Columns in **Table 7**, I find the association between $\sinh^{-1}(\textit{Innovative Efficiency})$ and *Exposure_Other* × *Post* is positive and significant (coef. = 0.59; t-stat = 4.17)[12]. After the adoption of CPC, one standard deviation increase in the firm-level exposure to non-English European patent disclosure will lead to a 10.85% increase in a firm's innovative efficiency. Further, **Figure 5** plots the coefficient for the interaction between *Exposure_Other* and the corresponding year dummy and show that pre-trends do not drive the result.

Combined with my result in **Table 2** and **Table 5**, these evidences suggest that the observed increase in innovation output is driven not only by greater innovation input but also by the fact that affected US firms have learned to use their R&D resources more efficiently following the adoption of the CPC.

4.9 Evidence of CPC's Effect on Patent Disclosure Dissemination

While I provide evidence that firms that are more exposed to non-English European patent disclosure increase their innovation activity, innovation quality, and innovative efficiency after the adoption of CPC, I still need to establish that patent disclosure dissemination drives this increase in innovation. To do so, I use patents' backward citations as a proxy for that, as prior research finds that patent citations indicate information transfer (Jaffe and Fogarty 2000, Jaffe, Trajtenberg, and Henderson 1993). If the increase in innovation is driven by patent disclosure dissemination, one would expect that firms operating in technology fields with more exposure to non-English European patent disclosures will actively cite more European patents following the adoption of the CPC.

Table 8 presents results from regression $\sinh^{-1}(\textit{EU})$ and $\sinh^{-1}(\textit{EU Appl})$ on *Exposure_Other* × *Post* and *Exposure_En* × *Post*. Column (1) and Column (3) present the baseline result with firm and year fixed effects. Column (2) and Column (4) add a set of controls. As I mentioned in

[12] In the untabulated table, my result is robust when I calculate innovative efficiency using #Patent as innovation output.

the variable measurement section, my $\sinh^{-1}(EU\ Appl)$ proxy will underestimate the number of European patent citations added by the applicant because the database I use classifies references cited by the examiner as "cited by examiner," regardless of whether the applicant also cites them or not. Further, patent applicants have an incentive to strategically conceal prior art to increase the likelihood of their patents being granted (Langinier and Marcoul 2016), and the current incentive structure for patent examiners, which emphasizes productivity, may not effectively encourage examiners to thoroughly detect such concealments (Langinier and Marcoul 2020). No matter what, the coefficient on *Exposure_Other* $\times$ *Post* is positive and significant, which means US firms with more exposure to non-English European patent disclosure cite more European patents after the adoption of CPC.

Corroborating with previous evidence which shows firms with more exposure to non-English European patent disclosure increase in innovation activity, innovation quality, and innovative efficiency, I establish the link that the adoption of CPC, which facilitates patent disclosure dissemination, increases corporate innovation. Further, **Figure 6** and **Figure 7** plot the coefficient for the interaction between *Exposure_Other* and the corresponding year dummy and show that pre-trends do not drive the result.

4.10 Cross-sectional Tests

4.10.1 No France and German presence vs. France and German presence

If patent disclosure dissemination drives my results, US firms with high information barriers prior to the CPC's adoption are expected to benefit the most from its implementation. This pertains to firms with no significant subsidiaries in France and Germany. US firms with significant subsidiaries in France or Germany will have access to regional patent networks, translation resources, and localized expertise, enabling them to navigate among non-English European patent disclosures, which are written in French or German. US firms without such subsidiaries face higher ex-ante costs in accessing non-English European patents. The adoption of CPC mitigates these information barriers by providing a standardized, language-neutral patent classification system,

effectively democratizing access to European technical knowledge. Thus, the adoption of CPC shall disproportionately benefit firms without significant subsidiaries in France or Germany.

To construct a proxy for a firm's presence in France and Germany, I look at a firm's exhibit 21, where firms disclose detailed information about their significant subsidiaries as required by the SEC. Under SEC regulations, U.S. firms must disclose any subsidiary that meets at least one of the following criteria: (1) the parent's and its other subsidiaries' investments in (advances to) a given subsidiary exceed 10% of consolidated parent assets; (2) the parent's proportionate share of the subsidiary's assets exceeds 10% of consolidated parent assets; (3) the parent's proportionate share of the subsidiary's pretax income before extraordinary items exceeds 10% of the consolidated parent's pretax income. Using this information, I construct an indicator variable, *No France and German Presence*, which equals one if a firm does not have any significant subsidiaries in France and Germany in 2012 (prior to the adoption of CPC). I hypothesize that firms without significant subsidiaries in these countries prior to the CPC's adoption will benefit the most from the improved dissemination of patent disclosures.

I interact *No France and German Presence* with *Exposure_Other* $\times$ *Post* and *Exposure_En* $\times$ *Post* to examine the cross-sectional effect. **Table 9** presents the baseline result and results with a set of controls. I find that the coefficient on *No France and German Presence* $\times$ *Exposure_Other* $\times$ *Post* is positive and significant while the coefficient on *Exposure_Other* $\times$ *Post* is insignificant, suggesting that the positive effect of the CPC adoption on innovation output is concentrated on firms with no significant subsidiaries in Germany and France in 2012. This evidence supports the idea that the adoption of CPC increases corporate innovation by facilitating patent disclosure dissemination.

4.10.2 Big Firm vs. Small Firm

To further examine whether the observed increase in innovation is driven by improved patent disclosure dissemination, I compare the effects of CPC adoption between large and small firms. Large firms, with abundant resources such as expensive commercial patent databases, in-house legal

patenting teams, and partnerships with patent agencies, are well-equipped to access non-English European patents. In contrast, small firms often lack the financial and institutional capacity to navigate foreign patent systems effectively. The adoption of CPC helps bridge this gap by lowering search costs for non-English European patents. Therefore, I hypothesize that CPC adoption will disproportionately benefit small firms, as it partially substitutes the size advantages that large firms already possess.

Small Firm is an indicator equal to one if the firm is below the median asset size in 2012. I interact *Small Firm* with *Exposure_Other* $\times$ *Post* and *Exposure_En* $\times$ *Post* to examine the cross-sectional effect. **Table 10** presents the baseline result and results with a set of controls. I find that the coefficient on *Small* $\times$ *Exposure_Other* $\times$ *Post* is positive and significant while the coefficient on *Exposure_Other* $\times$ *Post* is insignificant, suggesting that the positive effect of CPC adoption on innovation output is concentrated on small firms. This evidence supports the idea that the adoption of CPC increases corporate innovation by democratizing access to European patent disclosure.

4.10.3 High Import Competition vs. Low Import Competition

One tension of my hypothesis is that US firms may be discouraged from innovating due to the costs associated with patent classification harmonization. The effect of the adoption of CPC on US firms is nuanced. While it facilitates access to non-English European patents, it also increases the transparency of US patents to European competitors. For US firms already struggling with European import competition, the enhanced dissemination of their patent disclosures can raise their proprietary costs and reduce their innovation incentives (Verrecchia 1983; Verrecchia and Weber 2006; Glaeser 2018; Dambra, Mihov, and Sanz 2024). In contrast, US firms in industries with low European import competition face fewer such threats and are better positioned to leverage the benefits of CPC adoption. Thus, I hypothesize that the adoption of CPC disproportionately benefits U.S. firms shielded from European import competition.

Following prior literature, I use European import penetration to measure the level of European import competition across industries (Lie and Yang 2023). I calculate import penetration for each

industry as

$$Import\ Penetration = \frac{imports}{imports + domestic\ production\ -\ exports}$$

Industries are defined as three-digit SIC (Standard Industrial Classification) levels [13]. Import and Export data come from the United States Census Bureau. I obtain domestic production data from the NBER-CES Manufacturing Industry Database. I generate indicator variable *Low Competition*, which equals one if a firm face below-median European import penetration in 2012.

