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COMPUTER IMPLEMENTED INVENTIONS – PATENT TRENDS AT IP AUSTRALIA, EPO AND USPTO

IP Australia Economic Research Paper 16

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1 Introduction

IP Australia (IPA) commissioned the Centre for Transformative Innovation at Swinburne University of Technology to conduct a comparative analysis between computer implemented invention (CII) patenting activities, both the filing of patent applications and their outcomes, in Australia and other jurisdictions (namely, Europe and the United States). This report describes the research methodology and presents the findings of the study.

Patents provide exclusive rights for a limited period for innovators to exploit their inventions in the market to provide incentives for innovation. However, from a society-wide perspective, these exclusive rights can create static deadweight losses (such as inefficient monopoly pricing) which need to be offset against the dynamic benefits of better and cheaper products. Ideally, only inventions with positive net benefits to society should be eligible for patent protection.

In practice, it is often difficult to determine which inventions should be patented. In Australia, for an invention to be patentable it must be for a "manner of manufacture," that is, for an artificially created state of affairs with economic utility. It must belong to the 'useful arts' rather than the 'fine arts' and offer a material advantage in a field of economic endeavour. Ultimately, this test defines how the subject matter in patents is construed in determining its patent eligibility and how the patentability thresholds of novelty, inventive step and disclosure are evaluated. Other jurisdictions have their own definition of what constitutes patentable subject matter.

In recent years, the courts have expanded upon this test to account for technologies not envisioned when the manner of manufacture test was first devised. The recent rapid technological advances in CIIs (sometimes referred to as "software related inventions") have presented serious challenges both to patent offices and applicants across the world. Sherman (2019) has argued that a key reason for this difficulty comes from confusion around the question of "what is software?"

Further difficulty arises from the fact that patent jurisdictions may apply different approaches to what constitutes patent-eligible subject matter and the patentability of CIIs.

With CII's increasing penetration into other technologies and sectors (Branstetter, Drev, and Kwon, 2015), policy makers stand to benefit from a nuanced understanding of how differences in patent standards and outcomes for CIIs affect patent applicant and inventor behaviour. This needs to be understood in the context of significant changes to the relevant legal landscapes.

The research project described in this report has 4 objectives:

1. Develop a database containing a comprehensive sample of all CII patents (applications and granted patents) filed in Australia and their corresponding patent family members (patents for the same or similar inventions) filed overseas at the United States Patent and Trademark Office (USPTO) and the European Patent Office (EPO). Consistently identify applicants who file for CII patents across the 3 jurisdictions.
2. Using machine learning (ML), classify CII patents into 2 subsets, based on whether the ML predicts IPA patent examiners *would or would not* likely raise an objection to the CII patent on the grounds that it is not patentable subject matter in an adverse examination report (a "PSM adverse") based on the manner of manufacture test.
3. Estimate the difference in outcomes of CII patent applications filed across the 3 jurisdictions – at IPA, the EPO and the USPTO – with a particular focus on CII applications at the margins of patent eligibility in Australia, and analyse the role of time, patent characteristics and applicant characteristics in determining outcomes.

4. Estimate the propensity of patent applicants to file applications/claims for CIIs in Australia after filing for CII patents at the EPO and USPTO.
5. Assess how variation in legal standards has affected applicant behaviour and outcomes, by comparing CII and non-CII patenting trends, in Australia and overseas, and the impact of potentially significant and relevant court cases.

   These include:

   a. *Alice Corp v CLS Bank International* [2014], a US decision which affirmed that abstract ideas are not patentable and any generic computer implementation of an abstract idea is not sufficiently inventive to be patentable.
   b. *Research Affiliates LLC v Commissioner of Patents* [2014], an Australian decision which confirmed that claims to a computer implemented method are not patentable subject matter in Australia.

By addressing these objectives through statistical and econometric analysis, this study provides novel evidence on the experience of applicants seeking to patent CII across jurisdictions, how variation in legal standards shapes patent outcomes, and the behavioural responses of CII innovators. Evidence on these issues provides an important foundation for assessing the net benefits or costs of awarding protection to computer implemented inventions in Australia, complementing the evolving economic evidence base on the drivers and impacts of CII patents (e.g., Acikalin et al., 2022; Lerner et al., 2021).

2 Research methods

Construction of CII patent application database

As its first objective, the research project constructs a CII patent application database. This contains a comprehensive record of patent applications filed at IPA, EPO, and USPTO which are identified as CII patent applications. The CII patent applications are identified based on a combination of approaches provided by existing related works including, for example, Frietsch et al. (2015), Xie and Miyazaki (2013), Bessen and Hunt (2007), Chan et al. (2023), Baruffaldi et al. (2020), and Giczy et al. (2022).

Furthermore, the project develops a Machine Learning (ML) model to classify the set of CII patent applications into 2 subsets:

1. CII patent applications to which (ML predicts) IPA examiners would likely raise an objection in an adverse examination report on the grounds that the patent is not patentable subject matter (PSM). Subsequently, we refer to these applications as “CII-PSM-likely-adverse”.
2. CII patent applications to which (ML predicts) IPA examiners would not likely raise a PSM objection, resulting in a clear examination report with respect to PSM (the application may still be likely to receive an adverse report with respect to other matters such as novelty and fair basis). Subsequently, we refer to this second subset of CII patent applications as “CII-PSM-likely-clear”.

In essence, there are 4 steps to construct the CII patent application database:

1. Identifying CII patents. We identify the set of patent applications based on the approach of Frietsch et al. (2015) of filtering based on a combination of keywords and International Patent Classification (IPC) codes which classify patents into different technology areas.
2. Construction of the labelled data for developing the ML models. This is provided by IPA and consists of Australian CII patents for which actual PSM objections were raised in the examination process (“CII-PSM-adverse”), as well as Australian CII patent applications for which IPA did not raise PSM objections (“CII-PSM-clear”).
3. Development and fine tuning of ML models based on the labelled data in (2) to automatically classify CII patent applications into the 2 subsets: “CII-PSM-likely-clear” and “CII-PSM-likely-adverse”. The ML model contains predictive features, including metrics based on Natural Language Processing (NLP) of the patent application text including title, abstract and claims, as well as the International Patent Classification (IPC) codes.
4. Implementation of the approach in step 1 (identifying CII patents) and step 3 (deploying the ML model) to the patent application databases of IPA, the EPO, and the USPTO. For each of these databases, where the required texts are available, we classify patent applications into 3 groups: Non-CII, CII-PSM-likely-clear, and CII-PSM-likely-adverse.

It should be noted that applications filed and examined across the 3 jurisdictions (Australia, the US and the EU) are identified as “CII-PSM-likely-adverse” based on their similarity to applications examined in Australia that received an actual PSM objection. As noted in the Introduction, the PSM test in Australia is whether an invention is for a “manner of manufacture”; however, different jurisdictions apply different legal standards and tests. A key objective of this study’s method is to identify, where applications are filed and examined in the US and EU, whether they would have likely received a PSM objection were they filed and examined in Australia, enabling a comparison of Australia’s treatment relative to other jurisdictions. The method does not presuppose or imply standardisation across jurisdictions in the legal standards and tests used to determine patent subject matter eligibility.

Identifying CII patent applications

All patent applications filed at IPA, EPO, and USPTO from 2001-2020 are classified into CII and Non-CII based on a combination of:

a. the patent's IPC codes
b. keywords search on their corresponding texts including the title, abstract, claims, and/or description.

Using a combination of keyword and IPC technology class codes, rather than relying on a single method is preferable because CII patent applications are likely to originate from various industries and encompass multiple IPC technology classifications (Chabchouba and Niosi 2005; Bergstra and Klint 2007; Bessen and Hunt 2007; Bessen 2012; Noel and Schankerman 2013; Eberhardt et al. 2016).

Andersson et al. (2021) found that there has been a software bias shift in innovation in many different industries. Hence, focusing only on specific industries may result in under coverage of the true set of CII patent applications which is increasing over time.

The classic study by Hall and MacGarvie (2010) also found that using a combination of approaches to identify the set of software patents in the study led to the fewest false negatives.

Xie and Miyazaki (2013) developed a set of keywords (provided in Table 1 below) for identifying computer implemented inventions. We implement the same set of keywords in analysing the text data of patent applications from IPA, the EPO and USPTO. Data was sourced from the following databases:

- IPA's IPRAPID open data and its Australian Patent Search API
- The EPO's EP Register
- The USPTO's Patentviews open data
- Corresponding records from Google Patent Database, Google Public Patent Database, and Google Research Patent Database.

Table 1 | Keywords to identify CII patent applications.

Keywords	Precision (%)	Recall (%)
[Micro]processor	100.0	18.6
Chip	100.0	0.7
Comput* program	100.0	8.8
Controller	100.0	26.0
Data	100.0	31.9
Digital	100.0	7.8
Integrated circuit	100.0	2.0
Image processing	100.0	1.7
Processing unit	100.0	0.5
Program*	100.0	3.7
Software	100.0	13.7
Comput*	99.1	5.4
Signal processing	98.4	28.2
Identify*	97.6	15.0
Control unit	95.4	10.0
Memory	94.2	15.9
Calculat*	94.1	19.6
Electronic*	93.7	18.1
Monitoring*	93.3	10.3
Imaging*	92.3	2.9

Source: Frietsch et al. (2015)

Frietsch et al. (2015) and Neuhäusler and Frietsch (2019) found the above set of keywords to have a greater than 90% precision score (a high proportion of identified CII patents were manually verified as true CII patents). The last column in Table 1 presents the keywords' corresponding recall scores (the proportion of true CII patents classified as CII patents). The low recall scores reflect the trade-off from selecting keywords with high precision. This means relying only on keywords to identify CII patent applications could lead to underestimation of the true extent of CII patenting activities.

For this reason, we also follow Frietsch et al. (2015)'s study to combine the keyword filtering with IPC code filtering. Specifically, we use their IPC codes to exclude specific patents from the CII patent database because they represent inventions which are unlikely to be related to CII or because they represent "software as such", or pure software, rather than computer implemented inventions. Table 2 lists the technology and IPC codes to filter out potentially non-CII patents even if they satisfied the keyword filter.

Table 2 | Excluded IPC codes.

Keywords	IPC codes
Pharmaceuticals **Software "as such"**	A61K not A61K 8* (cosmetics) H04L 29/06, G06F 11/30, G06F 17/24, G06F 17/30, G06Q 10, G06F 9/00, G06F 9/06, G06F 9/2, G06 9/3, G06F 9/4, G06F 9/5

Source: Frietsch et al. (2015)

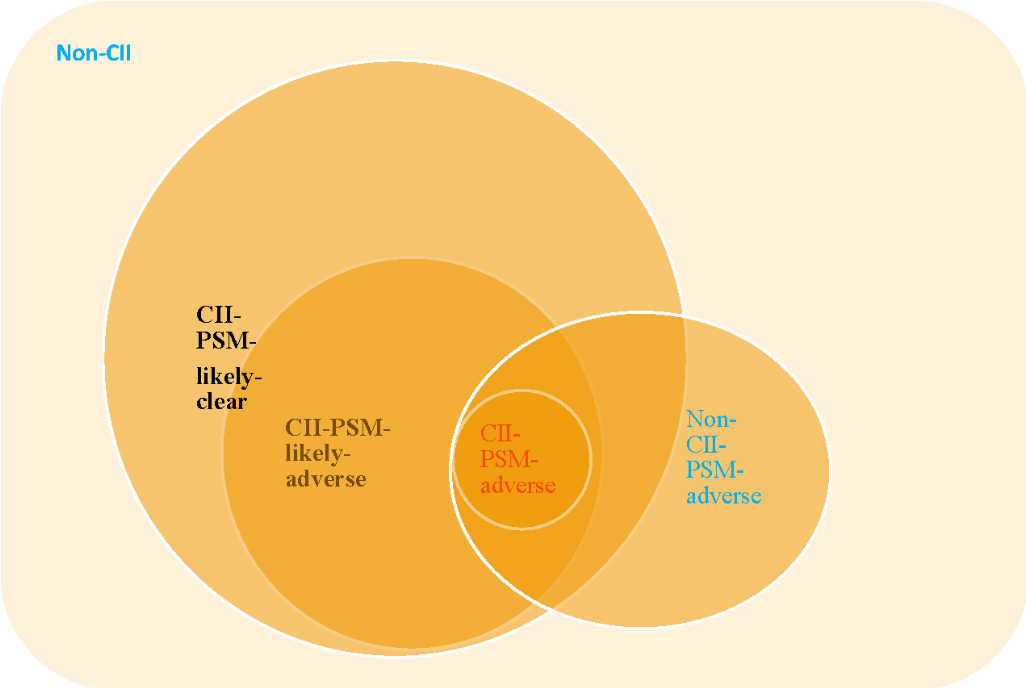
Construction of the labelled dataset

A key objective of the research is to investigate the potential influence on applicant behaviour and outcomes of variation in legal standards across jurisdictions, and before and after potentially significant and relevant court cases. These include Research Affiliates LLC v Commissioner of Patents (2014) in Australia and Alice Corp v CLS Bank International [2014] in the US.

To enable this, we need to further distinguish CII patent applications which are at the margins of patent eligibility and likely to have a PSM objection raised. Referring to the Venn diagram in Figure 1, our first objective was to classify patent applications in the full corpus into "Non-CII" and "CII". We then further classify the "CII" subset into "CII-PSM-likely-clear" and "CII-PSM-likely-adverse" by deploying the ML models. For this purpose, IPA provided us with a set of patent applications filed at IPA for which IPA patent examiners actually raised PSM objections based on the manner of manufacture test (these labelled as "CII-PSM-adverse"). In addition, IPA also provided as with the full list of patent applications (CII and non-CII) for which PSM objections were raised by IPA patent examiners based on the manner of manufacture test (these labelled as "PSM-adverse"). These provide the seed set for the ML model.

Based on these two labelled datasets, and the full set of CII patents identified using keywords and IPC filtering, we can identify the anti-seed set: a random sample of patent applications which are in the "CII" subset but are not in the "PSM-adverse" subset. This anti-seed set represents a random selection from the "CII-PSM-clear" subset shown in the Venn Diagram in Figure 1.

Figure 1 | Venn Diagram of patent application categories



ML models to identify CII-PSM-likely-clear and CII-PSM-likely-adverse

Recent patent studies including Kollmann and Palangkaraya (2023), Kollmann et al. (2023), Giczy et al. (2022), and Abood and Feltenberger (2018) have shown that ML models can be reliably used for identifying and classifying inventions based on bibliographic and textual information in patent documents. Other recent studies which have employed ML models for patent analysis include, for example, Lee et al. (2018), Kwon and Geum (2020), Choi et al. (2021) and Ponta et al. (2022).

This project develops and fine tunes ML models to identify CII patents on the margins of patent eligibility in Australia, and similar applications filed in other jurisdictions, using the seed and anti-seed datasets of CII patent applications described above as training data. The ML model with the highest predictive performance will be implemented on the 'raw' CII patent application database to produce a highly accurate and comprehensive final CII patent application database for statistical analysis. We selected Accuracy, the fraction of predictions the modelling correctly predicted as the primary method of scoring the predictive models.

Similar to the above studies, the development of the ML models primarily relies on features that can be engineered from the textual information contained in patent document titles, abstracts, claims, and, if feasible, descriptions. Additionally, features engineered from bibliographic information of the patent applications will also be considered in the modelling. The ML model development incorporates lessons from earlier work to improve predictive performance, including:

- The use of a large training and test sample size
- The use of pre-processed words, such as stemmed or lemmatised words according to their parts of speech
- Assessment of inclusion and exclusion of specific stop words
- Extensive visualisation to detect and, if necessary, exclude outliers
- The use of automated hyperparameters tuning.
- The consideration of various metrics for the ML objective function
- The implementation of multiple folds Cross-Validation to ensure robustness.

The above steps are taken in addition to standard preprocessing steps such as the conversion of all text to lower cases; removal of numbers, symbols, formulas, special characters and extra spaces. Based on the pre-processed text, features for ML model estimation/training are then generated as numerical value features such as a series of hot encoded binary features and/or as text encoded/embedded vectors. Lastly, the ML model development also considers generated features based on bibliometric information such as IPC codes. See Appendix for further details on the data sources, features generation, and ML model estimation.

Econometrics analysis

CII patent application outcomes at IPA, EPO, and USPTO

The final CII patent applications database constructed as above contains application-level information of all CII and Non-CII patent applications filed at IPA, EPO, and USPTO. The information available in the database includes, for example:

- patent application outcomes (grant, refuse, withdrawn, pending)
- year of filing
- bibliographic information such as patent family ID, priority year, IPC code, and the number of claims, and
- patent applicant information such as the country of the applicant and inventor.

Based on such information, we perform descriptive and visual analyses of patent examination outcomes of the different patent application subsets (CII-PSM-likely-adverse, CII-PSM-likely-clear, and Non-CII) and make comparisons between filing behaviour and outcomes at the 3 patent offices.

