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D4.1 Private Returns to Innovation

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Private Returns to Innovation (WATSON Project Deliverable D4.1)

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Abstract

This document describes the methodology used to estimate private returns to innovation. Private return estimates are used as a key input to estimate the external value of innovations and, by extension, the Industrial Strategy Index (IStra-X) reported in Deliverable 4.3. To infer the private return of an innovation, we rely on the extrapolation of estimates described in Kogan et al. (2017) to the relevant population of inventions. To do this, we use information on technological classification, time, geographic location and scope of protection that is available for (nearly) all patented innovations. Results suggest that our extrapolation models—whilst leaving room for improvement—capture a considerable amount of heterogeneity in the private returns to innovation.

1 Introduction

Basic economic theory suggests that marginal private returns from innovation should equal firms' marginal costs of R&D. In other words, the least profitable innovation project a firm is willing to undertake has an expected private return that is equal to its expected R&D investment. Barring market inefficiencies, this implies socially optimal amounts of R&D will be spent, and there is no need for industrial strategy. However, innovations—especially when they are disclosed publicly—might produce value above and beyond the private returns they generate for the innovating firms by 'inspiring' follow-on innovation by others. Knowledge embedded in an innovation can be a 'free' R&D input to others. Such knowledge spillovers clearly represent value to society, but are not taken into account by innovating firms that consider their own private returns. As such, the value created by knowledge spillovers represents a positive externality generated by innovation. The existence of this externality motivates active intervention by governments because it suggests that R&D investments are at socially sub-optimal levels. Indeed, from a societal perspective, the expected value of an R&D investment equals the sum of the private return and the value of the knowledge spillover externality. Therefore, even projects with negative private returns might be worthwhile from a societal perspective as long as they generate sufficient knowledge spillovers. This argument provides an economic justification to government support for innovation and suggests an effective industrial strategy will focus on areas of innovative activity with high expected knowledge spillovers.

Based on this rationale, we estimate the value of knowledge spillovers generated by innovations. We use the network defined by patents (nodes) and patent citations (edges) to uncover knowledge linkages between innovations. Simply put, our methodology suggests that a patented innovation derives a portion of its private returns from knowledge embedded in the patents it

cites.[1] It is exactly this portion of private returns that constitutes the value of the knowledge spillover induced by the cited innovation. As such, being the inspiration for innovations with high private returns suggests having induced a knowledge spillover with a high value. Therefore, estimating the private returns organizations reap from innovation is an important building block to the methodology we propose to measure and evaluate the external value innovations generate through knowledge spillovers.

We measure the private value for a large subset of patents using a new methodology proposed by Kogan et al. (2017). They measure the private value of a patent as the change in the value of the patenting firm's market value at the time when the firm is first granted the patent. The change in firm value is computed relative to the contemporaneous change in the value of a set of control firms that did not receive a patent grant, and is referred to as an abnormal stock return. The main drawback of this approach to measuring the private value of returns is that it provides information only for a relatively small set of US publicly-listed firms' patents. These patents amount to only 2.4% of the relevant population for our purposes. To estimate the private value of non-listed firms' patents, we extrapolate from the listed firms' patent sample computed and made available by Kogan et al. (2017) in order to derive estimates for (nearly) the entire population. In the remainder of the project, these extrapolated values are used as estimates for the private returns to innovation.

This document proceeds as follows. In the next section, we give a more detailed description of the rationale for using stock market reactions to a patent grant to estimate private values. We then turn to a discussion of the extrapolation model(s) used to derive our final private value estimates. The results section describes the distributions of the resulting private returns measure and compares them to the estimates based directly on stock market reactions. It also shows the distribution of private returns across various segments of innovative activity. We conclude with a summary and a discussion of potential future improvements.

2 Methods

2.1 Estimating private returns using stock market reactions

We use the methodology developed in Kogan et al. (2017) to measure the private value of an innovation. In this section, we give an overview of the event study design employed to obtain these estimates, but refer to Kogan et al. (2017) for a more detailed description.

Suppose PV_i captures the monopoly rents from exploiting the innovation patented in i. In the absence of any other news, the stock market reaction to the patent grant event is equal to

$$\Delta W_i = (1 - \pi_i) PV_i, \tag{1}$$

where ΔW_i is equal to the difference of a firm's value before and after the moment patent i is granted. π_i is the ex ante probability of any patent being granted conditional on it being public knowledge that the patent application has been made. This expression reflects the assumption that the market knows the value of patent i prior to granting. Expression (1) allows us to calculate $PV_i = \frac{\Delta W_i}{(1-\pi_i)}$ given an assumption on the ex-ante grant probability. π_i is assumed to be 56% for all patents i, which is the grant rate of US patents between 1991-2001.

This approach to estimating PV_i is subject to the fact that the observed stock market return of any firm might incorporate general movements of the market and unrelated events that might affect stock market returns of the patenting firm. To isolate firm-specific returns that are due

[1] For a more complete and detailed discussion of the methodology used to estimate the value of knowledge spillovers, we refer to deliverable D4.3

to the patent grant, a 'market-adjusted-return model' is used as in Campbell et al. (1997). We specify the firm's idiosyncratic return R_i (i.e. a firm's return around the event minus the return on the market portfolio), as:

$$R_i = v_i + e_i, \tag{2}$$

where v_i is the portion of the return associated to the patent grant event and e_i is the return's component due to unrelated news around the event date. Replacing ΔW_i with the product of the expected value of W_i conditional on the observed R_i and the market capitalization M_i of the firm on the day prior to the events, expression (1) is rewritten as

$$PV_i = (1 - \bar{\pi})^{-1} E[v_i | R_i] M_i. \tag{3}$$

In their preferred specification, Kogan et al. (2017) assume a normal distribution for e_i and a normal distribution truncated at zero for v_i. The variance of e_i, as well as the signal-to-noise ratio (the variance of the distribution of v_i divided by the sum of the variances of v_i and e_i) is estimated from the data (the former is allowed to vary by firm; the latter is assumed constant). These parameter estimates allow to calculate private values for a set of $1,801,879$ patent documents filed at the USPTO.

