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# Patent Boxes and the Success Rate of Applications

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# Patent Boxes and the Success Rate of Applications

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**Abstract**

Patent boxes significantly reduce the corporate tax rate applied to income earned from a patent. This incentivizes firms to increase the likelihood of a patent application being granted by creating more novel research and using more successful legal representation when filing the application. Conversely, it supports submitting applications for marginally novel innovations that otherwise would not have been submitted, lowering the probability of success. We use data from applications to the European Patent Office from 1978 to 2019 and find that the introduction of a patent box increases the average success rate of applications from large, corporate innovators by 6.9 percentage points. This impact only materializes two years after a patent box takes effect, suggesting that improved research effort is the dominant response by firms. Therefore patent boxes may help to increase innovation novelty and improve the overall quality of research.

**JEL classification:** H25; O31; O32.

**Keywords:** Patent Box; Patents; Application Success; Corporate Taxation.

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# 1 Introduction

Even as governments move to close down some methods firms use to reduce tax burdens they continue to open new ones. One example of this is the introduction of "patent boxes".[1] Under this policy, corporate income attributable to qualifying intellectual property (typically a patent) is taxed at a lower rate, often half that of the highest corporate income tax rate. While some nations such as Ireland and France have used patent boxes for decades, a wave of countries introduced new boxes in the years surrounding 2010. To date, the economic literature has largely focused on what the introduction of a patent box does to the *number* of patents in a country.[2] Examples here include Alstadsaeter, et al. (2018), Schwab and Todtenhaupt (2016), Griffith, et. al (2014), Becker, Fuest, and Riedel (2012), and Karkinsky and Riedel (2012). On the whole, this work tends to find that a reduction in the tax rate via the patent box leads to more granted patents.

Largely unexplored, however, is what patent boxes do to the *quality* of patents. An exception here is Ernst, et al. (2014), who use a composite measure of quality and find that lowering corporate taxes via a patent box increases patent quality. This work, however, focuses on granted patents and implicitly assumes that all successful innovations are patented. In fact, this is not the case. In our data, which covers applications to the European Patent Office (EPO) from 1978-2019, only 54% of applications are granted.[3] Thus the patenting process is highly uncertain. What is certain, however, is that applying for a patent is costly and includes the filing fee as well as fees for the patent attorneys who prepare the application.[4] Thus, a firm will only apply if it believes that the expected benefit of doing so

[1]While we use the term patent box, some governments call their policies innovation boxes or knowledge boxes, which explicitly acknowledges that in some cases, the policy covers more than just patents.

[2]As detailed below, the number of "patents" can be the number of applications, granted patents, transfers from one country to another, or patent registrations in EPO members depending on the study.

[3]Similarly, Carley, Hegde, and Marco (2015) report that from 1996-2013 only 55.8% of US patent applications were granted. Webster, et al. (2014) provide a comparison across the US, Japanese, and European patent offices.

[4]Note that this includes both the initial application as well as potential revisions. First drafts of patent applications are rarely accepted as-is, with the examiner making objections (office actions) to all or part of the patent claims based on the relevant prior art. This requires a revision and resubmission which takes additional legal advice.

outweighs the costs.[5] As discussed by the European Commission (2014), the total cost of protection can be significant and easily exceed €100,000.[6]

When a patent box comes into force it increases the after-tax value of holding a patent (even if the innovation has already been created). Because of this, a patent box can have three conflicting effects on the probability of success. First, a patent box incentivizes innovative firms to put more effort into creating novel ideas which will have a better chance of being granted. Second, it encourages additional effort in preparing the application. For example, hiring more experienced patent attorneys increases the success rate. Third, a patent box alters the decision of whether to submit an application at all. In particular, the patent box encourages the submission of applications for innovations that, due to their low novelty and small chance of being granted, otherwise would not have been submitted. This latter concern has been raised by the OECD (2016) and Bradley, et al. (2015) among others. This selection effect lowers the average success rate. Therefore, the average success rate of applications can rise or fall depending on which effect dominates. In addition, while the latter two effects can happen swiftly following the patent box's introduction, the research effort effect is likely to materialize only with a lag due to the time it takes for increased research effort to bear fruit. Thus, the net effect may vary over time.