To facilitate more objective inter-office comparisons, in which differences and similarities are inferred based on apple-to-apple comparisons, we also perform the analysis on a subset of the applications that comprise "patent triplets," patent applications which belong to the same patent families, where equivalent applications (for the same or similar inventions) are filed in the 3 patent offices. Consider 2 sets of patent applications which are not of the same family (patent application A and patent application B). These are filed at IPA and EPO, with patent application A granted by IPA but refused by EPO, and patent application B is granted by EPO but refused by IPA. In this case, we cannot be fully certain that the differences in outcomes are due to differences in the patent examination procedures of the 2 offices. Instead, it is possible that the owner of patent application A invested a lot more effort than the owner of patent application B to get a grant from IPA, and vice versa. By comparing outcomes within the same patent families, we can more confidently attribute any observed differences in the likelihood of grant across the 3 offices to variations in legal standards and practices across jurisdictions, rather than to the underlying characteristics of the invention, application or applicant.

Furthermore, we also estimate econometric models of patent examination outcomes controlling for other possible factors that could lead to different patent examination outcomes across the patent offices. More specifically, we estimate the probability of grant using linear regression models of the following generic form:

$$y_{ij}^{*} = f(X_i'\beta) + \varepsilon_{ij}$$

$$y_{ij} = \begin{cases} 1 \text{ if } \varepsilon_{ij} > 0 & (\text{application } i \text{ is granted by office } j) \\ 0 \text{ if } \varepsilon_{ij} \leq 0 & (\text{application } i \text{ is not granted by office } j) \end{cases} \quad (1)$$

where y_{ij} is the observed binary examination outcome of patent application i at patent office j, X_i represents a vector of patent application characteristics of interest (such as priority year, application year, number of claims, technology class, number of inventors, etc.), β is the associated vector of parameters to be estimated, and ε_{ij} is unobserved effects assumed to be random. The function $f(\cdot)$ can be a logit function $\Lambda(\cdot)$ such that $\mathrm{Prob}[y_{ij}=1|X_i,\beta]=\Lambda(X_i'\beta)$ or simple linear function. The linear function specification allows for a simpler interpretation of the estimated regression equation, especially when we include interaction effects in the set of regressors (such as a post-2014 indicator to assess the impact of relevant court cases on patent subject matter eligibility). It also aids interpretation, if necessary, when we control for unobserved applicant-level factors likely to influence their patenting behaviour using high-dimensional applicant fixed effects.

The propensity to file CII patent application in Australia

We analyse how likely CII patent applicants at the USPTO and the EPO are to apply for the same patent protection in Australia. To do this we identify each applicant using the harmonised assignee names available in the *Google Public Patent Database*. With data at the level of the patent application and applicant we construct an "apply at IPA" indicator as the dependent variable for a binary discrete choice problem. Then, we can ask whether every time an applicant filed for CII patent protection in EPO or USPTO, is he or she likely to subsequently apply at IPA. We assess the potential influence of different applicant and invention characteristics and other factors (such as the 2014 court decisions).

The actual setup for the empirical model in this simplified binary choice problem is similar to the one given by equation (1) above:

$$y^*_{ijk} = f(X_{ik}'\beta) + \varepsilon_{ijk}$$

$$y_{ijk} = \begin{cases} 1 \text{ if } \varepsilon_{ijk} > 0 & \text{(application } i \text{ is filed by applicant } k \text{ at office } j\text{)} \\ 0 \text{ if } \varepsilon_{ijk} \leq 0 & \text{(application } i \text{ is filed by applicant } k \text{ at office } j\text{)} \end{cases} \quad (2)$$

Impact of changes in legal standards on CII patent applications

The third empirical analysis of the CII patent applications involves a difference-in-differences (DID) analysis of the impact of variation in the relevant CII patenting legal standards within and across the different patent offices. In essence, the DID analysis aims to identify the causal effect of the changes in the legal standards by comparing the propensity of CII patent applications to be filed before and after the changes relative to the propensity of non-CII patent applications.

At the EPO and USPTO and other jurisdictions, the bars for the inclusion and exclusion of CII as patentable subject matter may have been raised or lowered following various court decisions (Ng, 2021). In this research project, the impact of 2 specific court rulings, which are potentially overlapping with respect of their timing and their implications on CII patenting legal standards, are analysed simultaneously:

1. The Full Federal Court of Australia's appeal ruling on the R*esearch Affiliates LLC v Commissioner of Patents* in Australia on 18 November 2014, and
2. The US Supreme Court's ruling on *Alice Corp v CLS Bank International* in the United States on 19 June 2014.

The Federal Court of Australia's appeal decision confirmed that Research Affiliates LLC's claims of a computer implemented method (as specified in Patent Application No. 2005213293) are not patentable subject matter. The appeal by Research Affiliates LLC was dismissed – a decision that would have important implications for the patentability of computer-implemented inventions in Australia. Similarly, the landmark 2014 US Supreme Court ruling in *Alice Corp v CLS Bank International* had a significant impact on CII patenting legal standards, first and foremost in the United States, with potential spillover effects worldwide. The ruling reaffirmed that abstract ideas are not patentable; and any generic computer implementation of abstract ideas is not considered inventive enough as to be patentable.

Due to their occurring in the same year, the impact of the 2 court rulings will be investigated simultaneously using the difference-in-differences (DID) method, comparing the measured change in the outcome variable before and after the court decision of the treated group to that of the control group. Two different outcome variables will be considered: Probability of patent grant and Probability of patent application.

First, the court rulings may have increased the patentability threshold. If that is the case, then the grant probability of CII patent applications will decrease more after the rulings (compared to the grant probability of non-CII patent applications). At the same time, the lower grant probability may reduce the extent of CII patent filing by the applicants. The empirical model to be estimated is of the following form:

$$y^*_{it} = \beta_0 + \beta_1 Post2014_{it} + \beta_2 CIIpatent_{it} + \beta_3 Post2014_{it} \times CIIpatent_{it} + X'_{it}\gamma + \varepsilon_{it}$$

$$y_{ij} = \begin{cases} 1 \text{ if } \varepsilon_{it} > 0 & \text{(application } i\text{'s outcome is positive)} \\ 0 \text{ if } \varepsilon_{it} \leq 0 & \text{(application } i\text{'s outcome is not positive)} \end{cases} \quad (3)$$

where $\mathbf{i}$ indexes patent application, t indexes filing year, $\mathbf{CIIpatent}_{it}$ is an indicator variable denoting computer implemented invention status (specifically, whether it is CII vs Non-CII, or whether it is CII-PSM-likely-adverse vs CII-PSM-likely-clear vs Non-CII), $\mathbf{Post2014}_{it}$ is another indicator variable with a value of 1 if the patent filing year is after 2014, $\mathbf{X'}_{it}$ is a vector of time-invariant and time-varying patent application and applicant characteristics that could be related to the outcome variable (probability of grant or probability of applying at IPA), and ε_{it} is a random error term. The main parameter of interest in equation (3) is β_3 which measures the average change in outcome probability of CII patent applications after the introduction of the court rulings. Furthermore, equation (3) can be estimated separately for each patent office to assess the size of the impact of the ruling in different offices.

3 Descriptive and visual analysis

Number of CII patent applications

We begin our analysis by showing, in Figure 2, a line chart displaying the trend in total number of patent applications filed at IPA, EPO, and USPTO over the period 2001 to 2020 based on the filing year of the application. In total, for the specified period, there are 524,879 patent applications filed at IPA (around 26 thousand per year), 2,839,709 patent applications filed at the EPO (around 142 thousand per year) and 10,105,616 patent applications filed at the USPTO (around 505 thousand per year). The scale differences between these offices have unfortunately flattened the appearance of an underlying sustained increase in patenting at the 3 offices. The annual growth rates for patent applications are 1.3% for IPA, 2.0% for EPO, and 3.3% for USPTO. Thus, patenting in the US grew at more than double the rate of patenting in Australia.

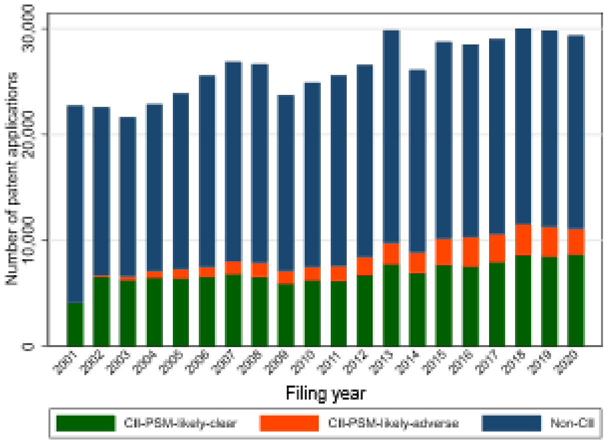
Figure 2 | Number of patent applications, all technology, IPA/EPO/USPTO, 2001-20.

Notes: Data represent all patent applications filed within each jurisdiction which we have access to the full set of text data for the title, abstract, and claims. Consequently, the count of patent applications may differ from the official count of patent applications provided by each patent office statistics.

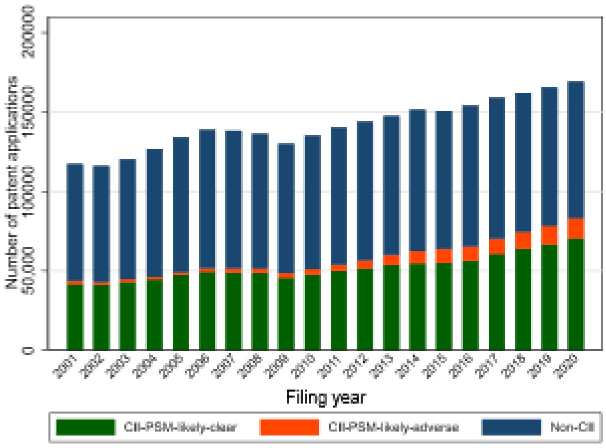
Now, using the CII classification, the bar charts in Figures 3A-C show the distribution of patent applications within the 3 offices according to whether they are for computer implemented inventions or not, and, if they are, whether they are similar to applications that received a PSM objection when examined by IPA.

Overall, 32% of Australian patent applications are classified as CII. These are further split with close to 6% classified as CII-PSM-likely-adverse and around 27% classified as CII-PSM-likely-clear. The overall share of CII patent applications is significantly higher at the EPO, at slightly more than 41%, and at the USPTO, at close to 50%. The exact counts suggest a more pronounced difference in technology mix across the offices.

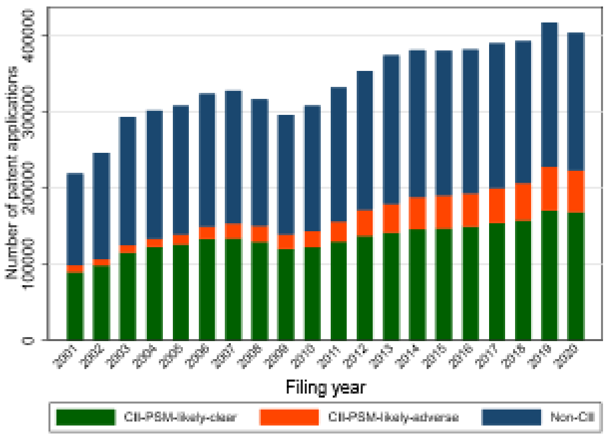
Figure 3 | Number of patent applications by CII group, IPA/EPO/USPTO, 2001-20.



(A) IPA



(B) EPO

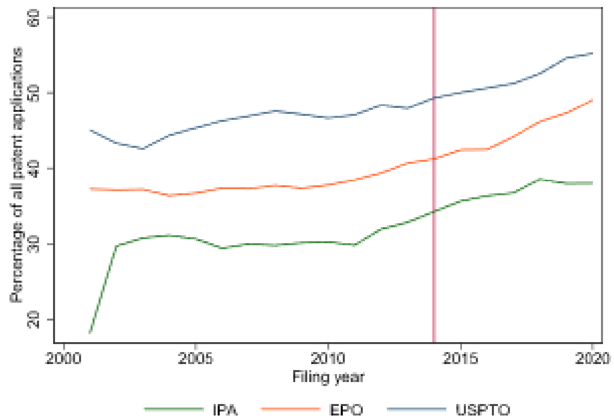


(C) USPTO

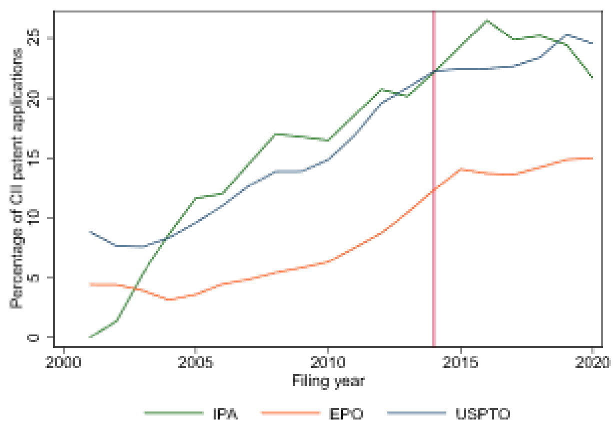
Notes: Data represent all patent applications filed within each jurisdiction which we have access to the full set of text data for the title, abstract, and claims. “CII-PSM-likely-adverse” are patent applications ML predicts IPA examiners would raise an objection to on the grounds of lack of patentable subject matter. “CII-PSM-likely-clear” are patent applications ML predicts IPA examiners would not object to on the grounds of lack of patentable subject matter. “Non-CII” patents are patent applications which do not have any matching keywords listed in Table 1 in the main text and/or are those in the excluded list of IPC codes listed in Table 2 in the main text.

The 2 charts in Figure 4 provide a clearer picture of the increase in CII patenting, showing both the increase in CII applications as a proportion of all applications filed at each office, and the increase in CII-PSM-likely-adverse patent applications as a proportion of CII applications. The 2 end periods could be affected by data truncation and uncharacteristically large changes in share due to low base numbers. Ignoring these periods, Figure 4A shows that at IPA, the share of CII patent applications in the total number of patent applications increased rapidly from around 30% in most years before 2010 to around 35% by 2018. Furthermore, the slope of the 3 lines, which represent the share of CII patent applications in the 3 patent offices, appear to be of relatively similar value. This suggests similar rates of increase in the CII share of patent applications across the 3 patent offices from 2010-2018.

Figure 4 | Share of CII and CII-PSM-likely-adverse, IPA/EPO/USPTO, 2001-20.



(A) Share of CII patent applications as percentage of all applications.



(B) Share of CII-PSM-likely-adverse patent applications as percentage of CII applications.

Notes: Data represent all patent applications filed within each jurisdiction which we have access to the full set of text data for the title, abstract, and claims. "CII-PSM-likely-adverse" are patent applications ML predicts IPA examiners would raise an objection to on the grounds of lack of patentable subject matter. "CII-PSM-likely-clear" are patent applications ML predicts IPA examiners would not object to on the grounds of lack of patentable subject matter. "Non-CII" patents are patent applications which do not have any matching keywords listed in Table 1 in the main text and/or are those in the excluded list of IPC codes listed in Table 2 in the main text.

Figure 4B shows that the increased incidence of CII patent applications was also accompanied by an increase in the share of CII-PSM-likely-adverse. The increase is particularly rapid for the case of IPA, which suggests that IPA examiners appear to have become significantly more likely to raise patentable subject matter objections to CII patent applications filed particularly from 2002 onward. We should note, however, that the original labelled data set of CII patent applications for which PSM objections were actually raised suggests IPA's rapid increase of CII-PSM-adverse actually started later at 2010.[1]

The figure also indicates that post-2010 the share of CII applications that are CII-PSM-likely-adverse is significantly lower at the EPO than at IPA and the USPTO. It is plausible that the difference reflects the more restrictive approach of the EPO to such patent applications which discouraged their filing in the jurisdiction.

Figure 4B seems to also suggest that the share of CII-PSM-likely-adverse at IPA has started to decline after reaching its peak in filings from 2016.

This later period decrease could be attributed to the increased likelihood of PSM objection being raised, which may discourage applicants from filing such patent applications at IPA. However, it could also be caused by data truncation.

Table 3 summarises the characteristics of the 3 different groups of patent applications (CII-PSM-likely-adverse, CII-PSM-likely-clear, and Non-CII) filed in each patent jurisdiction in the period 2001-2020. For example, the average number of claims of any patent application filed at IPA is significantly higher than those filed at the EPO or USPTO. The average number of claims at the EPO is 15, potentially reflecting the fees structure of the patent office, which strongly discourages having more than 15 claims.

In terms of CII patents, notable characteristics shown in Table 3 include the number of claims for CII-PSM-likely-clear, the high share of CII-PSM-likely-adverse which are Divisional applications, and the relatively high share of Australian-origin applications which are CII-PSM-likely-adverse. Applicants from EPO member states (EP assignee) appear to be less likely to apply for patent applications which could face the PSM objection. This is perhaps a reflection of the strictness of EPO in examining CII patent applications which are closer to what could be deemed as software patents.