2.2 Extrapolating to the population

As we are interested in the population of innovations, we extrapolate the private value estimates from stock market reactions to all patents in the data. To do this, we regress the estimated private value on a set of patent characteristics that are plausible predictors of private value. We then fit these models to the relevant population based on the observed characteristics of these patents. Our preferred specification is the following:

$$ln(PV_{i,\tau,a,c,f}) = \beta_0 + \alpha_{\tau,a,c} + \alpha_f + \epsilon_{i,\tau,a,c,f}, \tag{4}$$

where $PV_{i,\tau,a,c,f}$ refers to private values estimates of Kogan et al. (2017). We take the natural logarithm to avoid negative values after extrapolation and to better fit the skewed distribution of private values with a linear model. $\alpha_{\tau,a,c}$ refers to a set of interacted fixed effects for five-year time cohort dummies τ, technological classes a, and inventor country c. We expect that these fixed effects capture a great deal of heterogeneity in private value of innovative activity and, hence, assume they are a relatively good predictor of the private value of an innovation.

To assign innovations to technological classes, we use the International Patent Classification (IPC) system because of its worldwide coverage. This classification system is hierarchical in nature, which means we need to make a decision on the level of aggregation to use. While using lower levels of aggregation will result in a more precise account of the private value of a class, it also decreases the number of innovations we are able to classify, because not each class is present in the sample of patents we have estimates for. We use the second most detailed aggregation level ('IPC main groups') as experimentation, which suggests this level strikes a balance between precision and recall.

Using the same rationale, we use five-year application year windows, based on the first filing of a patent in a family, to construct time cohort dummies. Countries are assigned to patents based on the first inventor to which a country code was assigned within a patent family. If no such assignment exists, the first applicant country is used. If a patent is assigned to multiple countries, a random country is retained. A final predictor in the extrapolation model is α_f and refers to a set of dummies indicating the number of patent applications related to an innovation. An innovation might result in multiple patent applications when the innovator is interested in

obtaining patent protection across different jurisdictions. [2] Because each patent application incurs a cost, more valuable innovations have been argued to result in more patent applications. Therefore, the number of applications associated to an innovation is a (crude) value measure available for each innovation in the population.

Two complications warrant attention here. First, $\alpha_{\tau,a,c}$ does not refer to mutually exclusive categories because many patent documents are assigned to multiple technological classes. To avoid overestimating the importance of classes with many multi-class patents, we construct weights for each level of $\alpha_{\tau,a,c}$ so that the sum of the weights equals the number of distinct innovations for that level. Second, not all groups defined by the fixed effects $\alpha_{\tau,a,c}$ have a stock-market-based estimate and not all innovations are assigned a country and/or technological class. Our approach to estimating PV_i for these patents is to use an alternative model as described in Appendix A.

3 Results

3.1 Extrapolated private returns

In this section, we discuss the results from the extrapolation exercise. On the one hand, we compare the distribution of the stock market based estimates from Kogan et al. (2017) to those obtained after extrapolation to the population of patent families. On the other hand, we explore the correlation between the stock market based estimates and the results from the extrapolation for those patent families for which both types of estimates are available.

As described before, we use publicly available value estimates developed in Kogan et al. (2017) to obtain a reliable measure of the private value of an innovation. The approach yields parameter estimates for 1,801,879 patent documents filed at the USPTO. As these estimates are at the patent level, while our analyses are based on the entire patent family of an innovation, we need to aggregate these patent-specific values to the family level in case multiple patents in this dataset belong to one family. Columns 1 and 2 of Table 1 compare the original distribution to the distribution at the family level and show these distributions are highly similar. Column 3 restricts the sample of patent families to our analysis window. This restriction causes an increase in the mean patent value of about 50 percent, indicating that the private returns to the average innovation have increased over time.

[2] Geographical scope of patent protection is the most important reason one invention results in multiple patent applications. Additionally, one invention might be related to multiple patent applications filed for at one and the same patent authority because of so-called continuing applications (e.g. continuations, continuations-in-part or divisional applications).

Table 1: Comparing distributions of ξ in our sample to Kogan et al (2017)

	(1) ξ Patents	(2) ξ Families	(3) ξ Families (1995-2014)
mean	10.4	10.4	15.4
sd	32.0	32.4	47.3
p1	0.0097	0.0097	0.0074
p5	0.042	0.043	0.032
p10	0.11	0.11	0.078
p25	0.73	0.73	0.39
p50	3.22	3.25	3.85
p75	9.09	9.12	12.6
p90	22.1	22.1	34.1
p95	38.2	38.1	63.4
p99	121.4	121.6	195.8
count	1801879	1715339	646047

Notes: All values are in million CPI adjusted 1982 US dollars. The first column repeats the distribution of ξ reported in Kogan et al. (2017) based on patent documents. The second columns groups patent documents relating to one invention by taking the maximum. This grouping is based on the DOCDB patent family definition employed in the EPO PATSTAT 2018 Spring Edition database. Column 3 restricts the sample of column 2 to patent families with their first application date between 1995 and 2014, the time frame of our analyses.

Table 2: Comparing distributions of PV and ξ

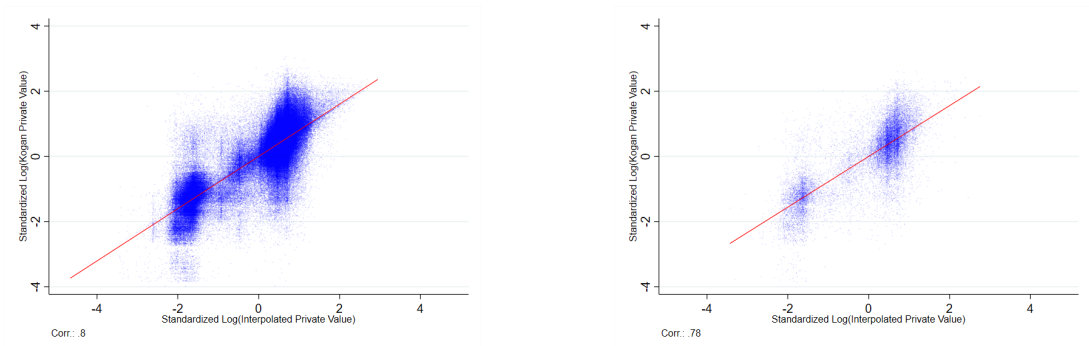
	(1) PV Population	(2) PV 1995-2014	(3) ξ Comparison Sample	(4) PV Comparison Sample
mean	3.58	4.27	15.4	5.99
min	0.000036	0.000036	0.00017	0.00036
p1	0.017	0.015	0.0074	0.048
p5	0.100	0.071	0.032	0.074
p10	0.21	0.14	0.078	0.1
p25	0.57	0.42	0.39	0.67
p50	2.20	2.4	3.85	5.31
p75	4.11	4.62	12.6	8.25
p90	7.03	9.03	34.1	11.8
p95	10.7	14	63.4	15.8
p99	25.1	34.7	196	28.4
max	9079.6	4452.8	3401.8	678.9
count	61868355	27067071	627627	627627