With this in mind, we contribute to the literature by using EPO data to estimate the effect of a patent box on the probability of success and how that effect varies across applicants and time. We find that a patent box increases the success rate of applications (also known as the allowance rate) by 6.9 percentage points, a 12% increase. This effect, however, is only

[5] Peeters and van Pottelsberghe (2006) find that the decision on whether or not to patent can also depend on the type of a firm's R&D, that is, whether it is basic or applied research and whether the innovations are product or process.

[6] When patenting with the EPO, the cost of protection includes the submission fee to the EPO and additional registration and translation fees in the member states where protection is desired. They estimate that to patent in thirteen members via the EPO costs €22,472. Harhoff, et al. (2009) find that translation costs significantly affect registrations. Alstadsaeter, et al. (2018) find that patent boxes do as well. Finally, to maintain protection, subsequent maintenance costs in those thirteen member states is estimated at another €93,243. These costs have led to the proposal for a multi-country unitary patent system in the European Union. See EPO (2017) for details. Note that these figures still do not account for the potential costs from disclosing a firm's proprietary knowledge in the application (see Hall, et al. (2014) for discussion).

found among the top 5% of innovators, large firms who are best able to take advantage of the corporate tax rate reduction. Furthermore, we find particularly strong effects for patent boxes with nexus requirements which require local development of the patented innovation to avail of tax reductions, suggestive of multinationals shifting their most novel R&D to these countries.[7] An important aspect of the patent box impact is that it does not materialize until two years following the introduction of the incentive. This lag suggests that increased research effort designed to generate more novel innovations is the chief mechanism by which patent boxes create their net positive effect. Although there are no estimates on the specific tax losses due to patent boxes per se, the estimates of Tørsløv, Wier, and Zucman point to over $600 billion shifted to tax havens annually, with Ireland, Luxembourg, and the Netherlands (all patent box users) alone accounting for approximately $100 billion. Thus, given the likely sizable tax revenue costs of patent boxes, fully understanding the benefits generated by patent boxes is critical to evaluating their efficacy. Further, our results provide a unique insight into potential tax avoidance by international firms because of patent boxes, one that again identifies large firms as those most able to reduce their tax burdens.[8]

Our results bridge two bodies of research. The first focuses on taxation and innovation and the second on the success rates of patent applications. We discuss each literature and our contributions to them in turn below.

The work on taxation and innovation has two main themes, one on the effect of taxes on the level of innovation, with patents being one measure of R&D, and the other on the location of innovation with a specific focus on the transfer of patents within a multinational.[9] Overall, the consensus is that lower taxation increases the amount of innovation and that

[7] As discussed in detail by Alstadsaeter, et al. (2018) nexus requirements are typically based on expenses attributed to the development of the innovation with a sufficiently high share of those costs needed for the patent to qualify for the box.

[8] See, for example, Davies, et al. (2018) who find that tax avoidance via transfer pricing is only evident in the largest firms.

[9] Measuring innovation by the number of patents is common and includes Blundell et al. (1995), Stiebale (2016), and much of the literature we cite. That said, it must be remembered that not all innovation leads to a patent application and that granted patents are a subset of even that. As discussed by Hall, et al. (2014) there are a number of issues that go into the strategic decision to apply for a patent making it only an approximate measure of innovative activity.

multinationals shift intellectual property to low tax jurisdictions in order to reduce their global tax burden.[10] It is important to note that part of the debate regarding the tax treatment of innovation has been a comparison of expenditure-based tax incentives versus income-based incentives. The first of these operates by lowering the tax burden on qualifying expenditures, for example through tax credits for R&D spending. This lowers the cost of innovation and is often measured by the "b-index", a measure capturing the marginal tax on R&D expenditures (see Bösenberg and Egger (2017) for discussion). Income-based incentives, which include patent boxes, instead operate by lowering the tax on the income from qualifying R&D. This raises the after-tax benefit of innovation rather than lowering its after-tax cost.[11] One feature of this difference is that income-based incentives only come into play following a commercially successful innovation. As such, the benefits of income-based incentives accrue much later than expenditure-based ones. Indeed, the OECD (2016) notes that income-based incentives may be less useful for small firms due to their relative difficulty in obtaining access to financing.