I interact *Low Competition* with *Exposure_Other* $\times$ *Post* and *Exposure_En* $\times$ *Post* to analysis the cross-sectional effects. **Table 11** shows the baseline result and results with a set of controls. Consistent with my hypothesis, I find that the coefficient on *Low Competition* $\times$ *Exposure_Other* $\times$ *Post* is positive and significant, while the coefficient on *Exposure_Other* $\times$ *Post* is positive and insignificant. This result suggests that import competition from Europe partially mitigates the overall positive effect of European patent disclosure dissemination on US firms' innovation. Due to high proprietary costs following the adoption of CPC, US firms in industries facing significant European import competition see diminished innovation benefits.

4.11 Robustness Checks

I further explore the robustness of my result to alternative dependent and independent variable measurements. Panel A of **Table 12** presents results using alternative dependent variables and fixed effect structures. Column (1) shows that my results continue to hold using untransformed *Forward Citation*. Further, in Column (2), I apply the log plus one transformation to my independent variable and find that my result is consistent and robust. To provide further assurance of my results, in Column (3) and Column (4), I check whether affected US firms file more patents and are more likely to file patents after the adoption of CPC. In both cases, I find my results are similar to my main results. I also consider alternative fixed-effect structures. In Column (5) , I include firm fixed effects and industry-by-year fixed effects, instead of firm and year fixed effects. The use of

[13] My result is also robust when I use three-digit NAICS (North American Industry Classification System) levels

industry-by-year fixed effects enables me to control for concurrent macroeconomic or regulatory events, allowing for an exploration of the variation in *Exposure_Other* and *Exposure_En* across firms within the same industry and year. I still find my inferences are unchanged.

Panel B of **Table 12**, I examine the robustness of my results to a variety of alternative *Exposure_Other* and *Exposure_En* proxies. One concern is that many patents are filed in both the United States and Europe, which could make my definition of European patents spurious. To address this concern, I redefine European patents as those filed exclusively in Europe and recalculate *Exposure_Other* and *Exposure_En*. Using these revised measures, I find that my results remain consistent and are even stronger, as shown in Column (1). In Column (2), I vary the technology area used to calculate *Exposure_Other* and *Exposure_En*. Specifically, I use the technology class instead of the technology subclass to measure *Exposure_Other* and *Exposure_En* and find that my results remain robust.

Finally, Prior literature argues that using log or log-like transformation as the dependent variable in a regression precludes a meaningful interpretation and can introduce bias (Cohn, Liu, and Wardlaw 2022). They suggest using fixed effects Poisson regression instead. Panel C of **Table 12**, I examine whether my result is robust in fixed effects Poisson regression, and I find largely similar and consistent results.

5 Conclusion

Recent accounting literature on patent disclosure has grown substantially (Glaeser and Lang 2023). Yet, our understanding of how the dissemination of patent disclosures influences corporate innovation remains limited. This study provides novel empirical evidence on these effects by exploiting the adoption of the Cooperative Patent Classification (CPC) as an exogenous shock that broadens the dissemination of patent disclosures. Our findings indicate that a one standard deviation increase in non-English European patent disclosures is associated with a 7.54% increase in innovation output and a 10.85% boost in innovative efficiency among affected US firms following

CPC adoption. Enhanced European patent disclosure dissemination appears to be the primary mechanism, as affected firms subsequently cite more European patents in their filings.

Moreover, the positive impact of CPC on corporate innovation is most pronounced among small firms or those without significant subsidiaries in Germany and France prior to CPC adoption, suggesting that CPC has democratized access to European technical knowledge. However, this increase in innovation activity is partially offset by import competition from Europe, indicating that harmonization may also impose proprietary costs on US firms by increasing the transparency of US patents to European competitors.

This paper contributes to the discussion on how disclosure processing costs influence the relationship between patent disclosures and subsequent innovation—a crucial aspect that previous accounting research on innovation has largely overlooked (Glaeser and Lang 2023). Moreover, my findings offer new insights into the ”real effects” of disclosure processing costs, demonstrating that the broader patent disclosure dissemination via the adoption of CPC has a real impact on corporate innovation. Finally, this study informs current policy debates by assessing the costs and benefits of a harmonized patent classification system, an issue of growing importance as both the EPO and USPTO push to expand CPC worldwide.

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Figure 1: The Relevance of English written/non-English Written European Patent Disclosure

This figure plots the relevance of English written/ non-English written European patent disclosure. I present the prevalence of European patent disclosure across technology sections (not subclasses), because there are around 600 technology subclasses. The technology section's definition is following; A - Human necessities, B - Performing operations; transporting, C - Chemistry; metallurgy, D - Textiles; paper, E - Fixed constructions, F - Mechanical engineering; lighting; heating; weapons; blasting engines or pumps, G – Physics, H – Electricity, Y – New technology. As one can see, there are relatively more non-English written European patents filed in the E section and F section, which presumably are technology sections that Germany and France are good at.

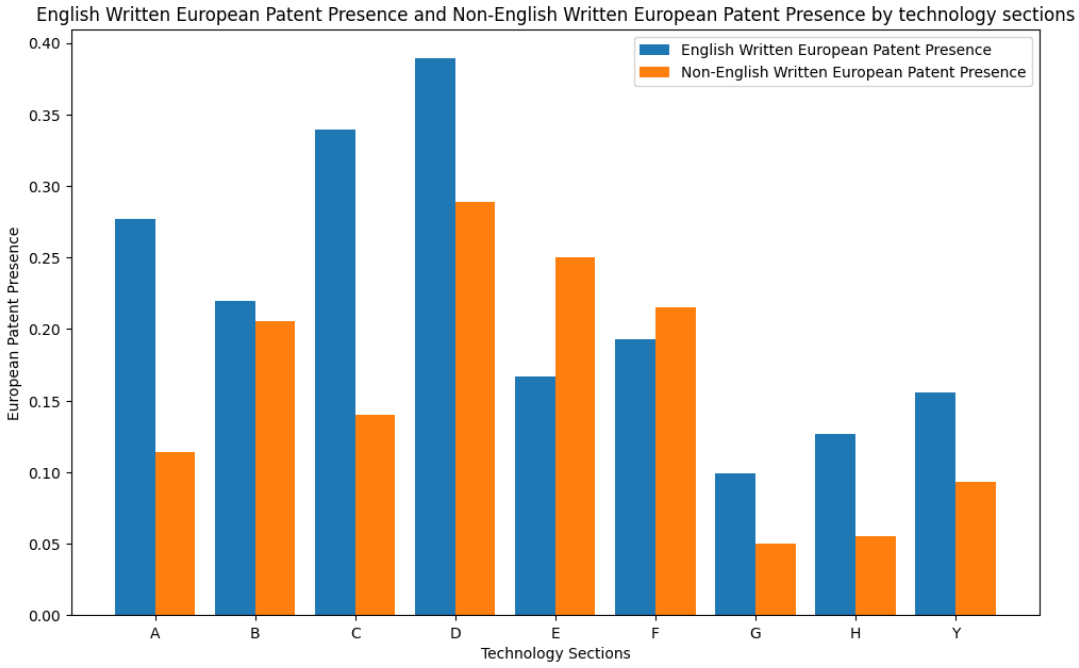


Figure 2: Pre-Trends in Innovation Output

This figure plots the coefficient estimates on the time dummy variables of the dynamic regression that estimate the effect of the adoption of CPC on innovation output. The dependent variable, $\sinh^{-1}(\textit{Forward Citation})$, is the inverse hyperbolic transformation of the total number of US patent-generated forward citations a firm receives for all patents filed in year *t*, where forward citations are measured through 2024. The variable *Exposure_Other* and *Exposure_En* are continuous variables which separately measure the firm's exposure to non-English written European patent disclosure and English written European patent disclosure. $\textit{Year}_t$ is an indicator variable that equals 1 for year *t*. The X-axis represents the year relative to the adoption of CPC year. The Y-axis represents the coefficient estimates on the time indicator variables surrounding the adoption of CPC. Vertical bars represent 90% confidence intervals.