Notes: All values are in million CPI adjusted 1982 US dollars. The first column shows the population distribution of the extrapolated private value estimates PV. Column 2 repeats extrapolated private value estimates for all innovations in our time frame (1995-2014). Column 3 repeats the last column of previous table and shows the distribution of stock-market-based estimates of PV for patent families between 1995 and 2014. Column 4 shows the distribution of PV in the sample of patent families for which we have estimates based on stock market reactions.

Table 2 shows the distribution of extrapolated private values across (our) population of innovations (column 1 and 2), and compares distributions of the stock-market-reaction-based estimates to the extrapolated values (columns 3 and 4). Comparing extrapolated values for the full population to the set of innovations for which we have a stock-market-reaction-based value, we see that that the latter group is on average 40% more valuable. This difference is mainly driven by innovations in the middle of the distribution (between the first and third quartile). Comparing the actual stock-market-reaction-based estimates to extrapolated values shows that the extrapolation decreases both the mean and the variance of the distribution. In other words, extrapolating values using our models of extrapolation—unsurprisingly—moves estimates closer to their mean value. Given the high skew in the value distribution, this pattern naturally translates to the value of the mean through the log-transformation used in the extrapolation.

To further compare the fit between the extrapolation model and stock-market-based private values, figure (1) allows to visually compare the two types of estimates. The left-hand side panel plots the extrapolated against the stock-market-based estimates after log-transforming and z-standardizing for a random sample of 250 000 innovations between 1995 and 2014. The right-hand side plot does the same for a random test sample of 5 percent that was not used for the extrapolation procedure (to avoid this validation test is a result of overfitting). Both figures show a noisy but strongly positive relationship between the extrapolated and stock-market-based values, with a correlation of around 0.8. The correlation between the non-transformed values is lower (around 0.35 for both samples), indicating a more noisy relationship.

Figure 1: Comparing extrapolated to stock-market-based estimates of private value



(a) extrapolation sample

(b) Test sample

Notes: Correlation between private return estimates based on stock market reaction (y-axis) and estimates using the extrapolation approach. Values are log-transformed and z-standardized. Left-hand panel is based on a randomly drawn sample of 250,000 patent families from the sample on which the extrapolation models are based. Right-hand panel is based on a test sample (5% out of a total of 1,715,339 families) that was excluded from the extrapolation exercise to avoid over-fitting when comparing the extrapolation results to the stock-market-based estimates.

3.2 Private returns across innovation segments

3.2.1 All 2005-2014 Innovations

In this section, we compare private return estimates by country and technological field for all innovations for which a patent was filed between 2005 and 2014. Technology field breakdowns are based on a sample of 15,068,373 patent families that are assigned to at least one technological class. The country breakdown is based on a sample of 4,995,619 patent families for which at least one OECD or EU country was assigned, either to the inventor or the applicant on a patent, in

the Spring 2018 version of the EPO PATSTAT database. Figure 2 shows the average estimated private returns by technology field. Technology fields correspond to IPC and CPC[3] classes assigned to patent documents. Table 3 in Appendix B shows the concordance between technology fields and IPC/CPC classes based on patent documents. It is adapted from the concordance scheme developed in Schmoch (2008), mainly by adding a number of technology fields of special (recent) interest, such as 'Artificial Intelligence', '3D Printing' or 'Clean' technologies. Note that these technological fields are not mutually exclusive; one innovation can be assigned to multiple technology fields and vice versa. The x-axis represents the average private returns in a technology field (in million CPI adjusted 1982 dollars). The width of each bar represents the number of innovations in the technological field. Consequently, the area of each bar represents the total estimated private return in the technological field. This estimate (in billion) is also printed next to each field on the y-axis. Colors of the bars correspond to labels for broader technological domains, such as 'Chemistry' or 'Electrical Engineering'. The bar charts for country breakdowns are organized analogously, but colors represent whether a country (denoted by its country code on the y-axis) is part of the EU, OECD or both.

The real potency of the private returns database lies in the flexibility it offers to the user by providing innovation-level estimates for a nearly comprehensive set of (patented) innovations. As such, the crude, aggregate comparisons described here do not exploit the full potential of the database. Still, at least three interesting patterns emerge.

First, there is substantial variation between technologies and countries in terms of private returns to innovation. For technology fields, average private returns range from about 1.5 million to about 12 million dollars per innovation – a range that covers about 50% of the entire distribution of private returns. Even starker is the variation between countries, where average private returns vary between 0.3 and 12 million dollars. This pattern seems to confirm that relevant heterogeneity is captured by our extrapolation models. Indeed, if the variation observed in the private returns distribution would entirely be noisy, such strong contrasts between countries and technologies would be highly unlikely.