Table 3 Characteristics of patent applications by CII group, IPA/EPO/USPTO, 2001-20

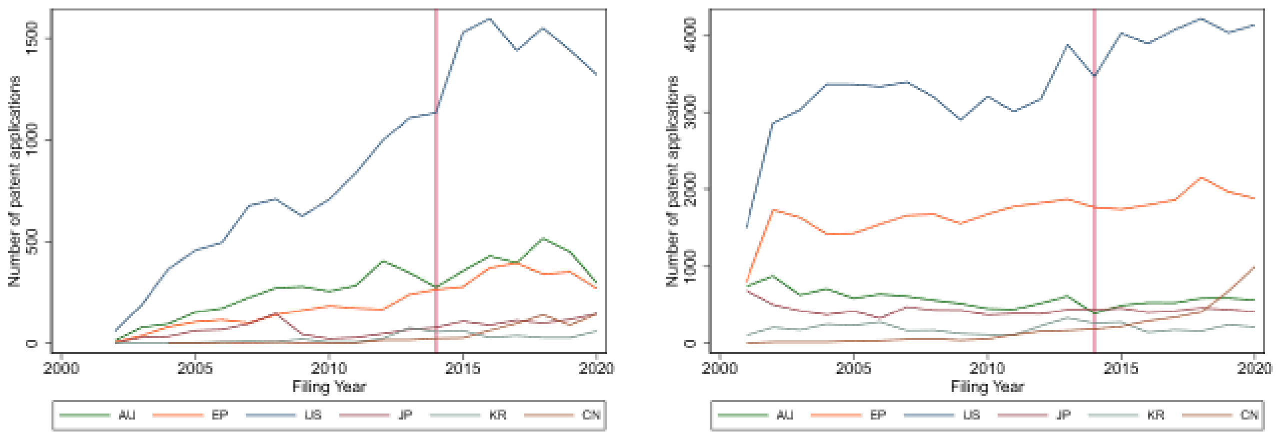
	IPA			EPO			USPTO		
	CII-PSM-likely-adverse	CII-PSM-likely-clear	Non-CII	CII-PSM-likely-adverse	CII-PSM-likely-clear	Non-CII	CII-PSM-likely-adverse	CII-PSM-likely-clear	Non-CII
No. of claims	25.6	29.6	23.9	14.9	15.5	13.1	20.6	20.8	18.5
No. of IPC4	2.5	3.8	4.4	1.8	1.8	1.8	1.7	1.7	1.7
Divisional (%)	41.6	25.4	22.3	N/A	N/A	N/A	N/A	N/A	N/A
PCT (%)	56.0	69.6	75.6	62.5	54.5	55.4	9.6	17.4	23.5
No. of assignees	1.2	1.3	1.3	1.1	1.1	1.1	1.1	1.1	1.1
No. of assignee countries	1.0	1.1	1.1	1.0	1.0	1.0	1.0	1.0	1.0
Small Entity assignee (%)	63.9	75.8	73.2	69.9	71.4	64.4	25.4	18.9	28.6
AU assignee (%)	17.3	8.4	9.9	0.9	0.6	0.7	0.6	0.5	0.6
US assignee (%)	56.3	49.1	43.5	43.4	28.4	24.9	66.7	42.8	39.7
EP assignee (%)	13.4	26.4	32.6	31.3	40.7	49.4	8.3	14.0	18.6
JP assignee (%)	5.0	6.7	6.7	8.7	15.6	15.9	9.6	20.8	20.3
KR assignee (%)	1.6	2.9	1.5	3.9	5.2	3.2	3.3	7.9	5.2
CN assignee (%)	2.2	3.0	2.1	5.9	5.7	2.6	3.0	3.8	2.9

Notes: IPC4 is four-digit IPC code. AU: Australia as the assignee country (US: United States; EP: EPO member states; JP: Japan; KR: South Korea; CN: China). Small Entity assignee is based on USPTO Small Entity classification of assignees which are eligible for discounted patenting fees. PCT refers to the share of patents filed using the Patent Cooperation Treaty.

The table also provides the proportion of patent applications which are associated with "Small entity" assignees. This indicator is obtained from USPTO, which provides a fee discount to eligible "small" scale patentees. We can use this indicator to flag assignees that are small and medium enterprises or SMEs. However, in interpreting this indicator, we need to remember that there may be many patent applicants with missing values because they never applied for a patent in the US.

Figure 5 shows the relative importance of top 6 assignee countries in Australia and how it varies over time and over patent jurisdictions. It is clear from the figure (also from Table 3) that Australian inventors are important players in CII patenting activities in Australia. Another thing to note from the figures is the rapid increase of applicants from China, particularly post-2015.

Figure 5 | Number of CII-PSM-likely-adverse and CII-PSM-likely-clear patent applications by top assignee country, IPA, 2001-20.



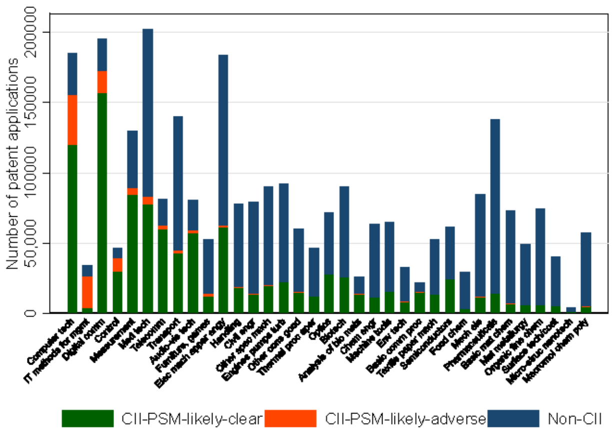
(A) CII-PSM-likely-adverse

(B) CII-PSM-likely-clear

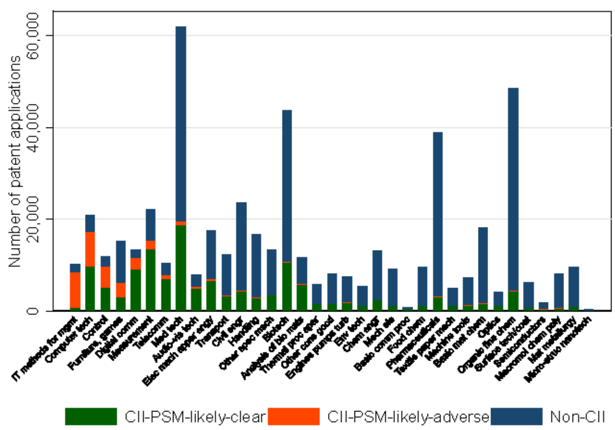
Notes: "CII-PSM-likely-adverse" are patent applications ML predicts IPA examiners would raise an objection to on the grounds of lack of patentable subject matter. "CII-PSM-likely-clear" are patent applications ML predicts IPA examiners would not object to on the grounds of lack of patentable subject matter. Patent applications with more than1assignee countries would be flagged with multiple assignee country codes respectively.

Our last focus for the descriptive visual analysis of the CII patent application database is the technological characteristics. For this purpose, we summarise the CII patenting activities in terms of the broad technological fields identified by the World Intellectual Property Organization (WIPO). Figure 6 provides the distribution of patent applications by WIPO fields of technology and CII classification in each of the 3 patent offices. From the charts in Figure 6, we first note the significant difference in terms of technological focus of patent applicants in the 3 jurisdictions. For example, in Australia, patenting activities in Medical technology appear to be the most important by far. In contrast, in the EPO jurisdiction, while Medical technology is important, as important are fields very closely related to CII patent applications such as Computer technology and Digital communication. In fact in the US, those last 2 fields mentioned are the most important fields.

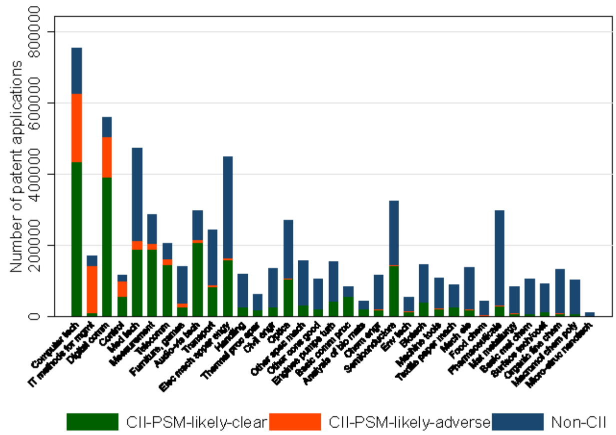
Figure 6 | Number of patent applications by CII group and WIPO field of technology, IPA/EPO/USPTO, 2001-20.



(A) IPA



(B) EPO



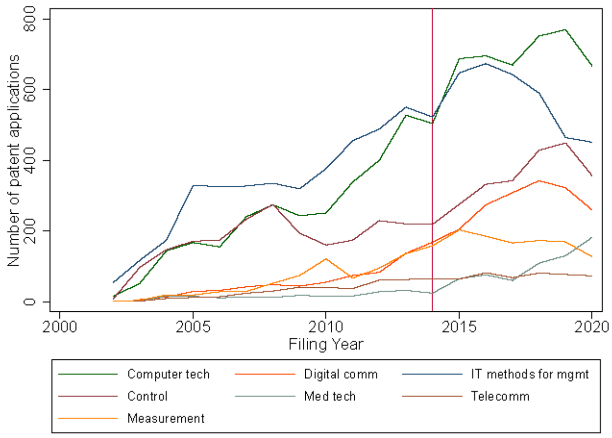
(C) USPTO

Notes: "CII-PSM-likely-adverse" are patent applications ML predicts IPA examiners would raise an objection to on the grounds of lack of patentable subject matter. "CII-PSM-likely-clear" are patent applications ML predicts IPA examiners would not object to on the grounds of lack of patentable subject matter. WIPO field of technology is based on the first listed IPC code (for EPO and USPTO) and the WIPO field id in IPA's IPRAPID database.[2]

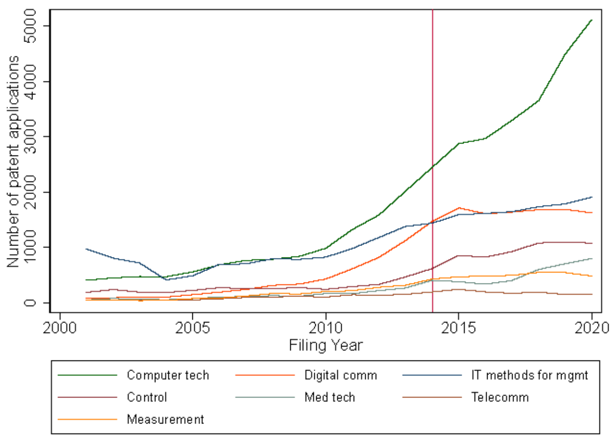
Despite this significant variation in technology focus, Figure 6 also highlights the fact that CII patent applications are mostly concentrated in a small number of fields including Computer technology, Digital communication, Measurement, Medical Technology, and Telecommunications. When we rank fields based only on accumulation of CII-PSM-likely-adverse applications, the field of IT methods for management rises to the top 2 fields. Software and business methods patents which are patentable in the US belong in this technology field. Hence, it is expected that most of patent applications in this field are classified as CII-PSM-likely-adverse.

Still on fields of technology, Figure 7 displays the dynamic of the top 7 fields of technology identified above over the period of study for us to better understand which technology fields have driven the observed upward trend in CII-PSM-likely-adverse patenting in the 3 patent jurisdictions. First, it is clear from the trend lines shown in the charts, Computer technology is the most significant driver for such patent filings. In Australia, this is almost mirrored by patenting activities in the IT for business management field, a field which has become less important in EPO and USPTO when compared to Computer technology.

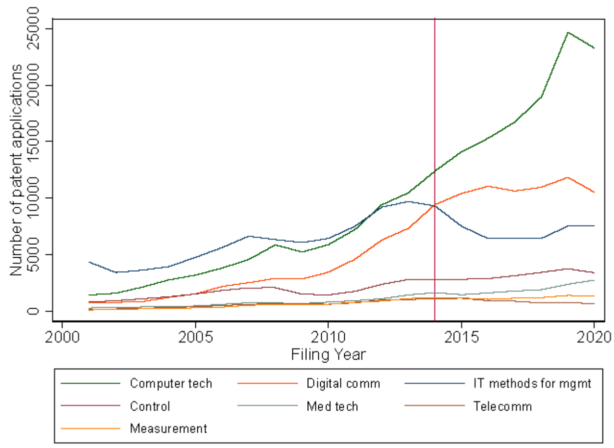
Figure 7 | Number of CII-PSM-adverse patent applications by top 7 WIPO fields of technology, 2001-20.



(A) IPA



(B) EPO

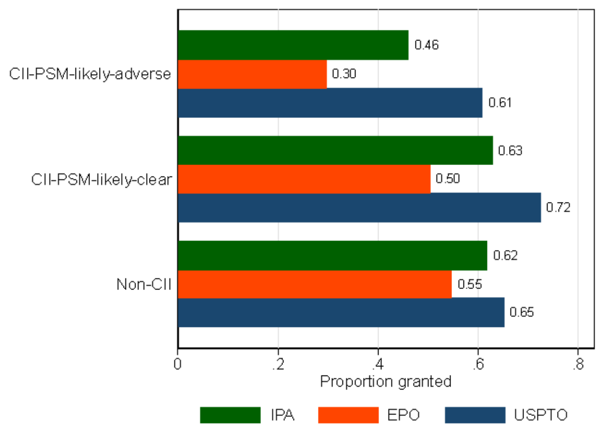


(C) USPTO

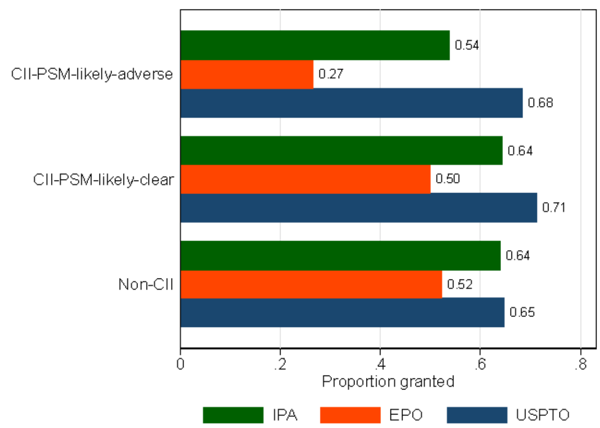
Notes: WIPO field of technology is based on the first listed IPC code (for EPO and USPTO) and the WIPO field id in IPA's IPRAPID database.

We now look at how different CII patent applications are with respect to the expected outcomes. For that purpose, Figure 8 summarises the proportion of granted patent applications ("not granted" includes refused, still pending, or withdrawn). As noted earlier, to facilitate a more objective apple-to-apple comparison across the 3 patent offices and the 3 patent classifications, the proportion of granted patent applications is also computed based on "equivalent" patents. These equivalent patents are members of the same patent families (patents for the same or similar inventions) filed at IPA, EPO and USPTO (as another term, these are described as patent triplets).

Figure 8 | Proportion of granted patent applications by CII group, IPA/EPO/USPTO.



(A) All patent applications



(B) Triplet patent applications

Notes: Triplet patent applications are patent applications filed at IPA, EPO, and USPTO which have the same family ID in Google patent database.

From Figure 8 we can infer that CII-PSM-likely-adverse are less likely to be granted by IPA and EPO than the USPTO. This is true regardless of the sample we use to compute the grant proportion. It is also consistent with our expectation that these 2 patent offices are less likely to grant patents for inventions which lack technical feature or manner of manufacture. For the USPTO, the triplet sample shown in Figure 8B suggests that CII-PSM-likely-adverse patent applications are more likely to be granted (68%) compared to non-CII patents (65%).

It is possible that the higher grant proportion for patents at the USPTO compared to the EPO and IPA shown in Figure 8B is due to sampling variation. For example, one may become concerned with an aggregate grant proportion comparison such as the one above if the alternative to grant contains an outcome that is not actually an outcome, that is an application still pending. In that case, it is possible for a lower grant proportion to be associated with a higher pending rate. This can potentially confuse the interpretation of the outcome measure and its comparison across patent jurisdictions.

In fact, different patent offices may have significantly different pendency periods. Appendix Table A9 shows that while IPA and USPTO have a pendency period (defined as the number of years between grant year and filing year) of around 3 years, EPO has a pendency period of more than 5 years. Furthermore, from Appendix Table A9, if we only look at filings from the early years of the 2001-2020 period we can say that the pendency period at EPO is probably closer to 6 years, since more recent grants are likely those which are granted faster. As a result, if our grant data includes grant decisions made up to the year of 2023 or early 2024 (which is the case for the complete CII patent application database), on average we expect to see "true" EPO grant outcomes only for patent applications filed by 2017 at the latest. For the EPO patent applications filed after 2017, we might see grant proportion to be lower simply because it has more pending patents.