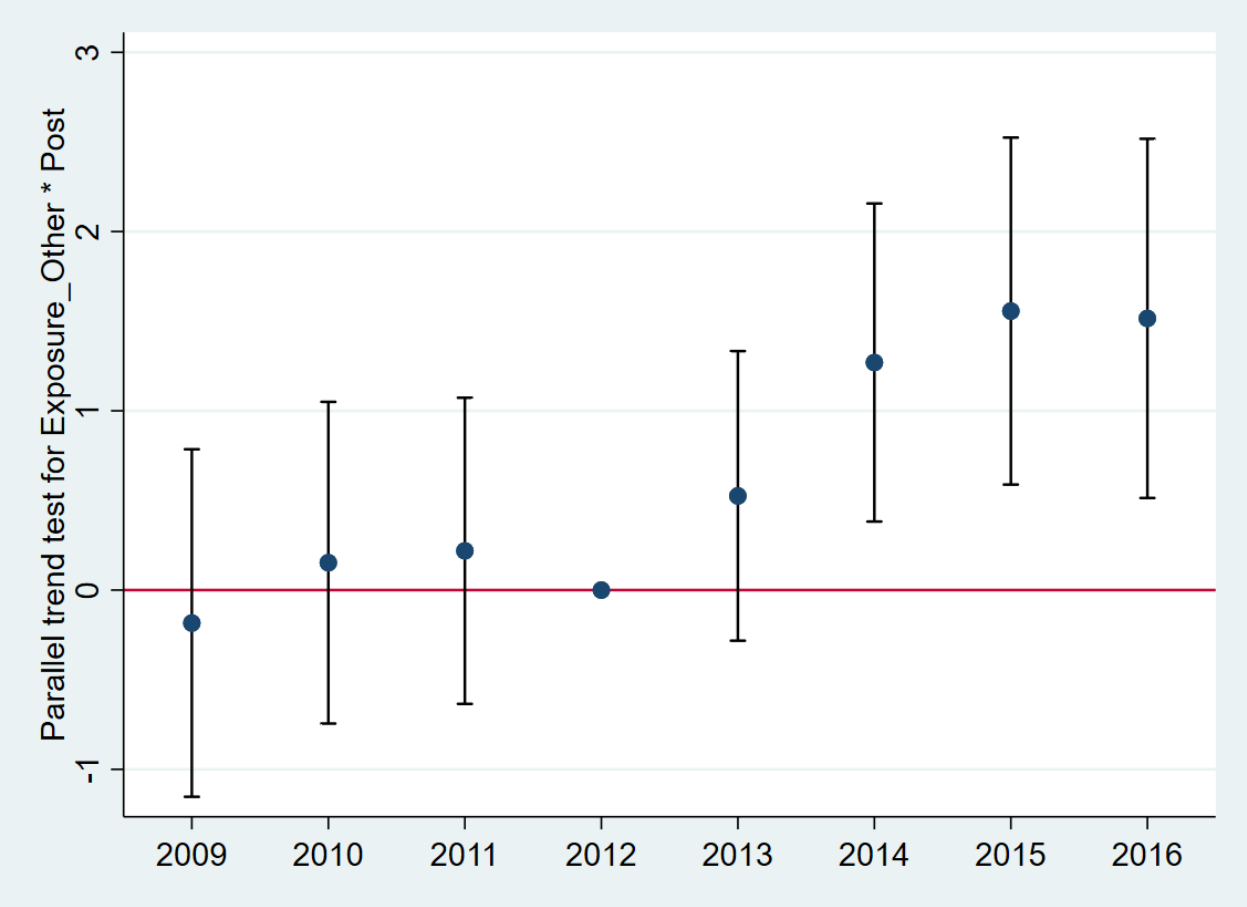


Figure 3: Placebo *Exposure_Other*×*Post* Coefficient

This figure displays the distribution of coefficients from 500 placebo regressions. For each experiment, I randomly shuffle *Exposure_Other* and re-estimate the regression equation. It is clear to see that the distribution of DiD estimates is centered around zero, contrasting starkly with the real estimated effects of β_1 represented by the solid red line

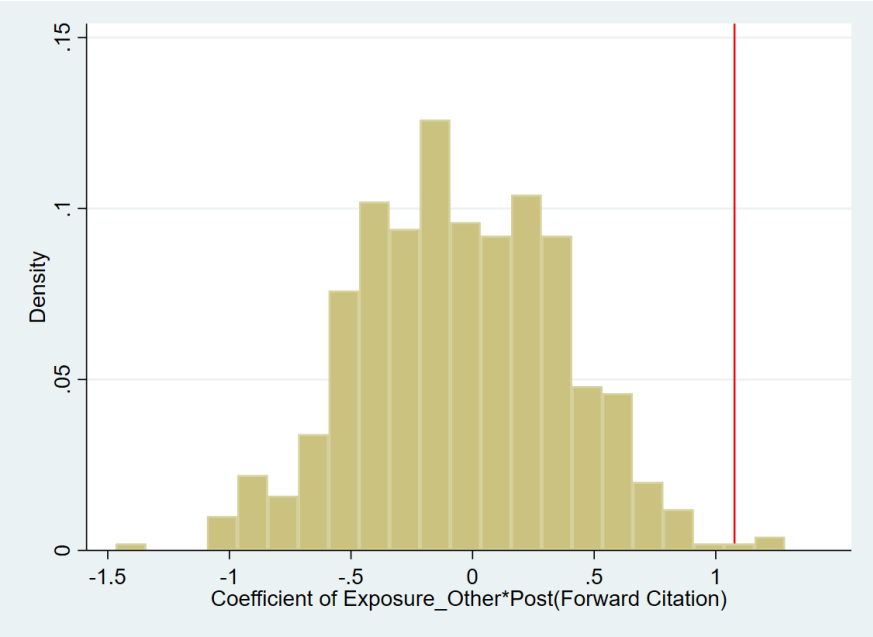


Figure 4: Placebo *Exposure_Other*×*Post* T-statistics

This figure displays the distribution of t-stats from 500 placebo regressions. For each experiment, I randomly shuffle *Exposure_Other* and re-estimate the regression equation. It is clear to see that the distribution of t-stats is centered around zero.

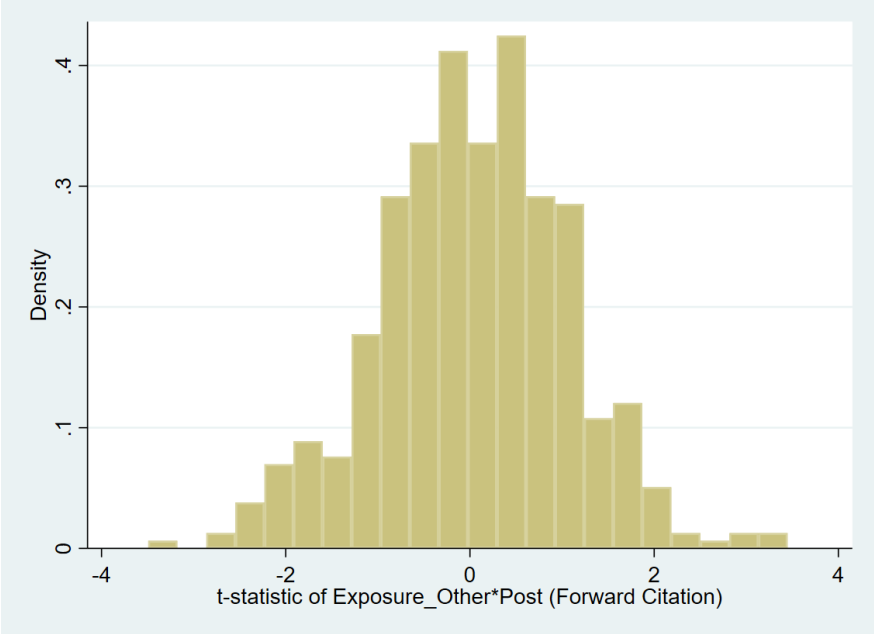


Figure 5: Pre-Trends in Innovation Efficiency

This figure plots the coefficient estimates on the time dummy variables of the dynamic regression that estimate the effect of the adoption of CPC on innovative efficiency. The dependent variable, $\sinh^{-1}(\textit{Innovative Efficiency})$, is the inverse hyperbolic transformation of the ratio of the total number of US patent-generated forward citations a firm receives for all patents filed in a year t scaled by the lagged R&D capital. R&D capital is defined as the cumulative R&D expenses over the last five years, with a depreciation rate of 20%. The variable *Exposure_Other* and *Exposure_En* are continuous variables which separately measure the firm's exposure to non-English written European patent disclosure and English written European patent disclosure. $Year_t$ is an indicator variable that equals 1 for year t. The X-axis represents the year relative to the adoption of CPC year. The Y-axis represents the coefficient estimates on the time indicator variables surrounding the adoption of CPC. Vertical bars represent 90% confidence intervals.