Focusing on the literature explicitly considering patent boxes, the standard approach for estimating the impact on the level of innovation is to estimate the number of patents per year across firms or countries. Examples operating at the country-level include Bösenberg and Egger (2017) and Bradley, et. al (2015); firm-level studies include Schwab and Totenhaupt (2019), Alstadsaeter, et al. (2018), and Ernst and Spengel (2011).[12] Note that one of the key contributions of the firm-level approach is the ability to combine patent information with firm level datasets (e.g. Bureau Van Dijk's Orbis dataset).[13] While this firm-matched data can be useful, it is generally only available for sufficiently large firms and fails to

[10]Examples of work in this vein that do not focus on patent boxes per se would include Karkinski and Riedel (2012) who look at the number of firm-level filings as a function of local taxes or Dischinger and Riedel (2011) who look at the influence of taxes on the location of intangible assets in a multinational.

[11]Intellectual property boxes can more generally extend tax reductions to income earned from trademarks, copyrights, and other types of intangible assets. Patent boxes specifically require a registered patent in order to obtain the tax benefit.

[12]In addition, Mohnen, et al. (2017) find that boxes increase R&D spending while Chen, et al. (2019) find that they increase both fixed investment and employment.

[13]In a similar disaggregated fashion, Gaessler, et al. (2019) consider the number of inventor filings in a given country-year.

capture the activities of smaller innovators and cannot speak to whether all innovators, or just the largest, are influenced by patent boxes.[14] Finally, matching firm and patent data leads to matching success rates that vary by country, potentially biasing the estimates. On the whole, the results suggest that patent boxes increase patenting activity.[15] This is not, however, universal. Bradley, et al. (2015) find that on average there is no effect, although they do find a positive effect when the inventor and applicant are from the same country. Gaessler, et al. (2019), meanwhile, find a weak, negative impact.[16]

Setting aside the issue of the amount of patenting, taxes also influence the location of patents within a multinational. Since income attributed to a patent is taxable in the country where the patent is held, this gives a multinational an incentive to shift patents to affiliates located where such income incurs a low tax, such as a tax haven or patent box country.[17] Note that this can be by shifting the location of R&D to a low tax country or by transferring ownership of a patent to that location. Examples here include Gaessler, et al. (2019), Bösenberg and Egger (2017), Ciaramella (2017), Böhm, et al. (2015), and Griffith, et al. (2014). All of these find that a firm is more likely to either do innovation in a country with a patent box and/or transfer its patents into that country.[18] This latter possibility in particular provides support for patent box nexus requirements which require local R&D expenditures in order to take advantage of the patent box since local R&D activities arguably generate more local spillovers than imported innovations.

In constructing their data sets, the above studies vary in several key dimensions which are important to understand our contribution. First, none of these consider the probability

[14]That said, since we find little impact of patent boxes on smaller innovators, the potential for selection bias may be relatively small.

[15]Further, Schwab and Totenhaupt (2019) find that innovation in one country can by influenced by patent boxes elsewhere when nations are connected via multinational investments.

[16]In addition, the IMF (2016) finds a mixed effect of a patent box on total R&D using a synthetic control method approach).

[17]Rather than focus on the transfer of intellectual property, Koethenbuerger, et al. (2019), Chen, et al. (2019), and Ludwig (2018) examine profitability within MNE affiliates and find that they are higher in patent box countries. Combined with the patent transfer results, this suggests that not only is intellectual property being located in low-tax countries, but that this enables significant profit shifting.

[18]Ciaramella, et al. (2017) estimates that 60% of transfers happen pre-granting with Gaessler (2016) suggesting that unofficial indications of likely success influences pre-granting transfers.

of a given application being granted which is the focus of our study. Second, the bulk of the above literature uses only granted patents.[19] While this can easily be justified in those studies looking at the location of patents or the registration of a granted patent across countries, it does limit the measure of the level of innovative activity since not all R&D leads to a patent application, much less a successful one. In contrast, we include both successful and unsuccessful applications. A third difference across studies is the patent offices they consider. While some, e.g. Alstadsaeter, et al. (2018) and Bösenberg and Egger (2017) focus on EPO patents, others such as Bradley, et al. (2015) use a variety of offices. While multiple offices is a virtue for some questions, for our purposes including multiple offices can introduce undue noise if the standards of novelty vary across offices and time as is found by Webster, et al. (2014) among others.