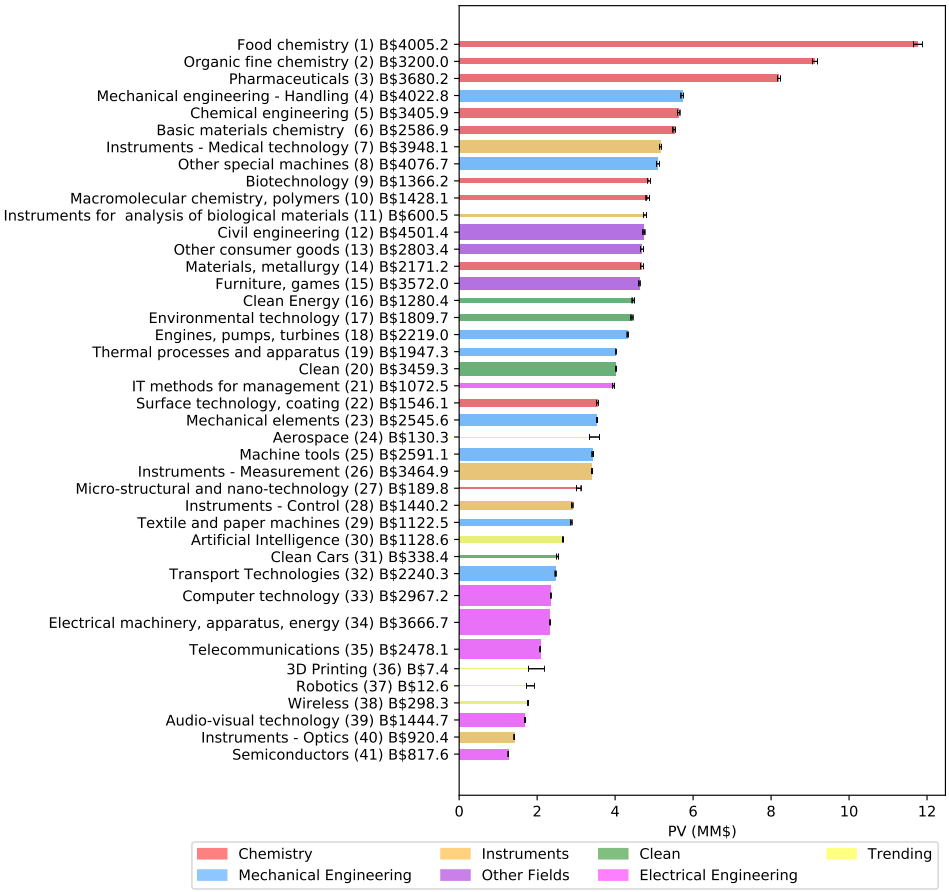
Second, technological fields with high private returns seem to be those fields with high R&D costs per innovation. This pairs with the economic intuition that organizations only pursue R&D projects when the expected returns from the resulting innovation are larger than the costs. For instance, innovation in the pharmaceutical industry is notoriously expensive (see, for instance, DiMasi et al. (2003)), which suggests that the private returns for the average innovation should be relatively high. Fields where the average project is less costly, on the contrary, need relatively low private returns to convince organizations to pursue an innovation idea. The fact that fields such as 'Computer Technology' and 'Artificial Intelligence' have lower average private returns seems to be consistent with this idea. A more speculative interpretation of the technology field ranking could be that fields in which more innovations per product are needed to really increase monopoly power score lower on private returns. Indeed, when a product consists of many, highly coupled components, an innovation pertaining to one of these components only might not suffice to increase margins much. As such, multiple innovations might be needed to increase profits, resulting in lower private returns per innovation in these fields. Examples of such fields could be 'Clean Cars', '3D printing' and 'Audio-visual Technology'.

Third, stark differences between countries exist in terms of private returns to innovation. However, when taking a closer look at the relative advantage of different countries with respect to technological fields (reported in D4.3), we see that these differences are, to a large extent, explained by the fields countries are active in. For instance, Germany's rather low private

[3]'CPC' refers to the Cooperative Patent Classification, which was initiated in 2010 in a joint partnership between the EPO and USPTO in order to harmonize their existing classification scheme. It builds upon and exists next to the IPC classification system and is especially useful for our purposes because it introduces specific classes for 'clean' technologies.

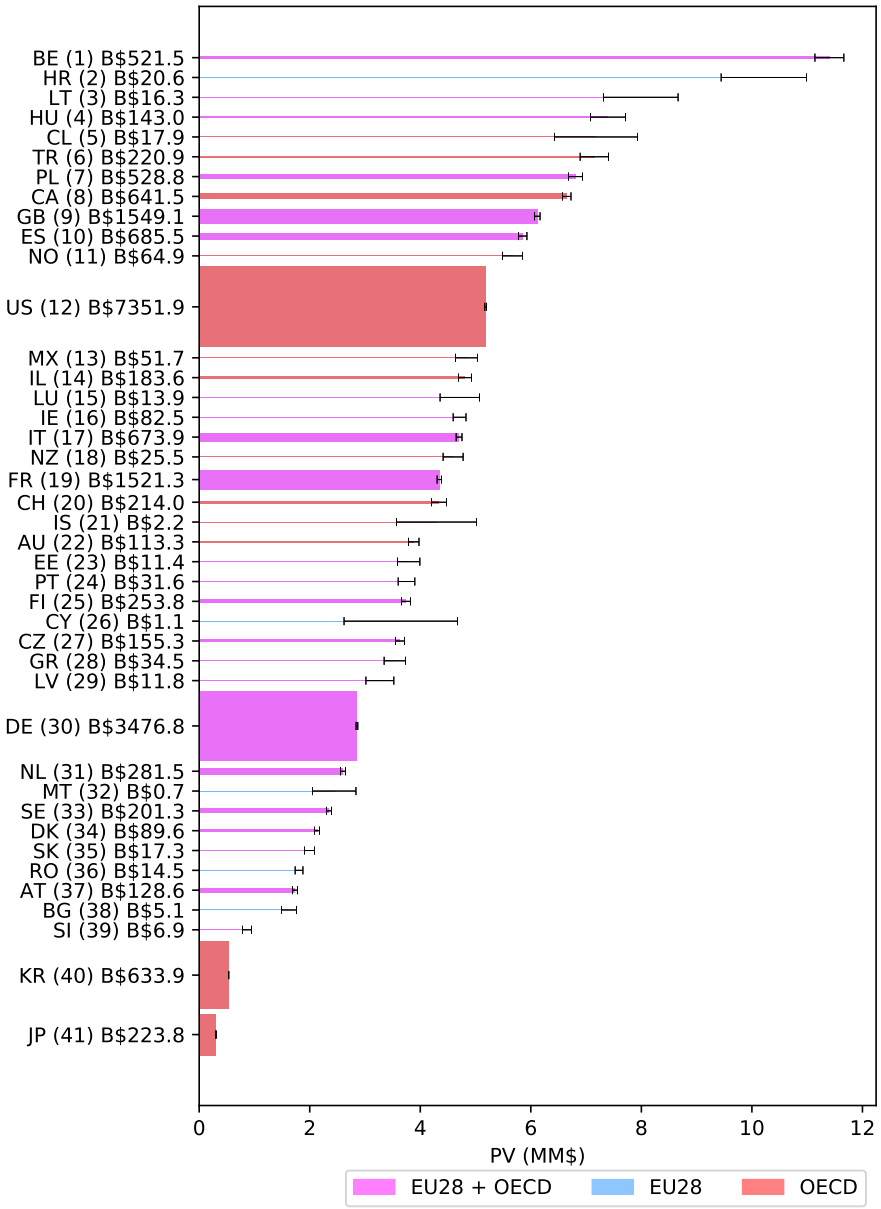
returns seem to be explained by the fact that they have a relatively large presence in technology fields such as 'Transport Technologies' and 'Mechanical Elements', which display low average private returns. Yet, as we observe below, interesting differences between countries persist even when comparing private returns within technology fields across countries. Of course, drawing permanent conclusions from any of these merely descriptive patterns would be incautious, and answering policy questions using these data requires a more in-depth and question-dependent analysis.