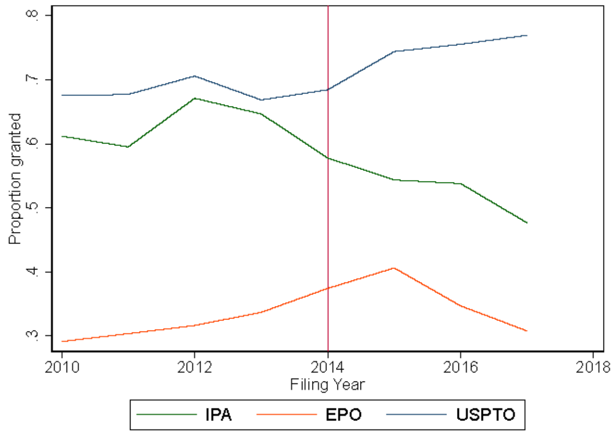
Furthermore, as illustrated especially by Figure A1 in the Appendix and to a lesser extent by Figure 5A and Figure 7A, for IPA the number of CII-PSM-likely-adverse applications prior to 2010 is relatively low. This low base number results in the computed grant proportion before 2010 that is likely to suffer from small sample bias.

Therefore, in Figure 9, to compare the trend lines of grant proportion across patent offices, we limit the sample period to 2010-2017. The reduction of the upper limit to 2017 is to minimise the likelihood of incorporating truncated/pending outcomes at the EPO and the reduction of the lower limit to 2010 is to minimise the small sampling bias resulting from lower count of CII patent applications, particularly those in the CII-PSM-likely-adverse group.

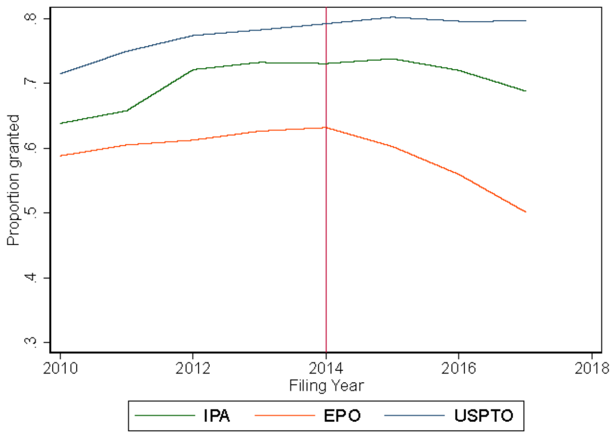
As seen from the charts in Figure 9, it is possible that the 2014 court decision is associated with a decline in the grant proportion of CII patent applications. In interpreting the graphs, it is important to bear in mind that there is a several year lag between filing a patent application and examination. For example, in the normal course of events there is every possibility that an application filed in 2012 would not be examined until post 2014. That application would then be assessed in accordance with the standard for patentable subject matter as it applied at the time of examination, taking into the decision of Alice (not the standard at time of filing). In Figure 9A we see a decline in grant proportion of CII-PSM-likely-adverse starting in 2013 and accelerating in 2014. The tapering in the rate of decline post 2014 could coincide with applicants becoming more ofay with the legal standards in Australia.

Furthermore, we also note for the USPTO the proportion of granted patent applications does not appear to be affected by the 2014 court decision. This observation appears to be inconsistent with the findings of a recent study which reveal increased first report rejection at the USPTO (Frumkin et al., 2024). There are two possible reasons for the apparent discrepancies. First, first report rejection does not rule out for the possibility of an ultimate grant. Second, it might be insufficient to just evaluate the impact of the 2014 court decision on the probability of grant. The impact may also manifest in the form of more narrowed granted patents. We leave these possibilities for future research.

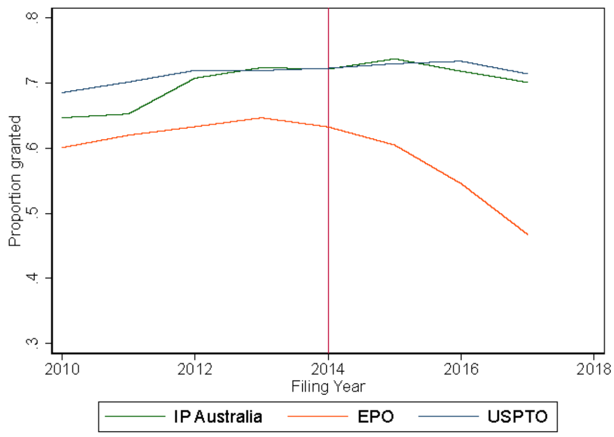
Figure 9 | Proportion of granted patent applications (triplet), CII groups, IPA/EPO/USPTO, 2010-17.



(A) CII-PSM-likely-adverse



(B) CII-PSM-likely-clear



(C) Non-CII

Notes: Non-grant outcome includes refused/rejected, withdrawn, abandoned, and pending. Grant and non-grant status is as of early 2024.

Lastly, Figure 9 suggests that grant proportion has decreased post-2014 at the EPO regardless of CII status. This could be due to the potentially higher proportion of pending outcome at the EPO as discussed earlier. In other words, we may still be able to interpret the post 2014 decline, particularly for the case of CII-PSM-likely-adverse in IPA, to be associated with the 2014 court cases discussed in the Introduction.

Moreover, we note that for Non-CII patent applications at IPA, there does not appear to be any effect of the 2014 court decisions. This is again to be expected, given that the 2014 court decisions are only relevant for CII patent applications. This observation supports the interpretation of Figure 9A and, to a lesser extent, Figure 9B, that for the case of Australia, the 2014 court decisions appear to matter in patent examination outcomes. In contrast, for USPTO, there is less clear evidence for how the 2014 court decisions impacted examination outcomes. Regardless of CII status, the grant proportion for patent applications at the USPTO increased after 2014.

4 Econometrics analysis

Determinants of probability of grant

We are now ready to conduct a more formal analysis of the determinants of patent application outcomes. Specifically, we estimate several versions of equation (2) using 2 sample sets: the full sample and the triplet patent family sample. We also split the full sample by patent office to compare how the same patent application characteristics may have different relationships with patent application outcomes in different patent offices.

Before we present the regression estimates, we note that given the discussion in the previous section about potential data truncation (the pending patent outcome problem), all the regressions of the probability of grant are based on the 2010-2017 sample period. This is done to reduce the effect of the much longer pendency period at the EPO resulting in lower probability of grant regardless of CII patent classification.

Table 4 summarises the coefficient estimates of the baseline regression. Comparing across offices, we can see that the conditional probability of an application being granted at IPA and EPO is around 1.8 and 1.5 percentage points lower, respectively, if it is for a CII patent. Given that the unconditional average probability of grant is greater than 40% in both offices, this lower grant probability is relatively small in magnitude. The other regressors suggest some variation across offices in the determinants of grants. For example, the number of assignees has a strong positive association with grant probability at IPA.

Table 5 presents the set of regression coefficient estimates which allow us to compare results for the subsamples of CII-PSM-likely-adverse and CII-PSM-likely clear. These are estimated using all patent families and the triplet patent families and results are compared across the 3 patent offices. The resulting estimates strongly suggest that CII-PSM-likely-adverse patents are less likely to be granted. The probability of grant is lower by around 11.5 percentage points at IPA, by around 4.6 percentage points at the USPTO, and by around 12.6 percentage points at the EPO. These effects are much more significant in magnitude than the effect identified when we did not distinguish CII patent applications based on PSM criteria. The effects are robust regardless of whether all patent families or the triplet families are used.

Table 4 | Regression estimates of probability of grant, All patent families.

Coefficient	All offices	IPA	EPO	USPTO
CII	**0.007*****	**-0.018*****	**-0.015*****	**0.010*****
No. claims	0.001***	-0.000***	0.002***	0.001***
No. IPC	-0.006***	0.001**	-0.001**	-0.004***
No. assignee	-0.036***	0.060***	-0.020***	-0.056***
No. assignee country	0.081***	0.006	-0.014	0.066***
Divisional	0.125***	0.038***	n/a	0.031***
US assignee	-0.027***	0.063***	0.010**	-0.027***
EP assignee	-0.080***	0.084***	0.003	-0.042***
AU assignee	-0.259***	-0.149***	-0.088***	-0.132***
JP assignee	-0.055***	0.142***	0.050***	-0.062***
CN assignee	-0.069***	0.156***	0.083***	-0.061***
KR assignee	-0.034***	0.213***	0.072***	-0.058***
Sample size	3,273,922	212,913	585,908	2,475,101
Adj. R-square	0.070	0.062	0.048	0.061

Notes: Non-grant outcome includes refused/rejected, withdrawn, abandoned, and pending. Grant and non-grant status is as of early 2024. The sample period is filing years of 2010-2017. Coefficient estimates represent the percentage points (e.g., 1.0 means 100 percentage points) of average marginal change on the probability of grant. Statistical significance is indicated by */**/*** which mean statistically significant at 10/5/1 per cent significance level. All regressions include filing- and priority-year fixed effects, assignee country fixed effects, WIPO field of technology fixed effects, and a set of control variables (experience filing at IPA, number of claims, number of four-digit IPC codes, number of assignees, number of assignee countries, and whether the patent application is divisional). US: United States; EP: EPO member states; AU: Australia, JP: Japan; CN: China; KR: South Korea.

It is also important to note that the base grant proportions vary across offices: as shown previously in Figure 8B, for non-CII applications, around 64% are granted at IP Australia, 52% are granted at the EPO and 65% are granted at the USPTO. Calculated from these base rates, if an application is identified as CII-PSM-likely-adverse, it's likelihood of being granted declines by 18.0% (=11.5/64) at IP Australia, by 7.1% at the USPTO and by 24.2% at the EPO.. Similar estimates are obtained using the grant proportion of Non-CII patents at each office.

Table 5 | Probability of grant regression, CII-PSM-adverse vs CII-PSM-clear, All vs Triplet families.

Coefficient	IPA	EPO	USPTO
All families			
CII-PSM-likely-adverse	-0.117***	-0.101***	-0.034***
CII-PSM-likely-clear	-0.007**	-0.010***	0.015***
Triplet families			
CII-PSM-likely-adverse	-0.115***	-0.126***	-0.046***
CII-PSM-likely-clear	-0.016***	-0.016***	-0.005***

Notes: Non-grant outcome includes refused/rejected, withdrawn, abandoned, and pending. Grant and non-grant status is as of early 2024. The sample period is filing years of 2010-2017. Coefficient estimates represent the percentage points (e.g., 1.0 means 100 percentage points) of average marginal change on the probability of grant. Statistical significance is indicated by */**/*** which mean statistically significant at 10/5/1 per cent significance level. All regressions include filing- and priority-year fixed effects, assignee country fixed effects, WIPO field of technology fixed effects, and a set of control variables (experience filing at IPA, number of claims, number of four-digit IPC codes, number of assignees, number of assignee countries, and whether the patent application is divisional). US: United States; EP: EPO member states; AU: Australia, JP: Japan; CN: China; KR: South Korea. Triplet families are patent applications with identical family ID and filed simultaneously at IPA, EPO, and USPTO.

The impact of 2014 court decisions on probability of grant

To estimate the impact of 2014 court decisions on the probability of grant, we implement difference-in-differences (DID) regression by slightly modifying the baseline regression model summarised in Table 5. We want to see how the estimated coefficient of “CII-PSM-likely-adverse” changes before and after 2014. To do this, as specified in equation (3) earlier, we introduce a new indicator variable into the regression. This indicator variable is “Post-2014”, which has a value of 1 for every filing year after 2014 and 0 otherwise.[3] In addition, we introduce into the regression an interaction term between “Post-2014” and “CII-PSM-adverse” indicators. The resulting regression estimates for the DID model are summarized in Table 6.

Table 6 | Probability of grant, difference-in-differences.

Coefficient	IPA	EPO	USPTO
All families			
Post-2014	0.025***	0.565***	0.125***
CII-PSM-likely-adverse	-0.052***	-0.122***	-0.060***
Post-2014 x CII PSM-likely-adverse	-0.135***	0.033**	0.057***
Triplet families			
Post-2014	-0.026**	0.431***	0.087***
CII-PSM-likely-adverse	-0.049***	-0.160***	-0.068***
Post-2014 x CII PSM-likely-adverse	-0.128***	0.066***	0.049**

Notes: Non-grant outcome includes refused/rejected, withdrawn, abandoned, and pending. Grant and non-grant status is as of early 2024. The sample period is filing years of 2010-2017. Coefficient estimates represent the percentage points (e.g., 1.0 means 100 percentage points) of average marginal change on the probability of grant. Statistical significance is indicated by */**/*** which mean statistically significant at 10/5/1 per cent significance level. All regressions include filing- and priority-year fixed effects, assignee country fixed effects, WIPO field of technology fixed effects, and a set of control variables (experience filing at IPA, number of claims, number of four-digit IPC codes, number of assignees, number of assignee countries, and whether the patent application is divisional). US: United States; EP: EPO member states; AU: Australia, JP: Japan; CN: China; KR: South Korea. Triplet families are patent applications with identical family ID and filed simultaneously at IPA, EPO, and USPTO.

As shown in Table 6, the 2014 court decisions appear to have a significant negative effect at IPA.[4] There is an 11.6 to 12.0 percentage points reduction (depending on if we only look at triplet samples or the full sample) in the probability of grant of CII-PSM-likely-adverse applications at the patent office of Australia. In contrast, the effects appear to be positive at the EPO and USPTO. The positive effect at the EPO is possibly caused by the pending period issue we discussed earlier (that is, applications which are more likely to be granted are granted faster and the fact that at the EPO, the average pendency period is more than 5 years). On the other hand, the positive effect of the USPTO may reflect the difference in the way the USPTO responded to the 2014 Supreme Court decision. As discussed earlier, this finding appears to contradict the findings of Frumkin et al. (2024) who found increased rejection in USPTO first action. We argue that these 2 findings may still be consistent with each other if regardless of the first action outcome, the patent applications were granted in the end. Also, we mentioned earlier that the use of post-2014 filing year to determine treatment period may mean we underestimated the negative impact of the 2014 court decision if patent applications filed prior to 2014 were only examined after 2014. At the extreme, the downward bias could lead to a positive effect estimate. However, it is not clear why the downward bias does not appear to have any effect on the estimates based on IPA data. We will investigate these questions in a future study.

The propensity to file CII patent application at IPA

We estimate equation (2) to investigate the determinants of the propensity to file CII patent applications at IPA. To estimate the regression model, we first identify all patent applicants filed at the USPTO (or, separately, the EPO). We then construct a measure for the dependent variable (y_ijk) where i indexes the specific patent application, j indexes the patent applicant who has filed patent application i at USPTO (or EPO), and k refers to IPA. In equation (2) notation, the dependent variable is specified as follows:

$$y_{ijk} = \begin{cases} 1 & \text{if USPTO or EPO applicant } k \text{ subsequently} \\ 0 & \text{filed patent application } i \text{ at IPA otherwise} \end{cases}$$

Hence, in this set up, we ask what influences the propensity for patent applicant j to file (within the same patent family) for patent protection in IPA after he/she filed for patent protection at the USPTO (or EPO). The key determinant variable that we want to investigate is the CII classification status as shown in a simple linear regression equation below:

$$y_{ijk} = \beta_0 + \beta_1 CII_i + X'_{ijk}\gamma + \varepsilon_{ijk} \qquad (4)$$

In the above equation, $CII_i=1$ if the patent application i is for a CII and $CII_i=0$ otherwise. Thus, if $\beta_1>0$ then on average, if the patent application is classified as CII application, USPTO (or EPO) patent applicants are more likely to follow his/her USPTO (or EPO) patent application by subsequently applying to IPA. X'_{ijk} is a vector representing a set of other patent application and patent applicant characteristics, such as a patent's number of claims and the applicant's prior experience filing at IPA. Before we present the coefficient estimates of the regression model specified in equation (4), Table 7 shows the average unconditional probability of USPTO patent applicants to file for patent protection to IPA by filing year and by CII classification subsamples. On average, from the table, a patent applicant who filed for patent protection at USPTO has 6% probability of filing a follow-up patent application at IPA. If the invention is CII-PSM-likely-adverse, the probability is 50% lower at around 3%. This suggests that CII patent applicants are less likely to seek for patent protection at IPA compared to non-CII patent applicants.

Table 7 | Probability of USPTO patent applicant filing the same patent application at IPA.

Filing year sample	Subsamples			All
	CII-PSM-likely-adverse	CII-PSM-likely-clear	Non-CII	
2001	0.02	0.01	0.02	0.02
2002	0.04	0.02	0.04	0.03
2003	0.06	0.04	0.07	0.06
2004	0.05	0.04	0.08	0.06
2005	0.05	0.04	0.09	0.07
2006	0.04	0.04	0.09	0.07
2007	0.05	0.04	0.08	0.06
2008	0.04	0.04	0.09	0.06
2009	0.05	0.04	0.10	0.07
2010	0.05	0.04	0.09	0.07
2011	0.05	0.04	0.08	0.06
2012	0.04	0.04	0.08	0.06
2013	0.05	0.04	0.08	0.06
2014	0.04	0.04	0.08	0.06
2015	0.04	0.04	0.08	0.06
2016	0.04	0.04	0.08	0.06
2017	0.04	0.05	0.08	0.06
2018	0.03	0.04	0.08	0.06
2019	0.02	0.02	0.04	0.03
2020	0.00	0.01	0.00	0.00
2001-20	0.03	0.03	0.07	0.05

Notes: This table presents the average proportion of US patent applications which are subsequently filed at IPA across different subsamples defined by the filing year and CII status. The identification of subsequent filing is based on patent family ID recorded in Google Patent Database. The proportion values that are significantly less than 1 reflect the fact that most USPTO patent applications were not subsequently filed at IPA.