The second strand of the literature we contribute to is that estimating the likelihood that a patent application is granted. A primary feature of this work is an attempt to control for the quality of an innovation.[20] This motivates the inclusion of controls including the numbers of inventors, number of claims, technology classes an application covers, and offices to which the same innovation is submitted (family size), all of which are presumed positively correlated with quality.[21] Indeed, they are generally found to be positively correlated with the probability of success.[22] While these characteristics act as controls, the focus of these investigations is often elsewhere. A major area of concern is the role nationality plays, particularly "home bias" in which applicants or inventors from the territories covered by the patent office have a higher success rate. Indeed, home bias is found by Drivas and Kaplanis

[19] This includes Schwab and Totenhaupt (2019), Alstadsaeter, et al. (2018), Ciaramella (2017), Böhm, et al. (2015), and others. Note that while many describe their data as applications (since it is important to use the filing date of the application to judge the applicability of a patent box), they limit themselves to applications that are eventually granted. Bradley, et al. (2015) and Ernst and Spengel (2011) are exceptions to this.

[20] In addition to the studies mentioned here, other examples include de Rassenfosse, et al. (2016) and de Rassenfosse, et al. (2017).

[21] van Zeebroeck, et al. (2009) caution on some measures of application quality, noting in particular that the number of claims and length of applications has grown over time as savvy applicants pad their application with sacrificial lambs they expect to lose during the application process.

[22] Kabore and Park (2019) find that weighting the patent family size by the markets covered by an office increase the measures predictive power when estimating the number of citations and patent renewal.

(2020), Webster, et al. (2014), Webster, et al. (2007), Guellec and van Pottelsburghe (2000), and more. Further, applications with international inventor teams and those where the applicant and inventor are from different countries also tend to find higher success rates (see, e.g. Drivas and Kaplanis, 2020). This latter result may be another indicator of quality since such combinations are relatively costly and will be undertaken only when there is a significantly large benefit in doing so.

In addition, only one other paper considers the role of patent attorneys, also known as the representatives or agents, in the application process.[23] While the use of patent attorneys is essentially universal in preparing an application, the impact a given attorney has on the success of an application can depend on their quality and the hours they dedicate to a given application. To our knowledge, only one other paper to date has included disambiguated representative data. de Rassenfosse, et al. (2018) split patent data to estimate a law firm fixed effect (average success rate for that firm) on a subsample of the data and used that fixed effect as a control when estimating the probability of success in the remaining data, finding that success in half the data predicts success in the other. We instead use rolling three-year windows so that the effect of individual representatives on the success rate is allowed to vary over time.[24] Given that a patent box can lead to an upgrade in the quality of legal representation used in an application's preparation, we also control for representative quality.

While we follow this literature in the choice of our control variables, ours is the only contribution that considers taxation. If taxes affect the quality of applications (either via the novelty of submitted innovations or the efforts put into the application itself), then

[23]See Reitzig (2004) or Hall and Ziedonis (2001) for useful descriptions of the role of the attorney in the application process. In addition, Reitzig (2004) looks at the impact the attorney has on whether a patent is opposed post-grant.

[24]A small number of studies focus on the role of the patent examiner (the patent office employee who makes the granting decision). Lemley and Sampat (2012) find that more experienced examiners are more likely to grant a patent. Lei and Wright (2017) and Frakes and Wasserman (2016) meanwhile find that examiner effort has an impact on success rates of the applications they consider. These studies use US patent data rather than EPO data as the latter does not provide examiner information which prohibits us from controlling for the examiner.

changes in tax policy may have a significant effect on success rates. Estimating this is our primary contribution to this second strand of the literature.

The paper proceeds as follows. Section 2 lays out a simple model of innovation and the decision of whether or not to apply for a patent. Section 3 describes our data and empirical approach. Section 4 discusses our results. Section 5 concludes.

# 2 A model of innovation and patent application

Here, we present a simplified model of innovation and patenting. The timing of the model is that a firm decides how many research projects to undertake and how much effort to put into each one. More effort devoted to a project increases the expected novelty of the resulting innovation. After observing an innovation's novelty, the firm then decides whether to apply for a patent and if so how much to spend on the application with greater expenditures linked to a higher probability of granting. Finally, the outcome of of the patent application is observed and payoffs are realized.