Figure 2: Private Returns by Technology - All 2005-2014 Innovations



Notes: Diagram of the average private returns in millions of CPI-adjusted 1982 US dollars (x-axis) by technology field (y-axis). Width of each bar represents the number innovations in the field. Area of each bar (in billions $) represents total private returns in the technology field and is printed next to y-axis labels.

Figure 3: Private Returns by Country - All 2005-2014 Innovations



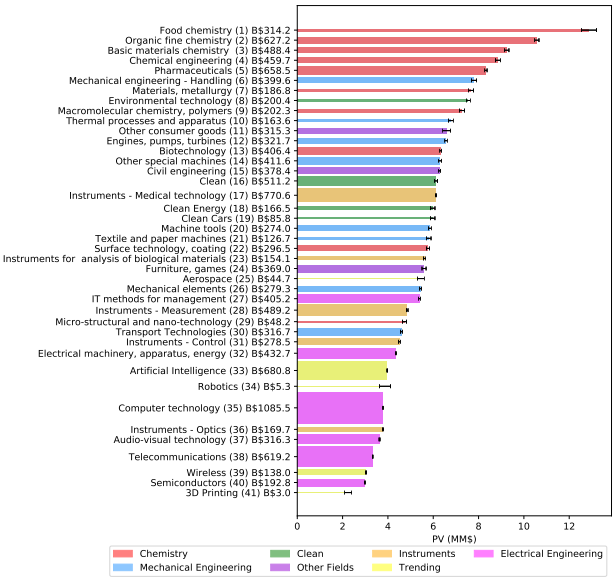
Notes: Diagram of the average private returns in millions of CPI-adjusted 1982 US dollars (x-axis) by country (y-axis). Width of each bar represents the number innovations from a country. Area of each bar (in billions $) represents total private returns in the technology field and is printed next to y-axis labels.

3.2.2 By Country

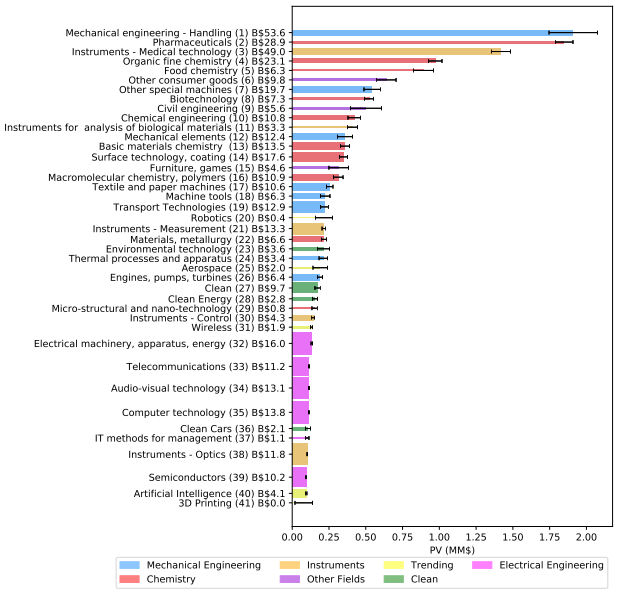
Finally, we break down private returns by category for a number innovation-intensive countries. These breakdowns confirm our observation that our value estimates are able to produce quite a lot of heterogeneity between different domains of innovative activity – even within countries. For each country, the variation between technology fields covers a rather substantial part of the overall private returns distribution – at least 50 percent of the distribution for most countries. Furthermore, these results confirm the pattern that some sectors score persistently high while others score rather low. This could be seen as further support for the explanations offered in previous section.

Yet, even within technological fields, interesting variation between countries exists. For instance, while mechanical engineering generates high private returns in the US, Germany and Japan, this is much less so in, for instance, France and Korea. In general, these estimates do not produce very consistent rankings of (even broad) categories across countries. While we want to refrain from speculating about the source of these differences, we believe very interesting patterns might be uncovered using this data in future analyses.