An applicant has up to 31 months from their earliest filing to decide whether to apply for an equivalent patent in Australia. As such, applications filed in more recent years are truncated in the information available about follow-up patenting activity. If we look at the year trend, accounting for this truncation, there does not appear to be any significant change around the year 2014. However, we note that these figures presented in Table 7 are unconditional probabilities. Various factors could mask any true effect of the 2014 court decisions that may exist. This is why we need to estimate equation (3), and later on, equation (4), to evaluate the potential impact on the conditional probability.

Table 8 summarises the average propensity of EPO patent applicants to subsequently file at IPA. Firstly, note that due to data truncation and family ID information, for EPO we only consider the sample period of 2010 to 2017 filing years. As shown in the table, comparing Tables 7 and 8, we find EPO patent applicants as much more likely to follow up their application with subsequent filing at IPA than are applicants to the USPTO. On average, the unconditional proportion of EPO patents subsequently filed at IPA is around 13%, slightly more than double the proportion for USPTO patent applicants. More interestingly, in contrast to USPTO applicants, EPO applicants of CII-PSM-likely-adverse applications appear to be more likely to file subsequently at IPA than applicants of CII-PSM-likely-clear. A more in-depth analysis (out of the scope for this report) is required to understand the possible drivers of this result. However, a plausible interpretation is that applicants with CII patent applications more likely to be considered as “software as such” by EPO patent examiners may think they have an improved chance if they also try to get patent protection at IPA.

Table 8 | Probability of EPO patent applicants filing the same patent application at IPA.

Filing year sample	Subsamples			All
	CII-PSM-likely-adverse	CII-PSM-likely-clear	Non-CII	
2010	0.20	0.10	0.16	0.14
2011	0.17	0.10	0.15	0.13
2012	0.17	0.10	0.14	0.13
2013	0.16	0.09	0.15	0.13
2014	0.16	0.10	0.15	0.13
2015	0.13	0.09	0.14	0.12
2016	0.13	0.09	0.14	0.12
2017	0.13	0.10	0.14	0.12
2010-17	**0.15**	**0.10**	**0.15**	**0.13**

Notes: This table presents the average proportion of EPO patent applications which are subsequently filed at IPA across different subsamples defined by the filing year and CII status. The identification of subsequent filing is based on patent family ID recorded in Google Patent Database. The proportion values that are significantly less than 1 reflects the fact that most EPO patent applications were not subsequently filed at IPA.

Table 9 summarises the main coefficient estimates from the regression in equation (4), estimated using 4 different subsamples: “CII-PSM-likely-adverse”, “CII-PSM-likely-clear”, “CII”, and “Non-CII”. Given that we have a very large sample size, even for each of these subsamples, all regression coefficients are statistically significant.

The more interesting point to note is obtained by comparing estimates from across the different subsamples. For example, the number of assignee countries associated with a patent is often considered an indicator of the potential technology and economic value of the invention. In our results, the more assignee countries associated with a patent, the more likely that patent protection is likely to be sought for a “CII-PSM-likely-adverse” invention in Australia following its filing at the USPTO. One additional assignee country in the team is associated with an average increase of probability to apply to IPA by close to 2 percentage points. Given the average unconditional probability of applying to IPA for “CII-PSM-likely-adverse” patents is 3 percentage points, this effect is significant in magnitude. In fact, compared to other subsamples, the effect of an additional assignee country is more than twice as large for “CII-PSM-adverse” inventions.

Other coefficient estimates in the table show the expected effects. For example, applicants are more likely to apply to IPA if they have applied there before or if the patent application is part of a divisional application. Applicants from leading assignee countries in terms of patenting activities (e.g., China, Japan and Korea) are less likely to apply for patent protection in IPA following their filing at the USPTO.

Table 9 Regression estimates of probability of USPTO applicants to subsequently file the same patent application at IPA, Baseline Model.

Coefficient	Subsamples			
	CII-PSM-likely-adverse	CII-PSM-likely-clear	CII	Non-CII
Has applied before	0.047***	0.034***	0.037***	0.056***
No. of claims	0.007***	0.000***	0.000***	0.001***
No. of IPC	0.004***	0.004***	0.004***	0.004***
No. of assignee	0.002	0.002***	0.002***	0.005***
No. of assignee countries	0.024***	0.006***	0.008***	0.003**
Divisional (0/1)	0.041***	0.034***	0.035***	0.056***
US assignee (0/1)	-0.008***	-0.002***	-0.003***	0.003***
EP assignee (0/1)	0.005***	0.008***	0.007***	0.037***
JP assignee (0/1)	-0.022***	-0.021***	-0.022***	-0.019***
CN assignee (0/1)	-0.013***	-0.003***	-0.005***	-0.001
KR assignee (0/1)	-0.022***	-0.020***	-0.021***	-0.024***
Sample size	354,406	1,876,942	2,231,348	2,278,815
Adj. R-square	0.048	0.068	0.064	0.125

Notes: Coefficient estimates represent the percentage points (1.0 means 100 percentage points) of average marginal change on the probability of applying at IPA. Statistical significance is indicated by */**/*** which mean statistically significant at 10/5/1 per cent significance level. All regressions include filing- and priority-year fixed effects, assignee country fixed effects, WIPO field of technology fixed effects, and a set of control variables (experience filing at IPA, number of claims, number of four-digit IPC codes, number of assignees, number of assignee countries, and whether the patent application is divisional). US: United States; EP: EPO member states; AU: Australia, JP: Japan; CN: China; KR: South Korea. The sample period for estimation is 2001-20 filing years.

Table 10 presents the coefficient estimates for the same regression equation presented in Table 9, except the estimation is based on EPO applicants instead of USPTO applicants. Comparing the coefficient estimates in the 2 tables, we find both USPTO and EPO applicants are more likely to subsequently file at IPA if they have applied there before and if the patent application is part of a divisional application.

There are some notable differences in the estimates, particularly those associated with assignee country. Assignees who filed at the EPO are less likely to subsequently file at IPA if they are from European Patent Office member states ("EP assignees"). In contrast, EP assignees who filed at the USPTO are more likely to file at IPA. This perhaps reflects the EP assignees' internationalisation strategy: those EP assignees who filed at USPTO are more likely to have a stronger internationalisation strategy than those who filed at the EPO.

Table 10 Regression estimates for the probability of EPO applicants to subsequently file the same patent application at IPA, Baseline Model.

Coefficient	Subsamples			
	CII-PSM-likely-adverse	CII-PSM-likely-clear	CII	Non-CII
Has applied before	0.014***	0.019***	0.018***	0.032***
No. of claims	0.001***	0.001***	0.001***	0.001***
No. of IPC	0.004**	0.002***	0.002***	0.003***
No. of assignee	0.008	0.001	0.001	0.004***
No. of assignee countries	-0.018	0.002	0.001	0.020***
Divisional (0/1)	0.174***	0.123***	0.128***	0.175***
US assignee (0/1)	0.009	0.014***	0.014***	0.001
EP assignee (0/1)	-0.034***	-0.012***	-0.014***	-0.039***
JP assignee (0/1)	-0.032***	-0.002	-0.005*	-0.016***
CN assignee (0/1)	-0.001	0.025***	0.022***	0.040***
KR assignee (0/1)	-0.032***	-0.001	-0.005*	-0.025***
Sample size	18,503	192,944	211,447	317,254
Adj. R-square	0.071	0.064	0.064	0.125

Notes: Coefficient estimates represent the percentage points (1.0 means 100 percentage points) of average marginal change on the probability of applying at IPA. Statistical significance is indicated by */**/*** for 10/5/1 per cent significance level. All regressions include these fixed effects: filing- and priority-year, assignee country, and WIPO field of technology, and a set of control variables (experience filing at IPA, number of claims, number of four-digit IPC codes, number of assignees, number of assignee countries, and whether the patent application is divisional). US: United States; EP: EPO member states; AU: Australia, JP: Japan; CN: China; KR: South Korea. The sample period for estimation is 2010-2017 filing years.

A contrasting pattern is observed for Chinese assignees, who are more likely to apply at IPA after they have applied at the EPO than at the USPTO. This may reflect a multi-stage internationalisation strategy in which Chinese assignees first decide whether to target markets beyond the US, if they do, they are more likely to target jurisdictions globally; otherwise, they concentrate primarily on the US market.

Comparing across CII groupings, the divisional status appears to be a more important driver for subsequent filing at IPA for Non-CII applications than for CII-applications. Divisionals status is a driver of Australian filing for CII-PSM-likely-adverse applications to a greater degree than for CII-PSM-likely-clear applications.

Similarly, Chinese assignees are more likely to file subsequent patent applications at IPA after filing at the EPO if their inventions are Non-CII than if they are CII. However, in this case, Chinese assignees with CII-PSM-likely-adverse applications are less likely to file subsequently to IPA than CII-PSM-likely-clear applicants.

The impact of 2014 court decisions on patenting propensity at IPA

Propensity of EPO and USPTO applicants to subsequently file at IPA

To assess any potential impact of 2014 court decisions, we conduct a difference-in-differences (DID) analysis with USPTO and EPO applicants' subsequent filing propensity to IPA as the outcome measure. We do this by adding 2 key variables to the same regressions summarised in Table 9 and Table 10. These variables are:

1. Post-2014: with a value of 1 for all applications filed after 2014, and 0 otherwise[5]
2. Post-2014 x CII status: an interaction term between Post-2014 and CII classification status. We consider "CII" and "CII-PSM-likely-adverse" as the CII status.

Table 11 summarises the main parameters of interest for the difference-in-differences regression based on 2 different sample periods.[6] The regressions include the same determinants shown in Table 8, but they are omitted since they are not our main interest. In the table, Model 1 is based on IPA subsequent filing data of USPTO applicants. Model 2 is based on the data of EPO applicants. In Models 1A and 2A, CII is compared to Non-CII. The estimates for Post-2014 x CII is statistically significant and positive (0.01) for USPTO applicants. This suggests that for CII applications, compared to Non-CII applications, the 2014 court decisions were actually associated with an increase in the relative probability of applicants subsequently filing at IPA. Qualitatively, this result is robust with respect to the sample period.

Table 11 | DID regression estimates of USPTO and EPO applicants' propensity to file subsequent patent application at IPA.

Coefficient	Model 1A	Model 1B	Model 2A	Model 2B
Sample: 2001-20				
Post-2014	-0.263***	-0.150***	-0.063***	-0.068***
CII	-0.012***		-0.010***	
Post-2014 x CII	0.010***		0.008***	
CII-PSM-likely-adverse		0.007***		0.026***
Post-2014 x CII-PSM-likely-adverse		-0.003***		-0.017***
Sample size	4,510,163	2,231,348	1,240,005	486,182
Adj. R-square	0.106	0.063	0.107	0.064
Sample: 2010-17				
Post-2014	-0.099***	-0.055***	-0.057***	-0.042***
CII	-0.011***		-0.008***	
Post-2014 x CII	0.002***		0.004***	
CII-PSM-likely-adverse		0.006***		0.029***
Post-2014 x CII-PSM-likely-adverse		0.003***		-0.018***
Sample size	1,910,397	942,581	528,701	211,447
Adj. R-square	0.110	0.067	0.105	0.065

Notes: Coefficient estimates represent the percentage points (1.0 means 100 percentage points) of average marginal change on the probability of applying at IPA. Statistical significance is indicated by */**/*** for 10/5/1 per cent significance level. All regressions include these fixed effects: filing- and priority-year, assignee country, and WIPO field of technology, and a set of control variables (experience filing at IPA, number of claims, number of four-digit IPC codes, number of assignees, number of assignee countries, and whether the patent application is divisional). US: United States; EP: EPO member states; AU: Australia, JP: Japan; CN: China; KR: South Korea.

In contrast, for Models 1B and 2B, CII-PSM-likely-adverse is compared to CII-PSM-likely-clear. The estimate for Post-2014 x CII-PSM-likely-adverse is statistically significantly negative for USPTO applicants (-0.003) and for EPO applicants (-0.017). However, the estimates for USPTO applicant appear to be sensitive to the sample period. For the 2010-2017 sample period estimates, the coefficient estimates of the interaction term (Post-2014 x CII-PSM-likely-adverse) are positive (0.003) and statistically significant for USPTO applicants. Since the 2010-2017 is the preferred sample period for EPO applicants as discussed earlier, the result suggests that Post-2014, compared to EPO patent applicants for CII-PSM-likely-clear applications, applicants with CII-PSM-likely-adverse applications are less likely to apply for patent protection in IPA after the 2014 Court Decisions. For USPTO, there is no clear conclusion. It seems that USPTO applicants of CII-PSM-likely-adverse patent applications are more likely to file for patent protection in IPA.

In summary, the difference-in-differences estimates in Table 11 provide mixed evidence with respect to how the 2014 court decisions affected USPTO and EPO applicants' propensity to apply for patents in IPA after they filed in the original jurisdiction. If anything, there appears to be a negative impact of the decisions on the propensity of EPO patent applicants with CII-PSM-likely-adverse invention to subsequently file at IPA. However, the magnitude of the impact, a reduction in the probability of applying by an average of 0.3 percentage points (for USPTO applicants) or 1.7 percentage points (for EPO applicants), is small compared to the 5% to 13% average propensity for subsequent filing at IPA.[7]

Propensity of past IPA CII applicants to apply for new CII patents at IPA

We now investigate the impact of the 2014 court decisions on the patent filing propensity of past IPA applicants. For this, we estimate a modified equation (4) as follows:

$$y_{jkt} = \beta_0 + \beta_1 Treated_{jk} + \beta_2 Post2014_t + \beta_3 Treated_{jk} \times \text{Post-2014} + \varepsilon_{jkt} \quad (5)$$

where, as in equation (4), j indexes applicant, k indicates IPA as the filing office, and t indexes the filing year. The equation is modified such that the dependent variable, $\mathrm{y}_{\mathrm{ijk}}$, is a binary variable equal to 1 if an applicant who previously filed a CII application at IPA prior to 2014 files a subsequent CII application at IPA post-2014. In the above equation, $\mathrm{Post2014}_{\mathrm{t}}=1$ "if filing year " $\mathrm{t}>2014$ and 0 otherwise. In other words, $\mathrm{Post2014}_{\mathrm{t}}$ indicates the treatment years.

As in the case of equation (4), the main parameter of interest in equation (5) is provided by the parameter of the interaction term $\mathrm{Treated}_{\mathrm{jk}} \times \text{Post-2014}$, namely β_3. In this case, $\beta_3<0$ could mean three different possibilities with respect to the impact of the 2014 court decisions: (i) a decrease in the propensity of CII innovation, (ii) a decrease in the propensity to apply for CII patent application (even if there is no decrease in the propensity of CII innovation), or (iii) a combined decrease in the propensities for CII innovation and for filing CII patent application.

Strictly speaking, the setup in equation (5) cannot identify the above three possible interpretations. However, let us further define the treatment groups (indicated by $\mathrm{Treated}_{\mathrm{jk}}=1$) in terms of 2 distinct subsets of CII applicants:[8]

1. $\mathrm{Treated}_{\mathrm{jk}}=1$ for all IPA applicants j who have ever filed for CII patent applications at IPA prior to 2014.
2. $\mathrm{Treated}_{\mathrm{jk}}=1$ for all IPA applicants j who have ever filed for CII patent applications at IPA prior to 2014 and have at least 1 IPA patent application (regardless of CII classification status) after 2014.

As defined above, the second definition of $\mathrm{Treated}_{\mathrm{jk}}=1$ could indicate whether the estimated impact of the 2014 court decisions can be interpreted as the impact on the propensity of producing a CII invention or the impact on propensity of filing for CII patent protection (given a CII invention has been produced). The intuition is as follows. If the 2014 court decision negatively affect inventor behaviour, then we will see this as a decrease in patent application filing. However, this decrease could be caused by a lower rate of innovation or a lower propensity to file for patent application (even if the rate of innovation is unchanged). The second treated $\mathrm{Treated}_{\mathrm{jk}}=1$ group definition above adds the condition "have at least 1 IPA patent application (regardless of CII classification status) after 2014". This is to control for the "rate of innovation is unchanged". If $\beta_3>0$ for this subset of the treated group, then we may infer there is unlikely a change in CII inventor to file for CII patent application post-2014. This is because a positive coefficient means if the CII inventor has an invention he or she will be more likely to file it as a CII patent application. In contrast, if $\beta_3<0$, we have an indication that the propensity to file for patent (and not the propensity to innovate) is negatively impacted. If we know that the underlying invention of the condition "have at least1 IPA patent application (regardless of CII classification status) after 2014" is a CII invention, then we can be more confident to conclude that there is a substitution away from filing a CII patent. However, if the underlying invention is non-CII, then it could mean the rate of CII innovation has decreased (given that the patent applicant has CII patent application pre-2014).