To formalize this, assume that in the first stage, where $M$ is the number of research projects undertaken, that setup costs are $d(M; s) + \alpha(s) M$. These setup costs have two components: a increasing convex cost $d(M)$ that depends on the total number of projects and a per-project fixed cost $\alpha(s)$. Both $d()$ and $\alpha()$ are decreasing in firm "size" $s$. The rationale for including size is that larger firms have better access to funding. Since R&D costs are incurred before the fruits of the research are brought to market and revenues can be earned, innovative activities need to be funded by borrowing and/or existing operating capital.[25] Because larger firms have better access to credit (see Angori, et al. (forthcoming) for a recent review) and deeper reserves, we believe this is a reasonable assumption.[26]

[25]Egger and Keuschnigg (2015) present a model in which larger firms invest optimally in R&D due to their deeper cash reserves and superior access to bank finance, with smaller firms forced to venture capital markets. The OECD (2016) notes that income-based incentives such as patent boxes may therefore be less useful in spurring innovation by small firms due to the relative difficulty those firms have in obtaining access to financing.

[26]Further, as shown below, this predicts larger firms will do more R&D which matches the empirical results

Each research project results in an innovation $i$ that has a level of novelty $n_i \geq 0$ which is independently drawn from a differentiable distribution function $F(n, e_i)$ where $e_i$ is the research effort put into that innovation. The notion behind this variation is that some innovations are groundbreaking, some are moderately so, and some are rehashes of the existing stock of knowledge. The expected novelty can be influenced by putting more effort into developing the innovation such that $F_e(n, e) < 0$ and $F_{ee}(n, e) > 0$, i.e. more research effort put into innovation $i$ increases the probability that its novelty is $n$ or greater but that the marginal change decreases as effort grows. The constant marginal cost of research effort is $\beta(s)$ where, as with the fixed cost, larger firms have a cost advantage.

After deciding how many innovations to develop, undertaking research, and learning the novelty of each innovation, the firm decides which to attempt to patent. In preparing an application for innovation $i$, the firm expends $c_i$ which represents features such as the number of hours spent and quality of the legal representatives that prepare the application.[27] To be granted a patent, the innovation must be deemed sufficiently novel by the patent examiner.[28] Thus, the probability that an innovation $i$ would be successful in the patenting process is $p(n_i, c_i)$ which is increasing and concave in both arguments, i.e. a more novel innovation and greater application effort both increase the chance of success.[29] Note that this probability function allows for randomness in the application process due to the patent examiner's need to decide whether an application meets the subjective threshold of novelty, an evaluation that may differ from the firm's subjective belief of the innovation's novelty.[30] Recognizing

of e.g. Shefer and Frenkel (2005).

[27] Although we do not make this a decreasing function of size based on the idea that this application costs are smaller and incurred less in advance than are research costs meaning that access to credit may be less important. That said, one could imagine that large, frequent innovators have in-house legal representation that leads to lower application costs (see de Rassenfosse, et al. (2018) and Süzeroglu-Melchiors, et al. (2017)). In any case, this modification would suggest that, all else equal, larger firms have better representation which would further boost their average success rates.

[28] The EPO has four requirements for patentability, which we jointly refer to as 'novelty' above. `https://www.epo.org/law-practice/legal-texts/html/guidelines/e/g_i_1.htm`

[29] Although it is not necessary to sign the cross-derivative for our purposes, given that de Rassenfosse, et al. (2018) conclude that a more successful legal team does more to boost the success of a low-quality patent than a high-quality one, it may be most reasonable to assume that $p_{nc} < 0$.

[30] In practice, both Type I and Type II errors occur in the granting decision. de Rassenfosse, et al. (2016) define type II errors as an application granted by one office yet rejected by another. They find that

the independence of costs and novelty across innovations, we now drop the $i$ subscripts and only reintroduce them when needed.

If the firm does not hold a patent on a given innovation, either because it does not apply for one or its application is rejected, there is a probability $1-q$ that its innovation is appropriated by a competitor and it earns no taxable profit from the innovation.[31] If this does not happen, it earns $r$ net of production costs which is taxed at the standard tax rate $t$.[32] Thus, expected after-tax profit generated from an innovation that for which no application is made is $q(1-t)r$ while that from a failed application is $(1-t)(qr-c)$.