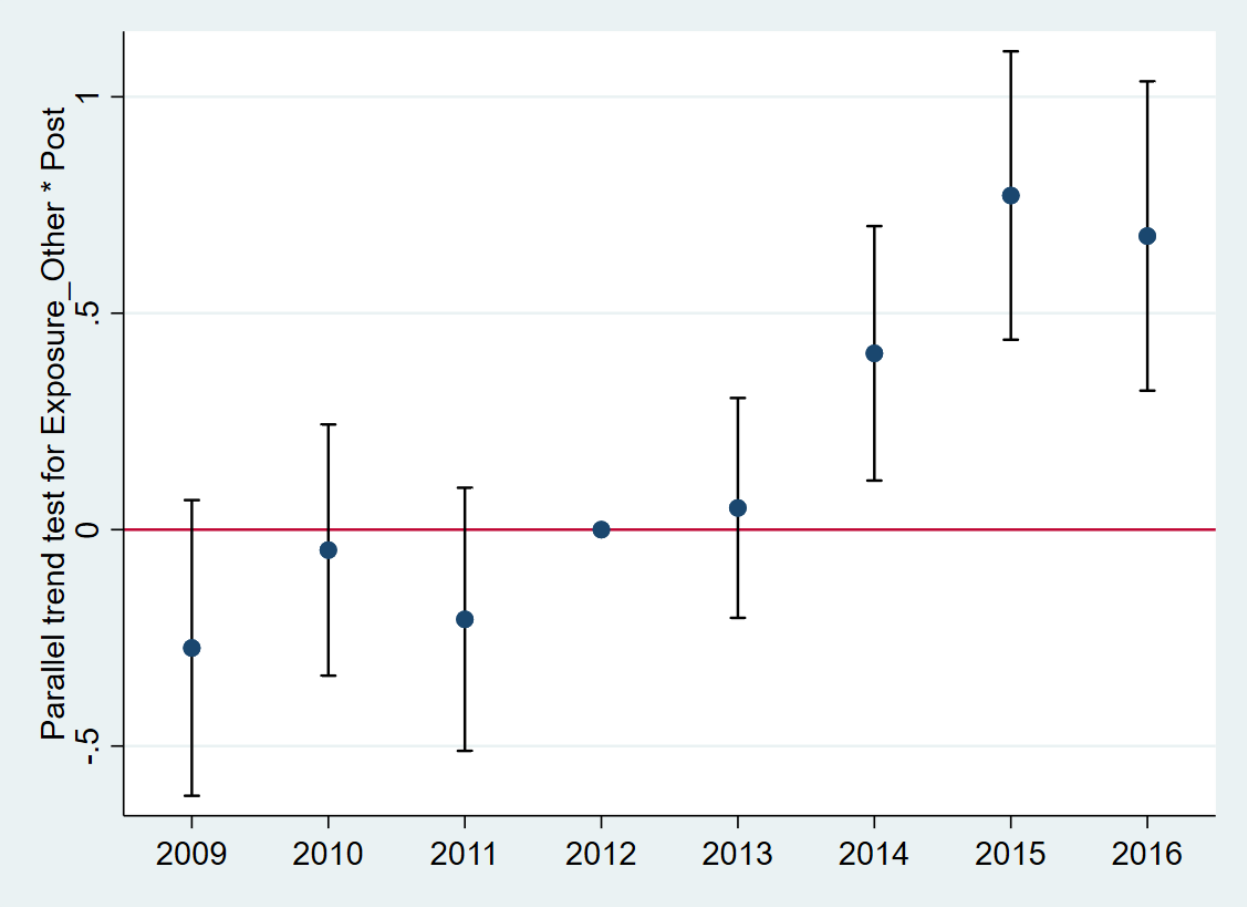


Figure 6: Pre-Trends in *EU Citation*

This figure plots the coefficient estimates on the time dummy variables of the dynamic regression that estimate the effect of the adoption of CPC on Knowledge Spillover. The dependent variable, $\sinh^{-1}(EU)$, is the inverse hyperbolic transformation of the total number of European patents cited by patent applicants or patent examiners for patent applications filed by a firm in year *t*. The variable *Exposure_Other* and *Exposure_En* are continuous variables which separately measure the firm's exposure to non-English written European patent disclosure and English written European patent disclosure. $Year_t$ is an indicator variable that equals 1 for year *t*. The X-axis represents the year relative to the adoption of CPC year. The Y-axis represents the coefficient estimates on the time indicator variables surrounding the adoption of CPC. Vertical bars represent 90% confidence intervals.

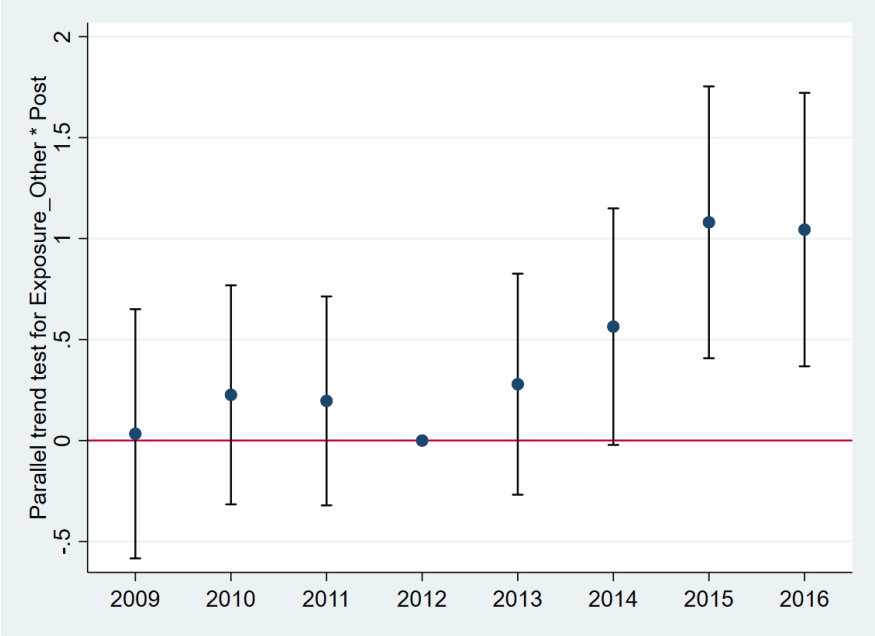


Figure 7: Pre-Trends in *EU Appl*

This figure uses $\sinh^{-1}(EU\ Appl)$, the inverse hyperbolic transformation of the total number of European patents cited by patent applicants for patent applications filed by a firm in year *t*, as the dependent variable.