As before, we estimate using the 2001–2020 and 2010–2019 sample periods separately. The latter accounts for possible data truncation and the low number of CII patent applications filed at IPA prior to 2010. The analysis is conducted separately with a focus on (a) prior applicants of CII applications filing subsequent CII applications, and (b) prior applicants of CII-PSM-likely-adverse applications filing subsequent CII-PSM-likely-adverse applications. The results of the regressions are summarised in Table 12.

Table 12 DID regression estimates of IPA applicants' probability of applying for CII patents

	Model 1A	Model 1B	Model 2A	Model 2B
Treated group:	Pre-2014 CII applicants	Pre-2014 CII-PSM-likely-adverse applicants	Pre-2014 CII applicants who also filed for any patent post-2014	Pre-2014 CII-PSM-likely-adverse applicants who also filed for any patent post-2014
Control group:	Pre-2014 non-CII applicants	Pre-2014 non-CII applicants	Pre-2014 non-CII applicants	Pre-2014 non-CII applicants
Sample: 2001-20				
Post-2014	0.036***	0.036***	0.081***	0.081***
Treated	0.116***	0.133***	0.217***	0.279***
Post-2014 x Treated	-0.098***	-0.098***	0.000	0.058***
Sample size	2,138,780	1,734,480	874,680	795,360
Adj. R-square	0.052	0.039	0.120	0.090
Sample: 2010-19				
Post-2014	0.051***	0.051***	0.087***	0.087***
Treated	0.282***	0.292***	0.399***	0.439***
Post-2014 x Treated	-0.226***	-0.226***	-0.140***	-0.092***
Sample size	629,970	549,160	381,500	353,530
Adj. R-square	0.089	0.044	0.134	0.072

Notes: Coefficient estimates represent the percentage points (1.0 means 100 percentage points) of average marginal change on the probability of applying at IPA. Statistical significance is indicated by */**/*** which mean statistically significant at 10/5/1 per cent significance level. Sample size is based on number of (applicant x filing year) observations.

As shown in the highlighted rows of Table 12 for the 2001-20 sample, past CII patent applicants to IPA (who filed CII patents prior to 2014) are on average 9.8 percentage points less likely to apply for CII patents after 2014 (Model 1A). The negative impact is similar at 9.8 percentage points if we focus on the subsample of applicants who filed CII-PSM-likely-adverse applications (Model 1B). These negative impacts are even larger with percentage point reductions of 22.6 (for both CII-applicants and CII-PSM-likely-adverse applicants) if we restrict the estimating sample period to 2010-19 to account for potential data truncation.

We now focus on the propensity of past applicants who file a subsequent patent after 2014 to file a CII or CII-PSM-likely-adverse application. The results, summarised in Models 2A and 2B, appear to be sensitive to the sample period used. Based on the 2001-20 sample, the estimated coefficients for $\textbf{Post-2014 x Treated}$ is either 0 (Model 2A) or 5.8 percentage point increase (Model 2B). These suggest that pre-2014 CII applicants are unlikely to substitute away from filing for CII patent applications after 2014. In contrast, the estimates based on the 2010-2019 sample period suggest a lower propensity to file for CII (or CII-PSM-likely-adverse) patents following the court decisions. However, the negative estimates from Model 2A and 2B based on the 2010-2019 sample do not provide any clear indicator of the real reason for the lower propensity. These estimates are plausibly consistent with a lower CII innovation output or a higher reluctance to file for CII patent (even if CII innovation output level is maintained). For example, the estimates in Model 2B show that, among patent applicants who filed CII-PSM-likely-adverse applications prior to 2014, and who actually filed for patents after 2014, there was an 9.2 percentage points reduced probability that the post-2014 application was CII-PSM-likely-adverse. This indicates that these applicants filed for Non-CII or CII-PSM-likely-clear patents instead.

Lastly, we note that the overall reduction in the propensity for applying for CII-PSM-likely-adverse patents regardless of patent filing status post 2014 is 22.4 percentage points (Model 1B). Hence, more than half of the reduction (22.6 – 9.8 =12.8) is due to a lack of post-2014 filing at all. Again, this can indicate a lower innovation output. Alternatively, it may suggest a higher reluctance to file for CII-PSM-likely-adverse patents and that the applicants were willing to consider filing for Non-CII or CII-PSM-likely-clear patents instead.

Lastly, we re-estimate equation (5) for each major assignee country (AU, US, EP, JP, CN, KR) to assess how the impact varies across applicants from different regions. The results are summarized in Table 13 in which only the coefficient estimates for $\textbf{Treated}_{jk} \times \textbf{Post-2014}$ are shown for easier comparison across the different applicant countries. Again, data from the 2010-2019 sample period provides the most consistent set of estimates compared to the 2001-2020 sample period due to data truncation problems. Comparing estimates specific for different applicant countries, we see differences in the magnitude of the estimated impact. These differences are relatively small. Nevertheless, the evidence suggests that Australian and Korean applicants are impacted the least.

Table 13 DID regression estimates of IPA applicants' probability of applying for CII patent at IPA post-2014, applicant country subsamples.

	Model 1A	Model 1B	Model 2A	Model 2B
Treated group:	Pre-2014 CII applicants	Pre-2014 CII-PSM-likely-adverse applicants	Pre-2014 CII applicants who also filed for any patent post-2014	Pre-2014 CII-PSM-likely-adverse applicants who also filed for any patent post-2014
Control group:	Pre-2014 non-CII applicants	Pre-2014 non-CII applicants	Pre-2014 non-CII applicants	Pre-2014 non-CII applicants
Sample: 2001-20				
Post-2014 x Treated				
AU	-0.091***	-0.087***	0.016***	0.075***
US	-0.108***	-0.112***	-0.008***	0.029***
EP	-0.101***	-0.117***	-0.032***	-0.031***
JP	-0.092***	-0.120***	-0.039***	-0.071***
KR	-0.101***	-0.073***	-0.031***	0.063***
CN	-0.098***	-0.080***	0.025***	0.260***
Sample: 2010-19				
Post-2014 x Treated				
AU	-0.212***	-0.212***	-0.074***	-0.018***
US	-0.232***	-0.241***	-0.149***	-0.125***
EP	-0.234***	-0.232***	-0.167***	-0.122***
JP	-0.221***	-0.227***	-0.183***	-0.150***
KR	-0.239***	-0.157***	-0.126***	-0.031***
CN	-0.228***	-0.191***	-0.105***	-0.073***

Notes: Coefficient estimates represent the percentage points (1.0 means 100 percentage points) of average marginal change on the probability of applying at IPA. Statistical significance is indicated by */**/*** which mean statistically significant at 10/5/1 per cent significance level. Sample size is based on number of (applicant x filing year) observations.

Also, for Australian applicants, the negative impact appears to be more likely to be associated with a reduction in CII innovative activities. Models 1A/B show higher coefficient estimates than Models 2A/B, with the latter based on patent applicants who filed both before and after 2014. Additionally, the positive coefficients in Models 2A/B suggest that pre-2014 CII applicants are more likely to file CII patent applications post-2014 if they have an invention post-2014.

In contrast, for Japanese applicants, substitution away from CII patents seems to be as important as the lower CII innovation output associated with a decreased propensity to apply for CII patents at IPA. The coefficients for Models 2A/B are almost as high as those for Models 1A/B. We leave it to further research to explore when and why the 2014 court decisions—which may have raised the patentability bar for CII patent applications—might result in a decrease in CII innovative activities and/or a shift in patent applicants' strategies for protecting their CII innovations.

Discussion

The main objective of this study is to provide a better understanding of how patenting for computer-implemented inventions (CII) in Australia differs from patenting for other types of inventions and how patenting for CII in Australia differs from patenting for CII in Europe and the United States. For this purpose, we conducted both descriptive and formal econometrics analyses to evaluate differences and potential drivers of these differences in the likelihood of patent applications being granted and the likelihood of applicants from around the world applying for patent protection in Australia. Included in these analyses is an impact evaluation of two 2014 court decisions which are closely related to the patentability of CII by providing new guidelines on the question of what constitutes patentable subject matter (a "manner of manufacture" in Australia):

The empirical analysis is based on a CII patent application database constructed in this research project. It contains a comprehensive set of patent applications filed at IP Australia (IPA), the European Patent Office (EPO), and the United States Patent and Trademark Office (USPTO) from 2001-2020. The total number of patent applications useable for the analysis exceeds 500,000 for IPA, 2.8 million for the EPO, and 10.1 million for the USPTO.[9]

Furthermore, to enable us to identify a "true" cause-and-effect relationship between CII patenting in Australia and the 2 court decisions mentioned earlier, we classified these patent applications into 3 subgroups: "CII-PSM-likely-adverse", "CII-PSM-likely-clear", and "Non-CII". The first group consists of CII patent applications at each office which are highly similar to patent applications which received manner of manufacture objections from IPA patent examiners. The intuition is that if the court decisions in *Alice Corp v CLS Bank International [2014] and Research Affiliates LLC v Commissioner of Patents* [2014] did have any impact then this impact should be the strongest for "CII-PSM-likely-adverse" patent applications and there should be no impact on "Non-CII" patent applications. If our impact estimates are not consistent with this intuition, then it is likely that our impact estimates are biased and possibly misleading.

Also, to ensure that we are comparing apples-to-apples and thus minimising bias, in some of our comparative analysis, for example on the likelihood of grant across the 3 jurisdictions, we restricted the sample to "triplet patent families". These patent families consist of "equivalent patent" applications which were filed at IPA, EPO, and USPTO. In this case, we can attribute any observed difference in their likelihood of grant across the 3 offices to the difference in the offices' patent examination procedures, rather than underlying characteristics of the invention or patent application.

Our main approach is to compare before and after the 2014 court decisions. We employed difference-in-differences (DID) where the change in the average outcome for CII patent applications is compared to the change in the average outcome for non-CII patent applications. The change in the average outcome for non-CII patent applications measures what would have happened had there been no 2014 court decision. In the DID terminology, the CII patent applications are in the treatment group and the non-CII patent applications are in the control group.

The first important finding from the analyses is that there is a significant difference in the likelihood of CII-PSM-likely-adverse applications to be granted across the 3 patent offices.[10] CII-PSM-likely-adverse applications are most likely to be granted by the USPTO, with a grant rate of close to 70%. Compared to USPTO, the grant rate of CII-PSM-likely-adverse applications at IPA is almost 23 per cent lower at 54%. The EPO grant rate of CII-PSM-adverse applications is less than 50 per cent of the USPTO grant rate at around 27%. The inter-office difference in grant rates for CII-PSM-likely-clear and Non-CII is much less significant. This result suggests a relatively high degree of inter-office disharmony in determining the patentability of CII patent applications with claims that are on the margins of patentable subject matter.

We also found evidence that following the decisions in *Research Affiliates* and *Alice* there was a significant reduction in the grant rate of CII-PSM-likely-adverse applications at IPA.[11] The probability of grant for CII-PSM-likely-adverse patent applications at IPA decreased by 11.6 percentage points (approximately 25 per cent reduction in the pre-2014 grant rate). In contrast, the court decisions appear to be associated with higher grant rates at the EPO and USPTO. The absence of observed negative impacts at these offices could be related to various factors which are beyond the scope of this research to identify.

To assess the impact of *Research Affiliates* and *Alice* on the propensity of applicants to file for CII patent applications at IPA, we also conduct a before and after comparison using the DID method. In this case, we set pre-2014 CII applicants as the treatment group. This group consists of patent applicants who have filed at least1 CII patent application at IPA prior to 2014. We ask, how likely is a past CII patent applicant at IPA to apply for a CII patent after 2014. As before, we need to normalise this before-and-after change by a control group. In this case, our control group consists of past non-CII applicants (that is, all applicants who filed non-CII patent applications at IPA prior to 2014).

From the DID analysis, we found past applicants for CII (or CII-PSM-likely-adverse) patents at IPA were significantly (statistically and in magnitude) less likely to apply for CII (or CII-PSM-likely-adverse) applications after the 2014 court decisions. On average, the propensity to apply for CII-PSM-likely-adverse applications at IPA decreased by as much as 22.4 percentage points.

We investigated whether the decrease in the propensity to apply for CII-PSM-likely-adverse patents was because there were fewer patented inventions per se (that is, lower rate of patented innovation) or because the owners of inventions were filing their applications in different categories (for example, as non-CII patent applications or as CII-PSM-likely-clear). To do this, we note that a lower number of CII-PSM-likely-adverse patent applications can be caused by:

1. Applicants in the treatment group not having any invention to file for patent protection post-2014 or not seeking patent protection at all, or
2. Applicants in the treatment group filing for patent protection post-2014 but not filing the invention as a CII patent.

We divided our treatment group into 2 distinct treatment groups according to the above 2 possible reasons. We conducted 2 DID analyses using each of these newly defined treatment groups. We interpret the negative effect for the treatment group defined by reason (1) as evidence that there is a lower number, on average, of CII patented inventions post-2014. In contrast, a negative effect for the treatment group defined by reason (2) cannot be interpreted as a reduced level of patented innovation. Instead, it indicates that when they apply for patents after 2014, the pre-2014 CII applicants are on average more likely to file for non-CII patent applications.[12] Furthermore, a positive effect for the treatment group defined by (2) would negate the possibility that the owners of post-2014 CII inventions may file their applications in different categories.

We found, based on the treatment group defined by reason (2), the 2014 *Alice* and *Research Affiliates* court decisions decreased the propensity of applicants to file CII-PSM-likely-adverse applications at IPA by 9.2 percentage points. Previously we found a 22.6 percentage points reduction in the propensity of applicants to file CII-PSM-likely-adverse applications at IPA, focused on the treatment group defined by reason (1). We conclude that slightly more than half ((22.6 – 9.2)/22.6) of the negative impact of *Alice* and *Research Affiliates* on the propensity of applicants to file at IPA is due to decreased CII innovation and changes in the patenting strategy (that is, patent applicants filing their invention as non-CII or CII-PSM-clear or no patent filing at all).

Lastly, we also assessed the impact of *Alice* and *Research Affiliates* on CII patent propensity for applicants to IPA. To this end, we looked at whether CII patent applicants who filed for patent protection at USPTO and the EPO file equivalent patents at IPA. Note that in this case, a negative effect, if any, cannot be interpreted as 'lower innovation'; instead, it is clearly an effect on the patenting strategy. Approximately 3% of CII-PSM-likely-adverse patent applications filed at the USPTO were subsequently filed at IPA. This compares to an overall follow-up rate at IPA for USPTO applications of 5%. Hence, it appears that USPTO applicants for CII-PSM-likely-adverse patents are not as likely to apply for patent applications at IPA as the average USPTO applicant. The follow-up rate for CII-PSM-likely-adverse applications filed at the EPO is significantly higher at 15% and there is no difference in EPO follow-up rate between CII-PSM-likely-adverse and Non-CII patents.

We then compare the follow-up propensity before-and-after the 2014 changes using the same DID method as above. We found that the effect is positive for USPTO and negative for the EPO. However, the magnitude of the estimates is relatively small compared to the baseline follow-up rates provided above.[14] Hence, the *Alice* and *Research Affiliates* decisions do not appear to have changed the patenting strategy of applicants who file CII-PSM-likely-adverse patents at the USPTO and EPO to file associated applications at IPA.

5 Appendix

Data sources and ML feature generation

Data Sources

European Patent Office

European Patent Office (EPO) data was extracted from EP Register Extensible Markup Language (XML) files. However, we found that the EP register does not appear to contain all EPO patent applications when compared to the list of EP patent applications within the Google Public Patent Database in Google's BigQuery Server and the online Google Patents database (https://patents.google.com/). As a result, our list of EPO patent applications is derived from both sources which are not fully-overlapping. More than half of the complete set of text (title, abstract, and claims) of EPO patent applications analysed in this report were extracted from Google Patents.

United States Patent Office

The United States Patent and Trademark Office (USPTO) data are obtained from several sources: PatentsView (https://patentsview.org/) which provide complete bibliographic and text data; USPTO (PatEx), which provides complete patent examination historical data; and Google patent databases, including Google Patents and Google BigQuery's Google Public Patent Database, and Google Research Patent Database.

IP Australia

Data from IP Australia (IPA) are obtained from IPA's IPRAPID, Application Programming Interface (API) for accessing the claims text, Google Patents, and Google BigQuery's. IPA's archives are currently available as PDF files. For approximately 60,000 patents filed through the Patent Cooperation Treaty, abstract data was not available in either source. For those patents, we merged abstract data from the equivalent family application within the USPTO or EPO, with preference being given to the USPTO patent application.