If the firm applies for the patent and is successful, then $q=0$. Furthermore, the revenues earned from the patent are taxed within the patent box where the rate is $bt$ with $b<1$.[33] In practice, $b$ is commonly 0.5. This results in after-tax profits from the innovation of $(1-bt)r-(1-t)c$. Note that this follows the practice of, for example, the Belgian patent box regime in which application and research costs are deductable at the more favorable standard tax rate, and not the lower patent box rate.[34] With this in mind, for each innovation the firm decides whether to apply for a patent and, if so, the representative effort to put into the application. If the firm applies, expected profits are given by:

$$(1-bt)\,p(n,c)\,r+(1-t)\,(1-p(n,c))\,qr-(1-t)\,c=(1-t)\,(p(n,e)\,\phi r+qr-c) \tag{1}$$

where $\phi=\frac{1-bt}{1-t}-q$ can be interpreted as the gains from patenting which stem from both the tax savings and the elimination of appropriation. Note that $\frac{d\phi}{db}=\frac{-t}{1-t}<0$, i.e. when

although these occur, they happen less than 10% of the time. Frakes and Wasserman (2016) also discuss "bad" patents. The novelty threshold for the EPO is described at `https://www.epo.org/law-practice/legal-texts/html/guidelines/e/g_iv.htm`.

[31]This amounts to assuming that appropriation occurs before the firm incurs production costs.

[32]For the sake of simplicity, here we treat $r$ as independent of the level of novelty. If this is increasing in $n$, then it remains the case that the most novel innovations lead to applications.

[33]Note that all successfully patenting firms use the patent box, suggesting it is costless to use one. In practice, the need to identify qualifying income and, when nexus requirements are part of the box, allocate research costs to patents create costs for using patent boxes. The results of den Hertog, et al. (2016) however suggest that these costs are negligible and we therefore ignore them here.

[34]In contrast, under the French system, research costs are deductable only at the reduced rate. If going this alternative route, using the patent box increases the after-tax cost of application and research, a complicating assumption that does not alter the fundamental insights.

$b$ falls due to the implementation of a patent box, this increases the gains from patenting. Further, note that the standard tax $t$ only influences $\phi$ if $b < 1$. This is because, in the absence of a box, taxes do not distort behaviour. With a box, however, a rise in $t$ increases the gains from patenting precisely because the same $b$ means a bigger percentage point reduction in the effective tax rate inside the box. Thus, the standard tax influences the incentive to patent only because it influences the tax reduction achieved by the box.

From Equation 1, for a given novelty, the optimal representative effort, $c(n,\phi)$, is determined when the marginal benefit equals the marginal cost, i.e.:

$$p_c(n, c(n,\phi))\,\phi r = 1. \tag{2}$$

From this, we see that:

$$\frac{dc(n,\phi)}{d\phi} = -\frac{p_c(n,\phi)}{p_{cc}(n,\phi)\,\phi} > 0 \tag{3}$$

i.e. the introduction of a patent box would lead to an increase in representative effort. We refer to this change as "representative upgrading" from a patent box which can come from using a better representative and/or having them spend more billable hours on the application.[35]

Knowing the effort it would then put into an application, the firm must decide whether or not to apply. It will do so whenever the expected profit from the application is at least as large as when it does not apply, i.e. when $p(n, c(n,\phi))\,\phi r - c(n,\phi) \geq 0$. This then points to a cutoff novelty level $\overline{n}$ for which the firm is indifferent between applying and not applying where, for $n \geq \overline{n}$, the firm applies. From this it is straightforward to show that:

[35] Note that this could also extend to efforts put into revisions of a rejected application. When an application is rejected by the EPO, the innovator has the option to revise and resubmit the application as practically many times as it wishes (paying further application fees of course). If a patent box leads applicants to pursue the application longer, then this could result in both greater success as well as an increase in the time it takes for the average application to be granted. This is discussed more below and in the appendix.

$$\frac{d\overline{n}}{d\phi} = -\frac{p\left(\overline{n}, c\left(n, \phi\right)\right)}{p_n\left(\overline{n}, c\left(n, \phi\right)\right)\phi r} < 0 \tag{4}$$

so that introducing a patent box lowers the novelty threshold, meaning that firms would seek applications for more innovations even if the number of innovations does not change. Further, these additional submissions will be for innovations of marginal novelty. This "selection effect" of patent boxes is raised as a potential concern by the OECD (2016) and Bradley, et al. (2015) and would lead to a reduction in the overall average success rate of submitted applications.[36]