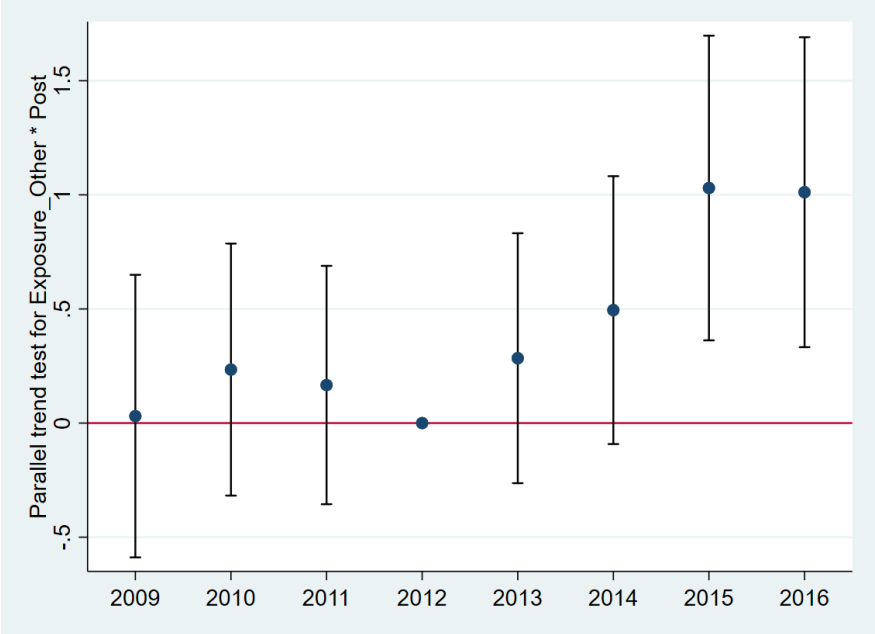


Table 1: Summary Statistics

This table presents descriptive statistics for the key variables used in my analysis, including mean, standard deviation, and percentile values. All continuous variables are winsorized at 1%.

	Mean	SD	Min	P25	P50	P75	Max	N
Forward Citation	191.17	716.78	0.00	0.00	1.00	42.00	5288.00	15907
#Claims	536.98	1978.45	0.00	0.00	18.00	156.00	14740.00	15907
#Patents	30.60	115.26	0.00	0.00	1.00	8.00	864.00	15907
R&D Intensity	0.10	0.18	0.00	0.00	0.03	0.12	1.00	15907
Capex	0.04	0.04	0.00	0.01	0.03	0.05	0.24	15907
#Forward Citation/Patent	4.15	8.85	0.00	0.00	0.50	4.35	58.50	15907
#Claims/Patent	10.18	10.08	0.00	0.00	11.32	18.65	37.09	15907
Innovative Efficiency	0.62	2.11	0.00	0.00	0.00	0.25	15.87	15907
EU	26.65	105.68	0.00	0.00	0.00	5.00	809.00	15907
EU Appl	26.09	103.45	0.00	0.00	0.00	5.00	791.00	15907
Exposure_Other	0.11	0.07	0.02	0.05	0.10	0.15	0.31	15907
Exposure_En	0.20	0.13	0.04	0.12	0.17	0.25	0.56	15907
Age	22.91	19.01	0.00	10.00	18.00	30.00	87.00	15907
Return on Asset	-0.07	0.29	-1.60	-0.06	0.03	0.07	0.29	15907
Leverage	0.19	0.20	0.00	0.00	0.15	0.30	0.95	15907
Firm Size	6.87	2.30	2.14	5.15	6.81	8.52	12.02	15907
Book to Market	0.54	0.47	-0.62	0.24	0.44	0.76	2.43	15907
Cash	0.27	0.26	0.00	0.07	0.18	0.40	0.97	15907
Number of Analyst	8.03	7.70	0.00	2.00	5.42	12.08	33.00	15907

Table 2: The adoption of CPC and Innovation Output

This table presents the results of a difference-in-difference analysis of the effect of CPC on innovation. The dependent variable, *Forward Citation*, is the total number of US patent-generated forward citations a firm receives for all patents filed in year *t*, where forward citations are measured through 2024. The variable *Exposure_Other* and *Exposure_En* are continuous variables which separately measure the firm's exposure to non-English written European patent disclosure and English written European patent disclosure. *Post* is an indicator variable that equals 0 for the year 2009 - 2012 and 1 for the year 2013 – 2016. Column (1) presents the baseline generalized Diff-in-Diff regression with firm and year-fixed effects with *Forward Citation* as the dependent variable. Column (2) adds a vector of control variables. The t-statistics reported below the coefficient estimates in parentheses are computed based on standard errors clustered by firm.

	(1) $\sinh^{-1}$(*Forward Citation*)	(2) $\sinh^{-1}$(*Forward Citation*)
Post × Exposure_Other	1.18***	1.14***
	(2.78)	(2.69)
Post × Exposure_En	-0.29	-0.37
	(-1.20)	(-1.54)
Return on Asset		-0.03
		(-0.42)
Leverage		-0.01
		(-0.06)
Firm Size		0.19***
		(5.94)
Book to Market		0.08
		(1.49)
Cash		0.31**
		(2.36)
Age		0.12*
		(1.71)
Number of Analyst		0.00
		(0.58)
Observations	15907	15907
Adjusted R^2	0.82	0.82
Firm FE	Yes	Yes
Year FE	Yes	Yes

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Dynamic Test of Innovation Output

This table presents the results of the dynamic effect of the adoption of CPC on innovation output. The dependent variable, *Forward Citation*, is the total number of US patent-generated forward citations a firm receives for all patents filed in year *t*, where forward citations are measured through 2024. The variable *Exposure_Other* and *Exposure_En* are continuous variables which separately measure the firm's exposure to non-English written European patent disclosure and English written European patent disclosure. $Year_t$ is an indicator variable that equals 1 for year *t*. $Year_{2012} \times$ *Exposure_Other* is omitted as the baseline result. Column (1) presents the baseline generalized Diff-in-Diff regression with firm and year-fixed effects with *Forward Citation* as the dependent variable. Column (2) adds a vector of control variables. The t-statistics reported below the coefficient estimates in parentheses are computed based on standard errors clustered by firm.

	(1) $\sinh^{-1}$(*Forward Citation*)	(2) $\sinh^{-1}$(*Forward Citation*)
Year_2009 × Exposure_Other	-0.34	-0.18
	(-0.58)	(-0.31)
Year_2010 × Exposure_Other	0.00	0.15
	(0.00)	(0.28)
Year_2011 × Exposure_Other	0.15	0.22
	(0.29)	(0.42)
Year_2013 × Exposure_Other	0.50	0.53
	(1.02)	(1.07)
Year_2014 × Exposure_Other	1.23**	1.27**
	(2.27)	(2.35)
Year_2015 × Exposure_Other	1.38**	1.56***
	(2.33)	(2.65)
Year_2016 × Exposure_Other	1.55**	1.52**
	(2.53)	(2.49)
Observations	15907	15907
Adjusted R^2	0.82	0.82
Controls	No	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: The adoption of CPC and Patent Claims

This table presents the results of a difference-in-difference analysis of the effect of CPC on innovation. The dependent variable, *#Claims*, is the total number of patent claims a firm has for all patents filed in year *t*. The variable *Exposure_Other* and *Exposure_En* are continuous variables which separately measure the firm's exposure to non-English written European patent disclosure and English written European patent disclosure. *Post* is an indicator variable that equals 0 for the year 2009 - 2012 and 1 for the year 2013 – 2016. Column (1) presents the baseline generalized Diff-in-Diff regression with firm and year-fixed effects with *Claims* as the dependent variable. Column (2) adds a vector of control variables. The t-statistics reported below the coefficient estimates in parentheses are computed based on standard errors clustered by firm.