Feature Generation

Before applying ML assessment to text-based data, it is necessary to convert the unstructured texts into suitable feature vectors. We follow the approach demonstrated in Abood and Feltenberger (2018), also used by Choi et al. (2019), Alderucci et al. (2020), and Gizcy et al. (2022).

We first apply standard text cleaning and preprocessing methodologies to clean and stem input texts. We then use the word2vec model (Mikolov et al, 2013) to generate models of the relevant patent text corpora. Developed by Google researchers, word2vec uses neural networks to generate vector embeddings of text, and has been shown to capture the nuances of semantics in natural language. When trained on natural language, this algorithm produces a multidimensional vector space model of the input language corpus, with each unique word assigned its own vector. Subsequent texts may then be parameterised to vector embeddings relative to this language model.

We use this model to produce separate language models for the corpora of patent application titles, abstracts, and claims across our Australian, EPO and USPTO data. We exclude from these corpora any texts associated with applications which have previously been excluded based on IPC (above). However, we include both keyword-matched and non-keyword-matched texts, as well as those associated with our training set. With language modelling complete, we vectorise the titles, abstracts, and claims texts of the training set data, and of the potential-CII applications for which we wish to obtain a ML label prediction. For each application, this produces 3 300-element vectors parameterising title, abstract and claims texts. These are the input feature vectors to the ML classification discussed in the main text.

ML Model Estimation

With the generated features and the labelled dataset (CII vs non-CII patents), the development of the ML model will: implement various supervised learning algorithms employed in this report; iterate through each feature; find the parameters that minimise the loss function; and then repeat the process for the next feature. This iterative process is due to an intractability issue of trying to optimise all branches simultaneously. This could be analogous to optimising solutions finding local rather than global minimums. Therefore, to train the model, we minimise an objective function:

$$\mathrm{obj}(\theta)=\mathrm{L}(\theta)+\Omega(\theta) \quad \text{(A1)}$$

where $\mathrm{L}(\theta)$ is a training loss function such as the mean squared error and $\Omega(\theta)$ is a regularisation term to help prevent overfitting.

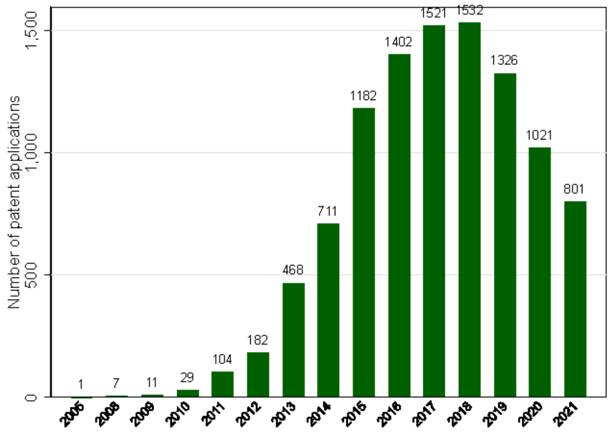
Various supervised learning algorithms summarised below, have their own strengths and weaknesses. They were implemented and the model with the best predictive performance will be used to refine the 'raw' CII patent application database:

a. Logistic Regression: a binary classification algorithm based on the logistic function as the training loss function in the objective function to be optimized.
b. Random Forest Classifier: a technique which incorporate randomness into bagging approach of decision tree model. The bagging (bootstrapping plus averaging) is a technique to improves model prediction performance by lowering error variance, which involves bootstrapping (repeated sampling of the training) followed with averaging across the independently bootstrapped sample.
c. XGB Classifier. eXtreme Gradient Boosting. Extra Trees Regression (XTR) deploys several trees for the same problem and generates a mean of all the trees that reflects the inclusion of all observations. It then maximises the quality of the predictive outputs. That is, this method implements a meta-estimator that fits and averages some randomised trees to control over-fitting.
d. Light Gradient-Boosting Machine (LGBM) Classifier scans all data instances to estimate the "gain", measured in terms of the reduction in the sum of squared errors, from all possible split points. Instead of changing weights for every incorrectly predicted observation at every iteration like other methods. LightGBM tries to fit the new predictor to the errors made by the previous predictor. It splits the tree level-wise, unlike eXtreme Gradient Boosting (XGB Classifier) algorithms which split the tree leaf-wise. The latter can reduce more loss than the former and can potentially lead to better prediction accuracy.
e. Multi-layer Perceptron Classifier (MLPC) is different from the other types of ML methods employed as it is based on an Artificial Neural Network (ANN). It attempts to model how biological brains can be used to solve computational tasks like predictive modelling. The capacity to predict is achieved through a multi-layered structure driven by an "Artificial Neuron" (Kuncheva, 2014).

Based on the predictive performance metric which considers accuracy, our preferred ML model is the one based on the LGBM classifier.

Figures

Figure A1 Count of CII-PSM-adverse (Actual number of CII patent applications which received IP Australia patentable subject matter objections), 2005-21.



Notes: Data represent all CII patent applications filed at IP Australia in 2005-21 which have received patentable subject matter objections from IP Australia patent examiners.

Tables

Table A1 | Number of patent applications, IPA/EPO/USPTO, 2001-20.

Filing Year	IPA	EPO	USPTO	Total
2001	22,740	117,309	218,691	358,740
2002	22,592	116,023	245,982	384,597
2003	21,646	120,404	293,214	435,264
2004	22,870	126,831	301,493	451,194
2005	23,900	134,272	307,798	465,970
2006	25,587	139,012	323,545	488,144
2007	26,828	138,352	327,728	492,908
2008	26,629	136,504	316,439	479,572
2009	23,731	130,187	295,912	449,830
2010	24,925	135,302	307,735	467,962
2011	25,598	140,405	331,981	497,984
2012	26,548	144,130	353,857	524,535
2013	29,832	147,678	373,573	551,083
2014	26,068	151,527	380,385	557,980
2015	28,725	150,758	379,777	559,260
2016	28,493	154,225	380,893	563,611
2017	29,015	159,359	389,386	577,760
2018	30,004	162,121	392,338	584,463
2019	29,815	165,867	416,777	612,459
2020	29,333	169,443	403,524	602,300
Total	524,879	2,839,709	6,741,028	10,105,616

Notes: Data represent all patent applications filed within each jurisdiction which we have access to the full set of text data for the title, abstract, and claims. Consequently, the count of patent applications may differ from the official count of patent applications provided by each patent office statistics.

Table A2 | Number of patent applications by CII group, IPA, 2001-20.

Filing Year	CII-PSM-likely-clear	CII-PSM-likely-adverse	Non-CII	Total
2001	4,109	0	18,631	22,740
2002	6,614	92	15,886	22,592
2003	6,298	356	14,992	21,646
2004	6,496	615	15,759	22,870
2005	6,466	850	16,584	23,900
2006	6,621	902	18,064	25,587
2007	6,868	1,168	18,792	26,828
2008	6,581	1,347	18,701	26,629
2009	5,947	1,197	16,587	23,731
2010	6,291	1,240	17,394	24,925
2011	6,211	1,418	17,969	25,598
2012	6,718	1,757	18,073	26,548
2013	7,814	1,971	20,047	29,832
2014	6,945	1,977	17,146	26,068
2015	7,736	2,489	18,500	28,725
2016	7,601	2,738	18,154	28,493
2017	8,001	2,648	18,366	29,015
2018	8,640	2,914	18,450	30,004
2019	8,547	2,764	18,504	29,815
2020	8,723	2,411	18,199	29,333
Total	139,227	30,854	354,789	524,879
Total share (%)	26.5	5.9	67.6	100.0

Notes: Data represent all patent applications filed within each jurisdiction which we have access to the full set of text data for the title, abstract, and claims. "CII-PSM-likely-adverse" are patent applications ML predicts IPA examiners would raise an objection to on the grounds of lack of patentable subject matter. "CII-PSM-likely-clear" are patent applications ML predicts IPA examiners would not object to on the grounds of lack of patentable subject matter. "Non-CII" patents are patent applications which do not have any matching keywords listed in Table 1 in the main text and/or are those in the excluded list of IPC codes listed in Table 2 in the main text.

Table A3 | Number of patent applications by CII group, EPO, 2001-20.

Filing Year	CII-PSM-likely-clear	CII-PSM-likely-adverse	Non-CII	Total
2001	41,712	1,924	73,673	117,309
2002	41,125	1,892	73,006	116,023
2003	42,971	1,751	75,682	120,404
2004	44,632	1,442	80,757	126,831
2005	47,458	1,768	85,046	134,272
2006	49,553	2,304	87,155	139,012
2007	49,011	2,496	86,845	138,352
2008	48,644	2,776	85,084	136,504
2009	45,745	2,822	81,620	130,187
2010	47,839	3,217	84,246	135,302
2011	49,905	4,047	86,453	140,405
2012	51,781	4,960	87,389	144,130
2013	53,768	6,250	87,660	147,678
2014	54,756	7,687	89,084	151,527
2015	54,940	8,992	86,826	150,758
2016	56,490	8,973	88,762	154,225
2017	60,802	9,579	88,978	159,359
2018	64,137	10,625	87,359	162,121
2019	66,747	11,652	87,468	165,867
2020	70,626	12,457	86,360	169,443
Total	1,042,642	107,614	1,689,453	2,839,709
Total share (%)	36.7	3.8	59.5	100.0

Notes: Data represent all patent applications filed within each jurisdiction which we have access to the full set of text data for the title, abstract, and claims. "CII-PSM-likely-adverse" are patent applications ML predicts IPA examiners would raise an objection to on the grounds of lack of patentable subject matter. "CII-PSM-likely-clear" are patent applications ML predicts IPA examiners would not object to on the grounds of lack of patentable subject matter. "Non-CII" patents are patent applications which do not have any matching keywords listed in Table 1 in the main text and/or are those in the excluded list of IPC codes listed in Table 2 in the main text.

Table A4 | Number of patent applications by CII group, USPTO, 2001-20.

Filing Year	CII-PSM-likely-clear	CII-PSM-likely-adverse	Non-CII	Total
2001	89,745	8,698	120,248	218,691
2002	98,311	8,142	139,529	245,982
2003	115,329	9,460	168,425	293,214
2004	122,432	11,139	167,922	301,493
2005	126,125	13,366	168,307	307,798
2006	133,126	16,437	173,982	323,545
2007	134,098	19,469	174,161	327,728
2008	129,525	20,853	166,061	316,439
2009	119,984	19,341	156,587	295,912
2010	122,092	21,290	164,353	307,735
2011	129,705	26,367	175,909	331,981
2012	137,486	33,504	182,867	353,857
2013	141,615	37,313	194,645	373,573
2014	145,802	41,727	192,856	380,385
2015	147,248	42,598	189,931	379,777
2016	149,416	43,271	188,206	380,893
2017	154,223	45,175	189,988	389,386
2018	157,818	48,160	186,360	392,338
2019	169,878	57,516	189,383	416,777
2020	167,969	54,605	180,950	403,524
Total	2,691,927	578,431	3,470,670	6,741,028
Total share (%)	39.9	8.6	51.5	100.0

Notes: Data represent all patent applications filed within each jurisdiction which we have access to the full set of text data for the title, abstract, and claims. “CII-PSM-likely-adverse” are patent applications ML predicts IPA examiners would raise an objection to on the grounds of lack of patentable subject matter. “CII-PSM-likely-clear” are patent applications ML predicts IPA examiners would not object to on the grounds of lack of patentable subject matter. “Non-CII” patents are patent applications which do not have any matching keywords listed in Table 1 in the main text and/or are those in the excluded list of IPC codes listed in Table 2 in the main text.

Table A5 | Number of patent applications by field of technology and CII group, IPA, 2001-20.

WIPO field of technology	CII-PSM-likely-clear	CII-PSM-likely-adverse	Non-CII	Total
IT methods for mgmt	796	7,838	1,661	10,295
Computer tech	9,771	7,547	3,567	20,885
Control	5,246	4,483	2,171	11,900
Furniture, games	3,145	3,122	8,968	15,235
Digital comm	9,201	2,442	1,685	13,328
Measurement	13,593	1,826	6,760	22,179
Telecomm	7,127	845	2,555	10,527
Med tech	18,861	825	42,303	61,989
Audio-vis tech	5,085	437	2,437	7,959
Elec mach appar engy	6,612	399	10,655	17,666
Transport	3,301	195	8,929	12,425
Civil engr	4,372	186	18,996	23,554
Handling	2,932	146	13,663	16,741
Other spec mach	3,480	106	9,788	13,374
Biotech	10,767	86	32,844	43,697
Analysis of bio mats	5,884	80	5,739	11,703
Thermal proc apar	1,682	40	4,210	5,932
Other cons good	1,630	32	6,576	8,238
Engines pumps turb	1,991	28	5,554	7,573
Env tech	1,209	25	4,186	5,420
Chem engr	2,482	24	10,744	13,250
Mech ele	1,256	19	7,964	9,239
Basic comm proc	667	18	219	904
Food chem	1,300	18	8,285	9,603
Pharmaceuticals	3,237	17	35,731	38,985
Textile paper mach	1,247	16	3,637	4,900
Machine tools	1,404	14	5,949	7,367
Basic mat chem	1,820	12	16,414	18,246
Optics	1,223	11	2,916	4,150
Organic fine chem	4,488	6	44,090	48,584
Surface tech/coat	808	6	5,370	6,184
Semiconductors	552	2	1,306	1,860
Macromol chem poly	806	1	7,417	8,224
Mat metallurgy	1,087	1	8,469	9,557
Micro-struc nanotech	162	1	248	411
N/A	3	0	2,792	2,795
Total share (%)	26.5	5.9	67.6	100.0

Notes: Data represent all patent applications filed within each jurisdiction which we have access to the full set of text data for the title, abstract, and claims. “CII-PSM-likely-adverse” are patent applications ML predicts IPA examiners would raise an objection to on the grounds of lack of patentable subject matter. “CII-PSM-likely-clear” are patent applications ML predicts IPA examiners would not object to on the grounds of lack of patentable subject matter. “Non-CII” patents are patent applications which do not have any matching keywords listed in Table 1 in the main text and/or are those in the excluded list of IPC codes listed in Table 2 in the main text. WIPO field of technology is based on the first listed IPC code (for EPO and USPTO) and the WIPO field id in IP Australia’s IPRAPID database.

Table A6 | Number of patent applications by field of technology and CII group, EPO, 2001-20.

WIPO field of technology	CII-PSM-likely-clear	CII-PSM-likely-adverse	Non-CII	Total
Computer tech	119,839	36,143	29,000	184,982
IT methods for mgmt	4,281	22,421	7,174	33,876
Digital comm	156,860	15,991	22,492	46,453
Control	29,924	9,863	6,666	195,343
Measurement	84,437	5,239	39,770	52,777
Med tech	77,882	5,205	119,129	129,446
Telecomm	60,239	2,428	18,288	80,955
Transport	43,248	1,951	94,503	202,216
Audio-vis tech	57,262	1,758	21,661	80,681
Furniture, games	12,469	1,647	38,661	183,387
Elec mach appar engy	61,354	1,426	120,607	79,374
Handling	18,109	682	59,333	139,702
Civil engr	13,573	374	65,427	78,124
Other spec mach	19,968	353	70,012	90,333
Engines pumps turb	22,469	309	69,658	25,657
Other cons good	15,119	302	44,877	89,811
Thermal proc apar	12,259	252	33,785	46,296
Optics	27,937	229	43,553	60,298
Biotech	25,744	174	63,893	63,456
Analysis of bio mats	13,838	154	11,665	92,436
N/A	14,493	98	15,051	52,415
Chem engr	11,803	87	51,566	29,309
Machine tools	15,694	86	48,772	84,546
Env tech	8,480	77	24,124	21,790
Basic comm proc	15,525	69	6,196	32,681
Textile paper mach	13,579	61	38,775	71,719
Semiconductors	24,578	49	36,754	64,552
Food chem	3,353	38	25,918	73,070
Mech ele	11,854	36	72,656	137,805
Pharmaceuticals	14,452	26	123,327	74,265
Basic mat chem	7,165	24	65,881	40,240
Mat metallurgy	6,233	21	43,063	49,317
Organic fine chem	6,280	18	67,967	61,381
Surface tech/coat	5,636	11	34,593	57,413
Micro-struc nanotech	1,337	7	2,617	3,961
Macromol chem poly	5,369	5	52,039	29,642
Total share (%)	36.7	3.8	59.5	100.0

Notes: Data represent all patent applications filed within each jurisdiction which we have access to the full set of text data for the title, abstract, and claims. “CII-PSM-likely-adverse” are patent applications ML predicts IPA examiners would raise an objection to on the grounds of lack of patentable subject matter. “CII-PSM-likely-clear” are patent applications ML predicts IPA examiners would not object to on the grounds of lack of patentable subject matter. “Non-CII” patents are patent applications which do not have any matching keywords listed in Table 1 in the main text and/or are those in the excluded list of IPC codes listed in Table 2 in the main text. WIPO field of technology is based on the first listed IPC code (for EPO and USPTO) and the WIPO field id in IP Australia’s IPRAPID database.