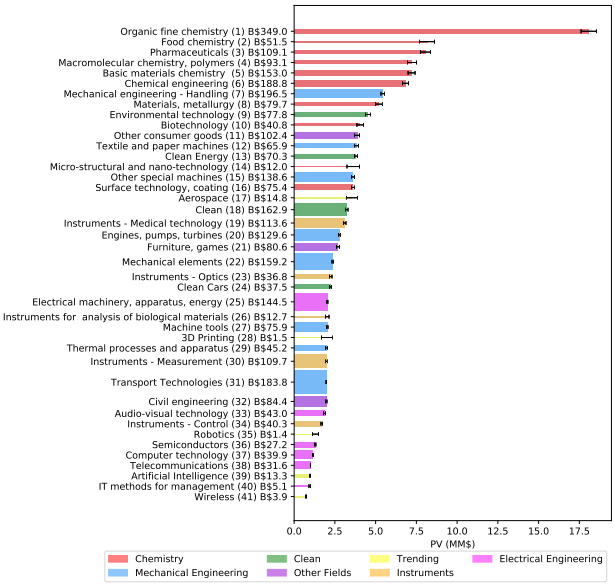
United States



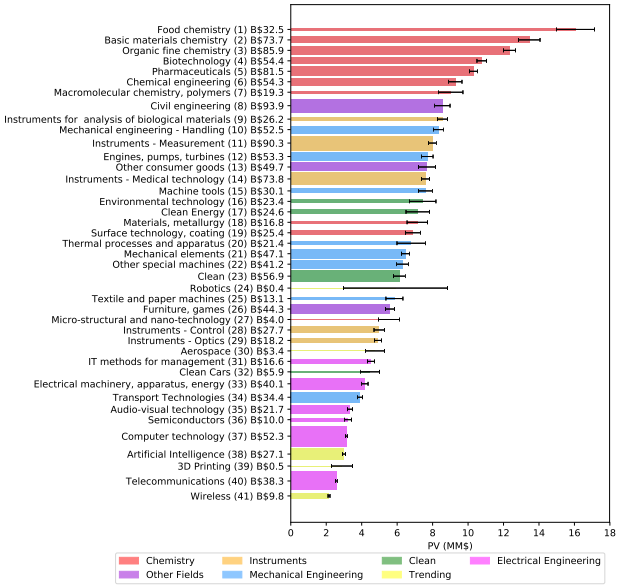
Japan

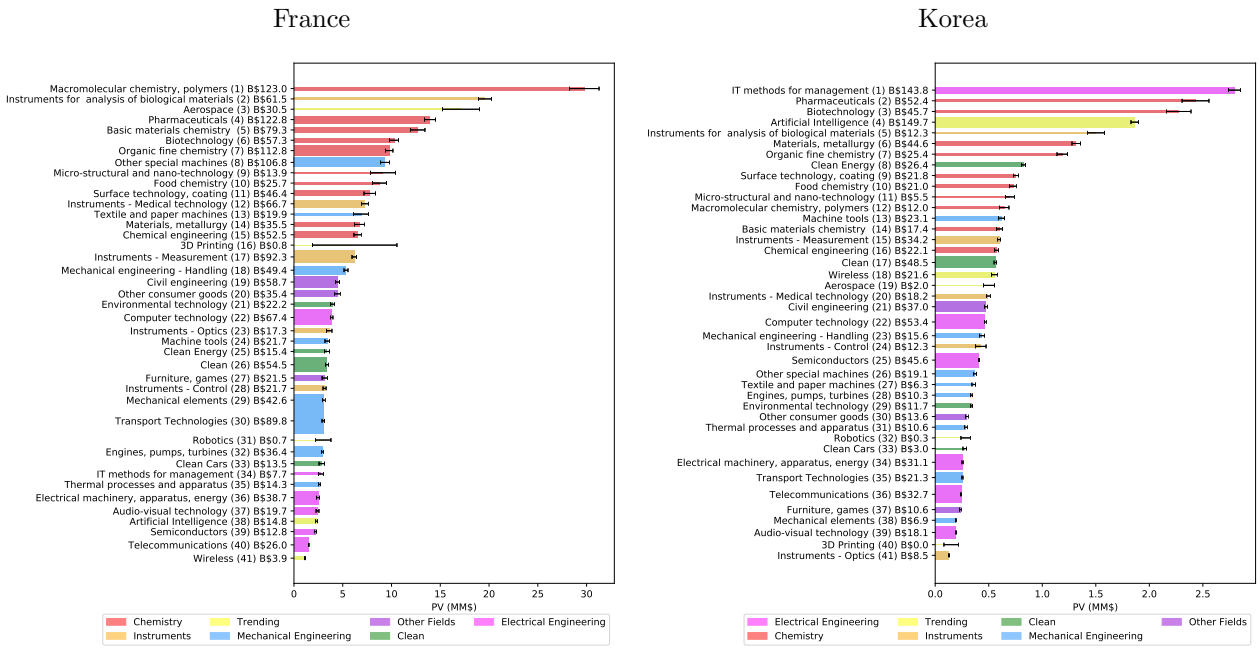


Germany



United Kingdom





Notes: Diagrams of the average private returns in millions of CPI-adjusted 1982 US dollars (x-axis) by technology field (y-axis) for different countries. Width of each bar represents the number innovations in the field. Area of each bar (in billions $) represents total private returns in the technology field and is printed next to y-axis labels.

4 Conclusion

The main purpose of this part of work package 4 was to lay the foundations required for spillover measurement. To do so, we estimated private returns to a nearly comprehensive sample of the population of patented innovations. Relying on stock-market-based estimates of private returns to innovation, we developed a methodology to estimate returns to innovation based on universally observed patent characteristics. Undoubtedly, improvements are possible, but the results strengthen our belief that our approach generates sensible estimates. Results suggest that much of the heterogeneity in stock-market-based estimates of private values can be captured using linear extrapolation models with simple, observable predictors.

The estimates produce heterogeneity between countries and—most notably—technological fields. Given the distinct underlying conditions of innovative activity across technological and geographic domains, this is an expected result. Further analysis of some descriptive patterns suggests that cost factors might be one of the important drivers of private returns. This has inspired the approach followed in the remainder of work package 4. Indeed, to formulate policy recommendations based upon the value of knowledge spillovers, one should clearly take into account such cost conditions as they do not only affect private, but also public spending on R&D. In other words, if there are important differences in the costs of R&D across technological sectors (which based on these results is likely), any amount of support should be corrected for the cost of one additional innovation project pursued. We take such correction into account when formulating an index that could be used for industrial policy in the next part of this work package. Next to serving as important conceptual input into the remainder of the work package, the work performed here has resulted in an arguably useful side product: a database of private returns that goes beyond stock-listed firms. This is useful because much of the innovative activity targeted in policy agendas involves start-ups and universities for which such estimates are important.

As with all academic work, a number of current limitations motivate follow-on research. First, future work can improve upon the extrapolation approach by including additional innovation features that relate to private values of innovations—for instance, the number of claims or renewal information—or by exploring supervised machine learning approaches. Second, the confidence we can place upon our results would increase with more intensive validation of the private returns estimates we have produced. For instance, one could compare the estimates to inventor-given estimates of value, or renewal decisions by firms that reflect the value of an innovation. Finally, the analyses would strongly benefit from a link of the private returns data to information on firms size and organization type in order to further scrutinize mechanisms driving private returns.