	(1) $\sinh^{-1}$(*#Claims*)	(2) $\sinh^{-1}$(*#Claims*)
Post × Exposure_Other	1.08**	1.03**
	(2.10)	(2.04)
Post × Exposure_En	-0.27	-0.42
	(-0.91)	(-1.44)
Return on Asset		-0.07
		(-0.81)
Leverage		0.21
		(1.26)
Firm Size		0.28***
		(7.18)
Book to Market		0.16***
		(2.60)
Cash		0.29*
		(1.92)
Age		0.07
		(0.68)
Number of Analyst		0.02**
		(2.45)
Observations	15907	15907
Adjusted R^2	0.81	0.81
Firm FE	Yes	Yes
Year FE	Yes	Yes

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: The adoption of CPC and Innovation Input

This table presents the result of a difference-in-difference analysis of the effect of CPC on Innovation Input. The dependent variable, *R&D Intensity* is the ratio of R&D expense to lagged total assets, where missing values are set to zero. The dependent variable, *Capex* is the ratio of capital expenditure to lagged total assets, where missing values are set to zero. The variable *Exposure_Other* and *Exposure_En* are continuous variables which separately measure the firm's exposure to non-English written European patent disclosure and English written European patent disclosure. *Post* is an indicator variable that equals 0 for the year 2009 - 2012 and 1 for the year 2013 – 2016. Column (1) and Column (3) present the baseline regression with firm and year-fixed effects. Column (2) and Column (4) add a vector of control variables. The t-statistics reported below the coefficient estimates in parentheses are computed based on standard errors clustered by firm.

	(1)	(2)	(3)	(4)
	R&D Intensity	*R&D Intensity*	*Capex*	*Capex*
Post × Exposure_Other	0.15***	0.14***	0.04***	0.04***
	(4.70)	(4.51)	(4.44)	(4.28)
Post × Exposure_En	-0.14***	-0.13***	0.00	0.00
	(-4.14)	(-3.99)	(0.33)	(0.10)
Return on Asset		-0.05***		0.01***
		(-4.06)		(5.40)
Leverage		-0.02*		-0.01***
		(-1.65)		(-2.99)
Firm Size		0.01***		0.01***
		(2.81)		(8.39)
Book to Market		-0.01***		-0.01***
		(-3.65)		(-3.85)
Cash		0.06***		-0.02***
		(4.29)		(-5.31)
Age		-0.01***		0.00
		(-5.28)		(0.11)
Number of Analyst		-0.00***		-0.00
		(-6.93)		(-1.50)
Observations	15907	15907	15907	15907
Adjusted R^2	0.79	0.80	0.63	0.65
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: The adoption of CPC and Innovation Quality

This table presents the result of a difference-in-difference analysis of the effect of CPC on Innovation Quality. The dependent variable, *#Forward Citation/Patent*, is the average number of US patent-generated forward citations per patent that a firm receives for all patents filed in year *t*, where Forward citations are measured through 2024. The dependent variable, *#Claims /Patent*, is the average number of US patent-generated forward citations per patent that a firm receives for all patents filed in year *t*, where Forward citations are measured through 2024. The variable *Exposure_Other* and *Exposure_En* are continuous variables which separately measure the firm's exposure to non-English written European patent disclosure and English written European patent disclosure. *Post* is an indicator variable that equals 0 for the year 2009 - 2012 and 1 for the year 2013 – 2016. Column (1) presents the baseline regression with firm and year-fixed effects. Column (2) adds a vector of control variables. The t-statistics reported below the coefficient estimates in parentheses are computed based on standard errors clustered by firm.

	(1) $\sinh^{-1}$(*#Forward Citation/Patent*)	(2) $\sinh^{-1}$(*#Forward Citation/Patent*)	(3) $\sinh^{-1}$(*#Claims /Patent*)	(4) $\sinh^{-1}$(*#Claims /Patent*)
Post × Exposure_Other	0.92***	0.87***	0.80**	0.75**
	(3.28)	(3.10)	(2.17)	(2.03)
Post × Exposure_En	-0.08	-0.07	-0.11	-0.18
	(-0.47)	(-0.44)	(-0.50)	(-0.83)
Return on Asset		0.01		-0.02
		(0.16)		(-0.28)
Leverage		-0.12		0.08
		(-1.31)		(0.70)
Firm Size		0.08***		0.16***
		(3.50)		(5.67)
Book to Market		-0.02		0.06
		(-0.63)		(1.24)
Cash		0.25***		0.23**
		(2.71)		(2.01)
Age		0.07**		0.02
		(1.98)		(0.29)
Number of Analyst		-0.00		0.01*
		(-0.81)		(1.89)
Observations	15907	15907	15907	15907
Adjusted R^2	0.61	0.62	0.63	0.63
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: The adoption of CPC and Innovative Efficiency

This table presents the result of a difference-in-difference analysis of the effect of CPC on Innovative Efficiency. The dependent variable, *Innovative Efficiency*, is the ratio of the total number of US patent-generated forward citations a firm receives for all patents filed in a year *t* scaled by the R&D capital, where forward citations are measured through 2024. R&D capital is defined as the cumulative R&D expenses over the last five years, with a depreciation rate of 20%. The variable *Exposure_Other* and *Exposure_En* are continuous variables which separately measure the firm's exposure to non-English written European patent disclosure and English written European patent disclosure. *Post* is an indicator variable that equals 0 for the year 2009 - 2012 and 1 for the year 2013 – 2016. Column (1) presents the baseline regression with firm and year-fixed effects. Column (2) adds a vector of control variables. The t-statistics reported below the coefficient estimates in parentheses are computed based on standard errors clustered by firm.

	(1) $\sinh^{-1}$(*Innovative Efficiency*)	(2) $\sinh^{-1}$(*Innovative Efficiency*)
Post × Exposure Other	0.66***	0.59***
	(4.58)	(4.17)
Post × Exposure En	-0.03	0.01
	(-0.39)	(0.10)
Return on Asset		0.03
		(1.09)
Leverage		-0.10**
		(-2.03)
Firm Size		0.01
		(0.57)
Book to Market		-0.05***
		(-2.76)
Cash		0.23***
		(3.89)
Age		-0.04***
		(-2.65)
Number of Analyst		-0.01***
		(-3.15)
Observations	15907	15907
Adjusted R^2	0.63	0.63
Firm FE	Yes	Yes
Year FE	Yes	Yes

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: The adoption of CPC and Patent Disclosure Dissemination

This table presents the result of a difference-in-difference analysis of the effect of CPC on Patent Disclosure Dissemination. The dependent variable, *EU*, is the total number of European patents cited by patent applicants or patent examiners for patent applications filed by a firm in year *t*. The dependent variable, *#EU Appl*, is the total number of European patents cited by patent applicants for patent applications filed by a firm in year *t*. The variable *Exposure_Other* and *Exposure_En* are continuous variables which separately measure the firm's exposure to non-English written European patent disclosure and English written European patent disclosure. *Post* is an indicator variable that equals 0 for the year 2009 - 2012 and 1 for the year 2013 – 2016. Column (1) presents the baseline regression with firm and year-fixed effects. Column (2) adds a vector of control variables. The t-statistics reported below the coefficient estimates in parentheses are computed based on standard errors clustered by firm.

	(1) $\sinh^{-1}$(*#EU*)	(2) $\sinh^{-1}$(*#EU*)	(3) $\sinh^{-1}$(*#EU Appl*)	(4) $\sinh^{-1}$(*#EU Appl*)
Post × Exposure_Other	0.59**	0.60**	0.56*	0.57*
	(1.98)	(2.03)	(1.87)	(1.93)
Post × Exposure_En	-0.23	-0.29	-0.23	-0.29
	(-1.21)	(-1.55)	(-1.21)	(-1.55)
Return on Asset		-0.08		-0.08
		(-1.53)		(-1.59)
Leverage		0.13		0.13
		(1.33)		(1.32)
Firm Size		0.10***		0.10***
		(4.92)		(4.93)
Book to Market		0.05*		0.05*
		(1.81)		(1.76)
Cash		0.14		0.14
		(1.62)		(1.56)
Age		0.08		0.08
		(1.48)		(1.38)
Number of Analyst		0.01		0.01
		(1.55)		(1.52)
Observations	15907	15907	15907	15907
Adjusted R^2	0.84	0.84	0.84	0.84
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9: No France and German presence and Innovation Activty

This table presents results on whether the effect of CPC on innovation output is concentrated on firms with no significant subsidiaries in France and Germany. The dependent variable, *Forward Citation*, is the total number of US patent-generated forward citations a firm receives for all patents filed in year *t*, where forward citations are measured through 2024. The variable *Exposure_Other* and *Exposure_En* are continuous variables which separately measure the firm's exposure to non-English written European patent disclosure and English written European patent disclosure. *Post* is an indicator variable that equals 0 for the year 2009 - 2012 and 1 for the year 2013 – 2016. *No France and German Presence* is an indicator variable which equal to 1 if a firm has no significant subsidiary in France and Germany in 2012. Column (1) presents the baseline regression with firm and year-fixed effects. Column (2) adds a vector of control variables. The t-statistics reported below the coefficient estimates in parentheses are computed based on standard errors clustered by firm.