Table A7 | Number of patent applications by fields of technology and CII group, USPTO, 2001-20.

WIPO field of technology	CII-PSM-likely-clear	CII-PSM-likely-adverse	Non-CII	Total
WIPO field of technology	CII-PSM-likely-clear	CII-PSM-likely-adverse	Non-CII	Total
Computer tech	435,547	192,550	127,232	755,329
IT methods for mgmt	11,634	132,851	26,394	170,879
Digital comm	391,989	114,810	54,205	117,888
Control	56,034	45,737	16,117	561,004
Med tech	190,624	23,265	260,783	139,798
Measurement	190,693	15,584	79,818	286,095
Telecomm	147,460	14,072	43,515	205,047
Furniture, games	27,375	12,066	100,357	474,672
Audio-vis tech	209,048	6,453	82,844	298,345
Transport	84,488	6,234	153,938	448,331
Elec mach appar engy	160,248	4,539	283,544	136,288
N/A	31,128	1,525	22,566	244,660
Handling	26,758	1,377	90,917	119,052
Thermal proc apar	19,469	1,150	43,228	157,284
Civil engr	27,447	1,101	107,740	42,822
Optics	107,587	1,023	163,120	145,317
Other spec mach	33,359	850	123,075	63,847
Other cons good	22,489	790	82,892	106,171
Engines pumps turb	43,277	634	110,367	118,028
Basic comm proc	57,818	322	25,735	154,278
Analysis of bio mats	22,247	244	20,331	89,100
Chem engr	21,928	225	95,875	42,754
Semiconductors	145,343	166	180,307	138,504
Env tech	15,365	136	39,975	83,875
Biotech	41,778	123	103,416	55,476
Machine tools	24,428	119	83,678	271,730
Textile paper mach	27,865	113	61,122	108,225
Mech ele	21,078	83	117,343	105,107
Food chem	5,086	68	37,600	298,463
Pharmaceuticals	32,859	68	265,536	132,648
Mat metallurgy	10,598	47	73,369	91,480
Basic mat chem	10,007	36	95,064	84,014
Surface tech/coat	14,758	36	76,686	325,816
Organic fine chem	10,932	25	121,691	103,160
Macromol chem poly	9,660	9	93,491	10,322
Micro-struc nanotech	3,523	0	6,799	55,219
Total share (%)	39.9	8.6	51.5	100.0

Notes: Data represent all patent applications filed within each jurisdiction which we have access to the full set of text data for the title, abstract, and claims. "CII-PSM-likely-adverse" are patent applications ML predicts IPA examiners would raise an objection to on the grounds of lack of patentable subject matter. "CII-PSM-likely-clear" are patent applications ML predicts IPA examiners would not object to on the grounds of lack of patentable subject matter. "Non-CII" patents are patent applications which do not have any matching keywords listed in Table 1 in the main text and/or are those in the excluded list of IPC codes listed in Table 2 in the main text. WIPO field of technology is based on the first listed IPC code (for EPO and USPTO) and the WIPO field id in IP Australia's IPRAPID database.

Table A8 | Share of CII patent applications by field of technology, IPA/EPO/USPTO, 2001-20.

WIPO field of technology	IPA			EPO			USPTO		
	CII-PSM-likely-adverse	CII-PSM-likely-clear	Non-CII	CII-PSM-likely-adverse	CII-PSM-likely-clear	Non-CII	CII-PSM-likely-adverse	CII-PSM-likely-clear	Non-CII
IT methods for mgmt	76.1	7.7	16.1	66.2	12.6	21.2	77.8	6.8	15.5
Control	37.7	44.1	18.2	21.2	64.4	14.4	38.8	47.5	13.7
Computer tech	36.1	46.8	17.1	19.5	64.8	15.7	25.5	57.7	16.8
Furniture, games	20.5	20.6	58.9	3.1	23.6	73.3	8.6	19.6	71.8
Digital comm	18.3	69.0	12.6	8.2	80.3	11.5	20.5	69.9	9.7
Measurement	8.2	61.3	30.5	4.1	65.2	30.7	5.5	66.7	27.9
Telecomm	8.0	67.7	24.3	3.0	74.4	22.6	6.9	71.9	21.2
Audio-vis tech	5.5	63.9	30.6	2.2	71.0	26.9	2.2	70.1	27.8
Elec mach appar engy	2.3	37.4	60.3	0.8	33.5	65.8	1.0	35.7	63.2
Basic comm proc	2.0	73.8	24.2	0.3	71.3	28.4	0.4	68.9	30.7
Transport	1.6	26.6	71.9	1.4	31.0	67.7	2.6	34.5	62.9
Med tech	1.3	30.4	68.2	2.6	38.5	58.9	4.9	40.2	54.9
Handling	0.9	17.5	81.6	0.9	23.2	76.0	1.2	22.5	76.4
Civil engr	0.8	18.6	80.7	0.5	17.1	82.4	0.8	20.1	79.1
Other spec mach	0.8	26.0	73.2	0.4	22.1	77.5	0.5	21.2	78.3
Analysis of bio mats	0.7	50.3	49.0	0.6	53.9	45.5	0.6	52.0	47.5
Thermal proc apar	0.7	28.4	71.0	0.5	26.5	73.0	1.8	30.5	67.7
Env tech	0.5	22.3	77.2	0.2	26.0	73.8	0.3	27.7	72.1
Other cons good	0.4	19.8	79.8	0.5	25.1	74.4	0.7	21.2	78.1
Engines pumps turb	0.4	26.3	73.3	0.3	24.3	75.4	0.4	28.1	71.5
Textile paper mach	0.3	25.5	74.2	0.1	25.9	74.0	0.1	31.3	68.6
Optics	0.3	29.5	70.3	0.3	39.0	60.7	0.4	39.6	60.0
Micro-struc nanotech	0.2	39.4	60.3	0.2	33.8	66.1	0.0	34.1	65.9
Mech ele	0.2	13.6	86.2	0.0	14.0	85.9	0.1	15.2	84.7
Biotech	0.2	24.6	75.2	0.2	28.7	71.1	0.1	28.8	71.2
Food chem	0.2	13.5	86.3	0.1	11.4	88.4	0.2	11.9	87.9
Machine tools	0.2	19.1	80.8	0.1	24.3	75.6	0.1	22.6	77.3
Chem engr	0.2	18.7	81.1	0.1	18.6	81.3	0.2	18.6	81.2
Semiconductors	0.1	29.7	70.2	0.1	40.0	59.9	0.1	44.6	55.3
Surface tech/coat	0.1	13.1	86.8	0.0	14.0	86.0	0.0	16.1	83.8
Basic mat chem	0.1	10.0	90.0	0.0	9.8	90.2	0.0	9.5	90.4
Pharmaceuticals	0.0	8.3	91.7	0.0	10.5	89.5	0.0	11.0	89.0
Macromol chem poly	0.0	9.8	90.2	0.0	9.4	90.6	0.0	9.4	90.6
Mat metallurgy	0.0	11.4	88.6	0.0	12.6	87.3	0.1	12.6	87.3
Organic fine chem	0.0	9.2	90.8	0.0	8.5	91.5	0.0	8.2	91.7
N/A	0.0	0.1	99.9	0.3	48.9	50.8	2.8	56.4	40.9

Notes: Data represent all patent applications filed within each jurisdiction which we have access to the full set of text data for the title, abstract, and claims. "CII-PSM-likely-adverse" are patent applications ML predicts IPA examiners would raise an objection to on the grounds of lack of patentable subject matter. "CII-PSM-likely-clear" are patent applications ML predicts IPA examiners would not object to on the grounds of lack of patentable subject matter. "Non-CII" patents are patent applications which do not have any matching keywords listed in Table 1 in the main text and/or are those in the excluded list of IPC codes listed in Table 2 in the main text. WIPO field of technology is based on the first listed IPC code (for EPO and USPTO) and the WIPO field id in IP Australia's IPRAPID database.

Table A9 | Average pendency period (in number of years), IPA/EPO/USPTO, 2001-20.

Filing Year	IPA	EPO	USPTO
2001	2.4	6.1	2.9
2002	2.4	6.1	3.2
2003	3.9	6.2	3.6
2004	3.7	6.3	3.8
2005	3.6	6.3	4.0
2006	3.6	6.3	4.1
2007	3.5	6.2	4.0
2008	3.4	6.1	3.9
2009	3.2	6.0	3.7
2010	3.1	5.9	3.4
2011	3.0	5.7	3.2
2012	2.5	5.4	3.1
2013	2.4	5.1	3.0
2014	2.3	4.8	3.0
2015	2.1	4.5	2.9
2016	2.2	4.2	2.8
2017	2.4	3.9	2.7
2018	2.4	3.6	2.6
2019	2.3	3.2	2.4
2020	1.8	2.7	2.1
Total	2.7	5.3	3.1

Notes: Average pendency period is defined as the number of years between grant year and filing year. The averages reflect available data with grant year information and data which represent all patent applications filed within each jurisdiction which we have access to the full set of text data for the title, abstract, and claims.

References

Abood, A. and Feltenberger, D. (2018). "Automated patent landscaping", Artificial Intelligence Law, 26, 103–125. https://doi.org/10.1007/s10506-018-9222-4.

Akikalin, U. U., Caskurlu, T., Hoberg, G. & Phillips, G. M. (2022). "Intelllectual property protection lost and competition: An examination using machine learning." NBER Working Paper 30671.

Andersson, M., Kusetogullari, A., and Wernberg, J. (2021). "Software development and innovation: Exploring the software shift in innovation in Swedish firms", Technological Forecasting & Social Change, 167, 120695, https://doi.org/10.1016/j.techfore.2021.120695.

Baruffaldi, S., van Beuzekom, B., Dernis, H., Harhoff, D., Rao, N., Rosenfeld, D., and M. Squicciarini (2020). "Identifying and measuring developments in artificial intelligence: Making the impossible possible", OECD Science, Technology and Industry Working Papers 2020/05.

Bergstra, J. and Klint, P. (2007). "How to find a Software Patent?", manuscript.

Bessen, J. (2012). "A generation of software patents", Boston University Journal of Science & Technology Law, 18(2), 241–261.

Bessen, J. and Hunt, R. M. (2007). "An empirical look at software patents", Journal of Economics and Management Strategy, 16, 157–189.

Chabchoub, N. and Niosi, J. (2005). "Explaining the propensity to patent computer software", Technovation, 25, 971–978.

Chan, T. H., Bharadwaj, A., and Varadarajan, D. (2023). "Business Method Innovation in U.S. Manufacturing and Trade", Manufacturing & Service Operations Management, 25(1), 50–69. https://doi.org/10.1287/msom.2022.1129.

Eberhardt, M., Fafchamps, M., Helmers, C., and Patnam, M. (2016). "The heterogeneous effect of software patents on expected returns: Evidence from India", Economics Letters, 145, 73–78.

Frietsch, R., Neuhäusler, P., Melullis, K.-J., Rothengatter, O., and Conchi, S. (2015). The economic impacts of computer-implemented inventions at the European Patent Office, 4IP Council and Fraunhofer ISI, ISBN: 978-3-945185-02-5.

Frumkin, J., Pairolero, N. A., Tesfayesus, A. and Toole, A. A. (2024). "Patent eligibility after Alice: Evidence from USPTO patent examination", *Journal of Economics, Management, and Strategy*, DOI: 10.1111/jems.12592.

Giczy, A. V., Pairolero, N. A., Toole, A. A. (2022). "Identifying artificial intelligence (AI) invention: a novel AI patent dataset", The Journal of Technology Transfer, 47, 476–505, https://doi.org/10.1007/s10961-021-09900-2.

Hall, B. H. and MacGarvie, M. (2010). "The private value of software patents", Research Policy, 39, 994–1009.

Kollmann, T. and Palangkaraya, A. (2023). “Raising the Bar Reforms Extension: Measuring the Impact on Relative Patent Scope”, A Report Prepared for IP Australia, Centre for Transformative Innovation, September 2023.

Kollmann, T., Palangkaraya, A., Sarwar, A. and Webster, E. (2023). “Raising the Bar Reforms: Measuring the Impact on Relative Patent Scope”, Final Report for IP Australia, Centre for Transformative Innovation.

Lerner, J., Seru, A., Short, N., & Sun, Y. (2021). “Financial innovation in the 21st century: Evidence from U.S. patents. NBER Working Paper 28980.

Ng, C. Y. (2021). “Whither Singapore’s harbour for patenting computer-implemented inventions?”, Singapore Academy of Law Journal, 33, 870–918.

Neuhäusler, P. and Frietsch, R. (2019). “Computer Implemented Inventions in Europe”, in W. Glänzel, H. F. Moed, U. Schmoch, & M. Thelwall (eds)., Springer Handbook of Science and Technology Indicators, Chapter 41, 1007–1022.

Noel, M. and Schankerman, M. (2013). “Strategic Patenting and Software Innovation”, The Journal of Industrial Economics, LXI (3), 481–520.

Rentocchini, F. (2011). “Sources and characteristics of software patents in the European Union: Some empirical considerations”, Information Economics and Policy, 23, 141–157.

Sherman, B. (2019). “Intangible machines: Patent protection for software in the United States” History of Science 2019, Vol. 57(1) 18–37. DOI: 10.1177/0073275318770781.

Xie, Z. and Miyazaki, K. (2013). “Evaluating the effectiveness of keyword search strategy for patent identification”, World Patent Information, 35, 20–30.

Endnotes

1 I See Appendix, Figure A1 Actual number of CII patent applications which received IPA manner of manufacture objections, 2005-21. Further analysis is required to investigate why the ML model's prediction indicates an earlier starting point for the increase in the share of IPA's "CII-PSM-likely-adverse". For example, see the decision on Invention Pathways Pty Ltd [2010] APO 10 (21 July 2010) http://www8.austlii.edu.au/cgi-bin/viewdoc/au/cases/cth/APO/2010/10.html which has been considered as a manifestation of operational change within IPA with respect to MoM objection.

2 I See www.wipo.int%2Fipstats%2Fen%2Fdocs%2Fipc_technology.xlsx

3I Using filing year to define the treatment period has the benefit of ensuring that all applications filed post-2014 will definitely be "treated" (i.e. subjected to the 2014 court decision). In contrast, if we use filing year post 2013 as the start of the treatment period, some of the applications may have been examined prior to the court decision. Furthermore, using fling year allows us to use the same treatment period definition to estimate the effect of the 2014 court decisions on both trends in patent examination outcome and patent applications. However, the use of filing year does have the disadvantage that some applications filed before 2014 may be subjected to the court decision if their examination occurs after 2014. If there were indeed such patents, then our DID estimate of the impact of the 2014 court decision on examination outcome maybe downward biased. In the extreme, it could be reversed if the impact is strongest on the earlier filed patent applications but examined after 2014. Figure 9A as discussed earlier does suggest that the effect of 2014 court decision may be apparent among IPA patent applications filed before 2014. We will investigate for the importance of the difference ways to define the treatment period when the outcome measure varies in a future study. Our preliminary analysis using IPA examination request year after 2014 to define the treatment period suggests that our estimates are robust with respect to the choice of the timing variable to define the treatment period.

4 I Given that our analysis is conducted at the year level, it is not possible to distinguish the effect of the 2014 Australian High Court decision separately from the effect of the 2014 US Supreme Court decision.

5 I Since the outcome variable is the probability of filing patent application at IPA, the use of post-2014 filing year to define treatment period does not have the potential for downward biased impact estimate as in the case of probability of grant as the outcome variable discussed earlier.

6I As mentioned earlier in the discussion of Table 8, EPO data appeared to have some truncation and other issues related to the identification of patent families, resulting in unreasonably low propensity of subsequent filing at IPA for applications filed outside 2010-2017. To assess whether the use of different sample period affects our inferences of the regression estimates, Table 11 provide 2 sets of estimates based on 2001-20 sample period and 2010-17 sample period.

7 I See Tables 7 and 8.

8 I In both definitions, the control or the untreated group $\mathbf{Treated}_{jk}=\mathbf{0}$ consists of all IP Australia patent applicants who have never filed for CII patent applications prior to 2014.

9 I See Appendix Table A1 Number of patent applications, IPA/EPO/USPTO, 2001-20 for more details. We also note that some of the analyses focused only on a subset of 2010-17 period in order to minimise the effect of data truncation (caused by long pendency period particularly at the EPO) and small sample size in the early period (especially for the case of CII-PSM-adverse at IPA).

10 I Note that there are four possible patent application outcomes: grant, refusal/rejection, withdrawal/abandonment, and pending.

11 I It is not possible in our analysis to disentangle the possible differential effect of "Alice" and "Research Affiliates".

12 I Strictly speaking, for example, we do not know if the post-2014 invention is CII or non-CII invention. If it is non-CII invention, then the negative impact on the second treatment group (defined by reason 2) can be interpreted as evidence of lower CII invention.

13 I In this case, the USPTO and follow-up IPApatent applications form a patent family.

14 I The impact estimates on the propensity of follow up CII-PSM-adverse application at IPA are 0.3 per centage points for USPTO and -0.6 percentage points for EPO.

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