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A Alternative extrapolation models

As discussed in section 2.2, not all groups defined by the fixed effects $\alpha_{\tau,a,c}$ have a stock-market-based estimate and not all innovations are assigned a country and/or technological class. These innovations cannot be extrapolated using the model described in the main text. To address these issues, we define nine alternative models for the extrapolation which are given below, in order of preference – i.e. for each innovation we choose the first model for which we can obtain an extrapolation.

$$ln(\xi_{j,\tau,a,c,f}) = \beta_0 + \alpha_{\tau,a} + \alpha_c + \alpha_f + \epsilon_{j,\tau,a,c,f} \tag{5}$$

$$ln(\xi_{j,\tau,a,c,f}) = \beta_0 + \alpha_{a,c} + \alpha_\tau + \alpha_f + \epsilon_{j,\tau,a,c,f} \tag{6}$$

$$ln(\xi_{j,\tau,a,c,f}) = \beta_0 + \alpha_a + \alpha_{\tau,c} + \alpha_f + \epsilon_{j,\tau,a,c,f} \tag{7}$$

$$ln(\xi_{j,\tau,a,c,f}) = \beta_0 + \alpha_a + \alpha_\tau + \alpha_c + \alpha_f + \epsilon_{j,\tau,a,c,f} \tag{8}$$

$$ln(\xi_{j,\tau,a,c,f}) = \beta_0 + \alpha_{\tau,a} + \alpha_f + \epsilon_{j,\tau,a,c,f} \tag{9}$$

$$ln(\xi_{j,\tau,a,c,f}) = \beta_0 + \alpha_\tau + \alpha_a + \alpha_f + \epsilon_{j,\tau,a,c,f} \tag{10}$$

$$ln(\xi_{j,\tau,a,c,f}) = \beta_0 + \alpha_{\tau,c} + \alpha_f + \epsilon_{j,\tau,a,c,f} \tag{11}$$

$$ln(\xi_{j,\tau,a,c,f}) = \beta_0 + \alpha_\tau + \alpha_c + \alpha_f + \epsilon_{j,\tau,a,c,f} \tag{12}$$

$$ln(\xi_{j,\tau,a,c,f}) = \beta_0 + \alpha_\tau + \alpha_f + \epsilon_{j,\tau,a,c,f} \tag{13}$$

where $\alpha_{\tau,a}$, $\alpha_{a,c}$, $\alpha_{\tau,c}$ refer to the interacted fixed effects for, respectively, time cohort and technology class, technology class and country, and time cohort and country. α_c, α_f, α_τ and α_a respectively refer to country, family size, time cohort and technology class fixed effects.

B Defining technological fields

Table 3: Concordance between technological fields and IPC/CPC classes

Label	Field	Classes	Scheme
Electrical Engineering	Electrical machinery, apparatus, energy	F21H, F21K, F21L, F21S, F21V, F21W, F21Y, H01B, H01C, H01F, H01G, H01H, H01J, H01K, H01M, H01R, H01T, H02B, H02G, H02H, H02J, H02K, H02M, H02N, H02P, H02S, H05B, H05C, H05F, H99Z	IPC
Electrical Engineering	Audio-visual technology	G09F, G09G, G11B, H04N 3, H04N 5, H04N 7, H04N 9, H04N 11, H04N 13, H04N 15, H04N 17, H04N 19, H04N 101, H04R, H04S, H05K	IPC
Electrical Engineering	Telecommunications	G08C, H01P, H01Q, H04B, H04H, H04J, H04K, H04M, H04N 1, H04Q, H04L, H04N 21, H04W, H03B, H03C, H03D, H03F, H03G, H03H, H03J, H03K, H03L, H03M	IPC
Electrical Engineering	Computer technology	G06C, G06D, G06E, G06F, G06G, G06J, G06K, G06M, G06N, G06T, G10L, G11C	IPC
Electrical Engineering	IT methods for management	G06Q	IPC
Electrical Engineering	Semiconductors	H01L	IPC
Instruments	Instruments - Optics	G02B, G02C, G02F, G03B, G03C, G03D, G03F, G03G, G03H, H01S	IPC
Instruments	Instruments - Measurement	G01B, G01C, G01D, G01F, G01G, G01H, G01J, G01K, G01L, G01M, G01N 1, G01N 3, G01N 5, G01N 7, G01N 9, G01N 11, G01N 13, G01N 15, G01N 17, G01N 19, G01N 21, G01N 22, G01N 23, G01N 24, G01N 25, G01N 27, G01N 29, G01N 30, G01N 31, G01N 35, G01N 37, G01P, G01Q, G01R, G01S, G01V, G01W, G04B, G04C, G04D, G04F, G04G, G04R, G12B, G99Z	IPC
Instruments	Instruments for analysis of biological materials	G01N 33	IPC
Instruments	Instruments - Control	G05B, G05D, G05F, G07B, G07C, G07D, G07F, G07G, G08B, G08G, G09B, G09C, G09D	IPC
Instruments	Instruments - Medical technology	A61B, A61C, A61D, A61F, A61G, A61H, A61J, A61L, A61M, A61N, G16H, H05G	IPC
Chemistry	Organic fine chemistry	A61K 8, A61Q, C07B, C07C, C07D, C07F, C07H, C07J, C40B	IPC
Chemistry	Biotechnology	C07G, C07K, C12M, C12N, C12P, C12Q, C12R, C12S	IPC
Chemistry	Pharmaceuticals	A61K 6, A61K 9, A61K 31, A61K 33, A61K 35, A61K 36, A61K 38, A61K 39, A61K 41, A61K 45, A61K 47, A61K 48, A61K 49, A61K 50, A61K 51, A61K 101, A61K 103, A61K 125, A61K 127, A61K 129, A61K 131, A61K 133, A61K 135, A61P	IPC
Chemistry	Macromolecular chemistry, polymers	C08B, C08C, C08F, C08G, C08H, C08K, C08L	IPC
Chemistry	Food chemistry	A01H, A21D, A23B, A23C, A23D, A23F, A23G, A23J, A23K, A23L, C12C, C12F, C12G, C12H, C12J, C13B 10, C13B 20, C13B 30, C13B 35, C13B 40, C13B 50, C13B 99, C13D, C13F, C13J, C13K	IPC
Chemistry	Basic materials chemistry	A01N, A01P, C05B, C05C, C05D, C05F, C05G, C06B, C06C, C06D, C06F, C09B, C09C, C09D, C09F, C09G, C09H, C09J, C09K, C10B, C10C, C10F, C10G, C10H, C10J, C10K, C10L, C10M, C10N, C11B, C11C, C11D, C99Z	IPC
Chemistry	Materials, metallurgy	B22C, B22D, B22F, C01B, C01C, C01D, C01F, C01G, C03C, C04B, C21B, C21C, C21D, C22B, C22C, C22F	IPC
Chemistry	Surface technology, coating	B05C, B05D, B32B, C23C, C23D, C23F, C23G, C25B, C25C, C25D, C25F, C30B	IPC
Chemistry	Micro-structural and nano-technology	B81B, B81C, B82B, B82Y	IPC
Chemistry	Chemical engineering	B01B, B01D 1, B01D 3, B01D 5, B01D 7, B01D 8, B01D 9, B01D 11, B01D 12, B01D 15, B01D 17, B01D 19, B01D 21, B01D 24, B01D 25, B01D 27, B01D 29, B01D 33, B01D 35, B01D 36, B01D 37, B01D 39, B01D 41, B01D 43, B01D 57, B01D 59, B01D 61, B01D 63, B01D 65, B01D 67, B01D 69, B01D 71, B01F, B01J, B01L, B02C, B03B, B03C, B03D, B04B, B04C, B05B, B06B, B07B, B07C, B08B, C14C, D06B, D06C, D06L, F25J, F26B	IPC
Clean	Environmental technology	A62C, B01D 45, B01D 46, B01D 47, B01D 49, B01D 50, B01D 51, B01D 52, B01D 53, B09B, B09C, B65F, C02F, E01F 8, F01N, F23G, F23J, G01T	IPC