	(1)	(2)
	$\sinh^{-1}$(*Forward Citation)*	$\sinh^{-1}$(*Forward Citation)*
Post × Exposure_Other × No France and German Presence	2.30**	2.28**
	(2.27)	(2.36)
Post × Exposure_En × No France and German Presence	-0.80	-0.81
	(-1.21)	(-1.22)
Post × Exposure Other	-0.18	-0.23
	(-0.22)	(-0.28)
Post × Exposure En	0.23	0.13
	(0.43)	(0.24)
Observations	10747	10747
Adjusted R^2	0.84	0.84
Controls	No	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Small Firm and Innovation Activty

This table presents results on whether the effect of CPC on innovation output is concentrated on small firms. The dependent variable, *Forward Citation*, is the total number of US patent-generated forward citations a firm receives for all patents filed in year *t*, where forward citations are measured through 2024. The variable *Exposure_Other* and *Exposure_En* are continuous variables which separately measure the firm's exposure to non-English written European patent disclosure and English written European patent disclosure. *Post* is an indicator variable that equals 0 for the year 2009 - 2012 and 1 for the year 2013 – 2016. *Small Firm* is an indicator variable which equal to 1 if a firm is below median in asset size in 2012. Column (1) presents the baseline regression with firm and year-fixed effects. Column (2) adds a vector of control variables. The t-statistics reported below the coefficient estimates in parentheses are computed based on standard errors clustered by firm.

	(1)	(2)
	$\sinh^{-1}$(*Forward Citation*)	$\sinh^{-1}$(*Forward Citation*)
Post × Exposure_Other × Small Firm	2.20***	1.96**
	(2.59)	(2.32)
Post × Exposure_En × Small Firm	-0.46	-0.47
	(-0.90)	(-0.95)
Post × Exposure_Other	0.39	0.46
	(0.65)	(0.77)
Post × Exposure_En	-0.14	-0.23
	(-0.34)	(-0.57)
Observations	14590	14590
Adjusted R^2	0.82	0.83
Controls	No	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Import Competition and Innovation Activty

This table presents results on whether the effect of CPC on innovation output is mitigated by import competition from Europe. The dependent variable, *Forward Citation*, is the total number of US patent-generated forward citations a firm receives for all patents filed in year *t*, where forward citations are measured through 2024. The variable *Exposure_Other* and *Exposure_En* are continuous variables which separately measure the firm's exposure to non-English written European patent disclosure and English written European patent disclosure. *Post* is an indicator variable that equals 0 for the year 2009 - 2012 and 1 for the year 2013 – 2016. *Low Competition* is an indicator variable equal to 1 if a firm faced below-median import competition from European firms in 2012, as measured by importance penetration. Column (1) presents the baseline regression with firm and year-fixed effects. Column (2) adds a vector of control variables. The t-statistics reported below the coefficient estimates in parentheses are computed based on standard errors clustered by firm.

	(1)	(2)
	$\sinh^{-1}$(*Forward Citation*)	$\sinh^{-1}$(*Forward Citation*)
Post × Exposure_Other × Low Competition	3.11**	3.02**
	(2.35)	(2.29)
Post × Exposure_En × Low Competition	-1.02	-0.78
	(-1.21)	(-0.93)
Post × Exposure_Other	1.31	1.15
	(1.61)	(1.40)
Post × Exposure_En	0.34	0.23
	(1.10)	(0.77)
Observations	9141	9141
Adjusted R^2	0.82	0.82
Controls	No	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Robustness Tests

This table presents results on whether the observed effect of CPC on innovation output is robust to alternative innovation proxies, FE structure, Exposure_Other and Exposure_En proxies, and Poisson regression. The specific definitions for the variables are in the appendix. The t-statistics reported below the coefficient estimates in parentheses are computed based on standard errors clustered by firm.

Panel A. Alternative Innovation Proxies and FE Structures

	Forward Citation	Ln(1+*Forward Citation*)	$\sinh^{-1}$(*#Patent*)	1{# Patent > 0}	$\sinh^{-1}$(*Forward Citation*)
Post × Exposure_Other	506.32***	1.07***	0.45*	0.20**	1.32**
	(4.46)	(2.89)	(1.70)	(1.96)	(2.34)
Observations	15907	15907	15907	15907	15902
Adjusted R^2	0.86	0.83	0.89	0.63	0.82
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry x Year FE	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	No	No

Panel B. Alternative Exposure_Other and Exposure_En Proxies

	$\sinh^{-1}$(*Forward Citation*)	$\sinh^{-1}$(*Forward Citation*)
Alternative_Proxy_Other	Exposure_Other_Restrict	Exposure_Other_Class
Alternative_Proxy_En	Exposure_En_Restrict	Exposure_En_Class
Post × Alternative_Proxy_Other	2.50***	1.70***
	(3.09)	(3.24)
Observations	15907	15907
Adjusted R^2	0.83	0.83
Firm FE	Yes	Yes
Year FE	Yes	Yes

Panel C. Possion Regression

	#Forward Citation	*#Patent*	*#Claims*
Post × Exposure_Other	0.10	0.97**	1.04**
	(0.13)	(2.32)	(2.31)
Observations	11902	12437	12437
Pseudo R^2	0.94	0.95	0.96
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

A Appendix

Variable	Definition
Forward Citation	The total number of US patent-generated forward citations a firm receives for all patents filed in year *t*. Forward citations are measured through 2024.
Number of Patents	The inverse hyperbolic sine of the number of granted patents that the firm filed in year *t*
$1\{\#\text{ Patent} > 0\}$	An indicator variable that equals 1 if the firm applies for at least 1 granted patent in year *t*
Number of Claims	The total number of patent claims a firm has for all patents filed in year *t*.
R&D Intensity	The ratio of R&D expense to lagged total assets. Missing values are set to zero.
Capex	The ratio of capital expenditure to lagged total assets. Missing values are set to zero.
#Forward Citation/Patent	The average number of US patent-generated forward citations per patent that a firm receives for all patents filed in year *t*. Forward citations are measured through 2024.
#Claims/Patent	The average number of patent claims that a firm has for all patents filed in year *t*.
Innovative Efficiency	The ratio of the total number of US patent-generated forward citations a firm receives for all patents filed in a year *t* scaled by the lagged R&D capital. R&D capital is defined as the cumulative R&D expenses over the last five years, with a depreciation rate of 20%.
EU	Total number of European patents cited by patent applicants or patent examiners for patent applications filed by a firm in year *t*

Variable	Definition
EU Appl	The total number of European patents cited by patent applicants for patent applications filed by a firm in year *t*
Exposure_En	A firm's exposure to English European patent disclosure, where detailed calculation procedure is in section 4.2.4
Exposure_Other	A firm's exposure to non-English European patent disclosure, where detailed calculation procedure is in section 4.2.4
Age	The number of years since IPO from CRSP.
Return on Asset	Operating income before extraordinary items divided by total assets (IB/AT).
Leverage	Total liabilities divided by total assets (DLTT+DLC)/AT.
Firm Size	The natural log of one plus market capitalization.
Book to Market	Book value of equity divided by market capitalization (CEQ+TXDB)/(PRCC_F$\times$CSHO).
Cash	Cash holdings divided by total assets (CHE/AT).
Number of Analysts	The average number of analysts that follow this firm in year *t*

B Appendix

Criteria	Firm-year observations
Public firm observations from 2009 to 2016	43,905
Require firms to have non-missing *Exposure_Other* and *Exposure_En*	16,286
Require firms to have non-missing primary dependent variables, control variables, and drop singleton observations	15,907

Notes: This table presents the sample selection criteria for our main analyses. Since we do not explicitly require firms to have non-missing observations for alternative dependent variables or cross-sectional variables, the number of observations used in certain analyses may be lower than the above, depending on data availability.

C Appendix - Cooperative Patent Classification (CPC)

A comprehensive discussion of the Cooperative Patent Classification (CPC) and its predecessor, the International Patent Classification (IPC), is provided here to establish the institutional and historical context relevant to my research setting.

C.1 International Patent Classification (IPC)

The International Patent Classification (IPC) system was established in 1971 under the Strasbourg Agreement and is administered by the World Intellectual Property Organization (WIPO). Designed as a hierarchical framework, it classifies patents based on their technical subject matter, facilitating patent searches and ensuring uniformity across jurisdictions. The IPC organizes patents into sections, classes, subclasses, and groups, providing a systematic approach to identifying innovations across various fields.

Despite its widespread adoption, the IPC faces several challenges that limit its effectiveness in today's rapidly evolving technological landscape. One of its primary weaknesses is its inability to keep pace with technological advancements. Initially, updates occurred approximately every five years, but in response to growing demands for timely revisions, the IPC now undergoes annual updates, with new editions taking effect each year. However, even an annual revision cycle remains insufficient in a world where groundbreaking innovations—such as artificial intelligence models like ChatGPT and DeepSeek—reshape industries within weeks or even days. This lag makes it difficult for the IPC to remain an accurate and effective tool for categorizing patents in emerging fields.

Another major limitation is the IPC's lack of granularity in certain technological domains. While it covers a broad range of technologies, some rapidly evolving fields lack sufficiently detailed classifications. This lack of specificity can hinder precise patent searches and obscure the tracking of technological progress. Without finer distinctions, patents in cutting-edge sectors may be grouped into overly broad categories, reducing the system's utility for patent analysts, researchers, and

policymakers.

Additionally, major patent offices—such as those in the United States and Europe—have developed their own more detailed classification systems. The United States Patent and Trademark Office (USPTO) previously used the United States Patent Classification (USPC) system, while the European Patent Office (EPO) employed the European Classification System (ECLA). These offices rely on their own classification systems for internal examination and application assignments, relegating the IPC to a supplementary role in patent classification.

Since it is not the primary classification tool, inconsistencies in its interpretation and application across different jurisdictions have become prevalent. Variations in classification practices across patent offices complicate international patent searches and examinations. This lack of uniformity makes it more challenging for inventors, businesses, and researchers to navigate the global patent landscape effectively.

In short, while the IPC provides a standardized framework for patent classification, its slow adaptation to technological change, lack of granularity in emerging fields, and inconsistencies in international application limit its effectiveness in the modern innovation-driven economy.

C.2 Cooperative Patent Classification (CPC)

The Cooperative Patent Classification (CPC) system was developed, maintained, and used jointly by the United States Patent and Trademark Office (USPTO) and the European Patent Office (EPO) to overcome the limitations of the IPC. By enhancing granularity, ensuring continuous updates, and improving classification consistency, the CPC provides a more effective framework for modern patent examination.

Unlike the IPC, which undergoes annual updates, the CPC is updated continuously. This dynamic approach ensures that emerging technologies are promptly incorporated into the classification system. As a result, industries experiencing rapid innovation benefit from more precise and up-to-date patent classifications.

Furthermore, the CPC expands upon the IPC by introducing a more detailed hierarchical

structure. It contains approximately 250,000 classification entries, compared to the IPC's 70,000, significantly increasing classification specificity. This enhanced granularity allows for more precise categorization of patents, improving prior art searches, innovation tracking, and policy assessments.

Another key advantage of the CPC is its ability to address variability in interpretation across different patent offices. While the IPC has been criticized for inconsistent classifications across jurisdictions, the CPC mitigates this issue by serving as a shared classification system jointly maintained and used by the USPTO and EPO. This collaboration ensures that resources are shared for classifying documents, revising classification schemes when necessary, and reclassifying documents accordingly. The CPC reduces discrepancies in patent categorization and simplifies international patent searches and examinations.

In short, the CPC effectively addresses the IPC's shortcomings by providing continuous updates, greater classification detail, and international consistency. By rendering European patent disclosure easily accessible to US firms, the adoption of CPC can be viewed as a shock to patent disclosure dissemination. It's implementation provides a near ideal setting in which to empirically examine the real effects of patent dissemination on corporate innovation.

D Appendix - Examples of How CPC Facilitates Patent Dissemination

The following is an example of a European patent disclosure written in German. With the adoption of the Cooperative Patent Classification (CPC), U.S. companies engaged in innovations related to CPC codes—B62D 29/043, B62D 31/00, H03K 17/97, H02G 3/12, and H03K 2217/96015—can efficiently identify relevant European patents. By leveraging standardized CPC classifications, U.S. firms can streamline their search and analysis of European patents aligned with their technological interests.

Prior to CPC implementation, U.S. companies primarily relied on the United States Patent Classification (USPC) system, which differed notably from international standards like the International Patent Classification (IPC). This disparity made international patent searches less efficient. Additionally, IPC codes were often less granular and could be outdated, as seen in the attached patent documents where the assigned IPC code is from the 2006 version.

The adoption of CPC has addressed these challenges by standardizing patent classification between the European Patent Office (EPO) and the United States Patent and Trademark Office (USPTO), enabling more precise and comprehensive searches. By aligning U.S. and European classification systems, CPC facilitates seamless access to non-English European patent information, reducing the complexities associated with differing classification standards. As a result, U.S. companies can more easily access non-English European patents.

Figure 8: German-language European Patent Office (EPO) document

(19) Europäisches Patentamt
European Patent Office
Office européen des brevets

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(54) **REISEMOBILKAROSSERIEVORRICHTUNG**

(57) Die Erfindung geht aus von einer Reisemobilkarosserievorrichtung, mit zumindest zwei Seitenwandmodulen (12, 14), einem Dachmodul (16) und einem Heckmodul (18), die zusammen zumindest einen Teil eines Karosserieaufbaus eines Reisemobils ausbilden, wobei das Heckmodul (18) eine rückwärtige Wandung des Karosserieaufbaus ausbildet.

Es wird vorgeschlagen, dass das Heckmodul (18) zumindest ein flächiges Sandwichelement (20), das einen Großteil des Heckmoduls (18) ausbildet, und zumindest zwei Seitenelemente (32, 34) aufweist, die jeweils an einem der Seitenwandmodule (12, 14) angebunden sind und jeweils einen Seitenbereich des Heckmoduls (18) ausbilden..

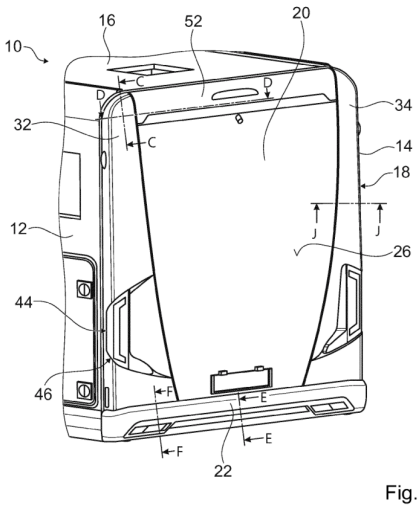


Fig. 1

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Figure 9: USPC vs. CPC