Mechanical Engineering	Mechanical engineering - Handling	B25J, B65B, B65C, B65D, B65G, B65H, B66B, B66C, B66D, B66F, B67B, B67C, B67D	IPC
Mechanical Engineering	Machine tools	A62D, B21B, B21C, B21D, B21F, B21G, B21H, B21J, B21K, B21L, B23B, B23C, B23D, B23F, B23G, B23H, B23K, B23P, B23Q, B24B, B24C, B24D, B25B, B25C, B25D, B25F, B25G, B25H, B26B, B26D, B26F, B27B, B27C, B27D, B27F, B27G, B27H, B27J, B27K, B27L, B27M, B27N, B30B	IPC
Mechanical Engineering	Engines, pumps, turbines	F01B, F01C, F01D, F01K, F01L, F01M, F01P, F02B, F02C, F02D, F02F, F02G, F02K, F02M, F02N, F02P, F03B, F03C, F03D, F03G, F03H, F04B, F04C, F04D, F04F, F23R, F99Z, G21B, G21C, G21D, G21F, G21G, G21H, G21J, G21K	IPC
Mechanical Engineering	Textile and paper machines	A41H, A43D, A46D, B31B, B31C, B31D, B31F, B41B, B41C, B41D, B41F, B41G, B41J, B41K, B41L, B41M, B41N, C14B, D01B, D01C, D01D, D01F, D01G, D01H, D02G, D02H, D02J, D03C, D03D, D03J, D04B, D04C, D04G, D04H, D05B, D05C, D06G, D06H, D06J, D06M, D06P, D06Q, D21B, D21C, D21D, D21F, D21G, D21H, D21J, D99Z	IPC
Mechanical Engineering	Other special machines	A01B, A01C, A01D, A01F, A01G, A01J, A01K, A01L, A01M, A21B, A21C, A22B, A22C, A23N, A23P, B02B, B28B, B28C, B28D, B29B, B29C, B29D, B29K, B29L, B33Y, B99Z, C03B, C08J, C12L, C13B 5, C13B 15, C13B 25, C13B 45, C13C, C13G, C13H, F41A, F41B, F41C, F41F, F41G, F41H, F41J, F42B, F42C, F42D	IPC
Mechanical Engineering	Thermal processes and apparatus	F22B, F22D, F22G, F23B, F23C, F23D, F23H, F23K, F23L, F23M, F23N, F23Q, F24B, F24C, F24D, F24F, F24H, F24J, F24S, F24T, F24V, F25B, F25C, F27B, F27D, F28B, F28C, F28D, F28F, F28G	IPC
Mechanical Engineering	Mechanical elements	F15B, F15C, F15D, F16B, F16C, F16D, F16F, F16G, F16H, F16J, F16K, F16L, F16M, F16N, F16P, F16S, F16T, F17B, F17C, F17D, G05G	IPC
Mechanical Engineering	Transport Technologies	B60B, B60C, B60D, B60F, B60G, B60H, B60J, B60K, B60L, B60M, B60N, B60P, B60Q, B60R, B60S, B60T, B60V, B60W, B61B, B61C, B61D, B61F, B61G, B61H, B61J, B61K, B61L, B62B, B62C, B62D, B62H, B62J, B62K, B62L, B62M, B63B, B63C, B63G, B63H, B63J, B64B, B64C, B64D, B64F, B64G	IPC
Other Fields	Furniture, games	A47B, A47C, A47D, A47F, A47G, A47H, A47J, A47K, A47L, A63B, A63C, A63D, A63F, A63G, A63H, A63J, A63K	IPC
Other Fields	Other consumer goods	A24B, A24C, A24D, A24F, A41B, A41C, A41D, A41F, A41G, A42B, A42C, A43B, A43C, A44B, A44C, A45B, A45C, A45D, A45F, A46B, A62B, A99Z, B42B, B42C, B42D, B42F, B43K, B43L, B43M, B44B, B44C, B44D, B44F, B68B, B68C, B68F, B68G, D04D, D06F, D06N, D07B, F25D, G10B, G10C, G10D, G10F, G10G, G10H, G10K	IPC
Other Fields	Civil engineering	E01B, E01C, E01D, E01F 1, E01F 3, E01F 5, E01F 7, E01F 9, E01F 11, E01F 13, E01F 15, E01H, E02B, E02C, E02D, E02F, E03B, E03C, E03D, E03F, E04B, E04C, E04D, E04F, E04G, E04H, E05B, E05C, E05D, E05F, E05G, E06B, E06C, E21B, E21C, E21D, E21F, E99Z	IPC
Trending	Robotics	B25J 9	CPC
Trending	Wireless	H04W	CPC
Trending	3D Printing	B29C64	CPC
Trending	Artificial Intelligence	G06F17, F06N5, G06N3, G10L15, G06F3, G06Q10, G06Q30, G06F9, G06Q50	CPC
Trending	Aerospace	C22F1, C08K3, B64G1, C08G59, C22C21, B64C1, C22C1, C08G73	CPC
Clean	Clean Energy	Y02E	CPC
Clean	Clean Cars	Y02T10	CPC
Clean	Clean	Y02	CPC