Anticipating the novelty threshold for application and the representative effort it would use, we can now describe the firm's optimal research effort. For a given innovation, expected profits (ignoring the set-up costs $d\left(M; s\right) + \alpha\left(s\right)M$) are given by:

$$\left(1-t\right)\left(qr - \beta\left(s\right)e + \int_{\overline{n}}^{\infty}\left(p\left(n, c\left(n, \phi\right)\right)\phi r - c\left(n, \phi\right)\right)dF\left(n, e\right)\right) \tag{5}$$

where the last term represents the expected benefits from patenting. Taking the derivative with respect to research effort $e$, using the fact that the expected patenting gain from novelty $\overline{n}$ is zero, employing the envelope theorem for changes in the optimal representative effort, and assuming an interior solution, optimal research effort $e\left(\phi, s\right)$ is where:

$$\int_{\overline{n}}^{\infty}\left(p\left(n, c\left(n, \phi\right)\right)\phi r - c\left(n, \phi\right)\right)dF_e\left(n, e\right) - \beta\left(s\right) = 0 \tag{6}$$

in which $dF_e\left(n, e\right) > 0$ is the shift in the distribution towards higher novelty due to an marginal increase in research effort. From this, two results are found. First:

$$\frac{de\left(\phi, s\right)}{ds} = \frac{\beta'\left(s\right)}{\int_{\overline{n}}^{\infty}\left(p\left(n, c\left(n, \phi\right)\right)\phi r - c\left(n, \phi\right)\right)dF_{ee}} > 0 \tag{7}$$

meaning that larger firms undertake more research effort.[37] Since this greater research effort

[36] Although somewhat different, it also relates to the potential for unused "zombie" patents discussed by Gaessler, et al. (2019).

[37] In this recall that due to the declining marginal effect of research effort $dF_{ee} < 0$, i.e. the marginal shift

increases expected novelty, larger innovators will have more success in the patent application process all else equal. Second:

$$\frac{de\left(\phi,s\right)}{d\phi}=-\frac{\int_{\overline{n}}^{\infty}p\left(n,c\left(n,\phi\right)\right)r}{\int_{\overline{n}}^{\infty}\left(p\left(n,c\left(n,\phi\right)\right)\phi r-c\left(n,\phi\right)\right)dF_{ee}}>0 \tag{8}$$

so that as the benefits of patenting rise (such as when $b$ falls under a patent box) the research effort increases. We refer to this as the "effort effect" of patent boxes.

Combining the above, when a patent box comes into effect, three changes in the average success rate of applications take place. First, because getting the patent has become more valuable, more effort is put into application preparation. This representative upgrading will increase the average success rate of applications. Second, an increase in research effort will reinforce this increase in success rates. Third, the selection effect will lead to more marginally novel applications being submitted, countering the first two effects. Thus, the net effect of a patent box is ambiguous.

One important thing to note, however, is that the relative size of the effects may vary over time. This is because whereas increased research effort requires time to bear fruit, implying a time lag before the effort effect is felt, this is not true for representative upgrading and the selection effect (so long as the firm already has innovations it could potentially submit). If representative upgrading is the dominant force, patent boxes may be associated with an immediate increase in the success rate, one which can be captured by controlling for the quality of the legal representative. On the other hand, if selection is the dominant effect, then there should be a drop in the success rate even in the short run.[38] Over time, however, increased research effort will begin to result in more novel innovations, leading to an increase in the average success rate of applications that persists even when controlling for representative quality. Therefore, in our analysis, we will use changes in the effect of patent

in the novelty distribution is smaller as research effort increases.

[38] Unlike other jurisdictions that allow 12-month filing grace periods after public disclosure, the EPO treats any prior public disclosure of an invention as novelty destroying, with very limited exceptions: `https://www.epo.org/law-practice/legal-texts/html/guidelines/e/b_vi_5_5.htm`

boxes over time to tease out the relative importance of the three different effects.

The standard tax rate $t$ only influences research effort, the novelty cutoff, and representative effort through its impact on the benefit of the box. Therefore we do not expect a significant effect of the standard tax rate on the success of applications. Although not modeled, we could introduce the b-index (where a lower b-index implies greater subsidies to research, lowering the cost of research effort). Comparable to an impact of firm size, we would anticipate that a lower b-index increases research effort and thus the success rate of applications.

Finally, the above analysis takes the number of innovations $M$ as given. Since the introduction of the patent box increases the expected after-tax value of generating innovations, it should increase the number of innovations the firm develops. Thus, the number of aggregate applications should increase as more innovations are developed (a rise in $M$) and because more innovations are submitted (the selection effect). This would then match the evidence provided by Schwab and Todtenhaupt (2019), Alstadsaeter, et al. (2018), and others.[39] Three items, however, should be noted on this point. First, if the fixed cost $\alpha(s)$ is large or the cost $d(M; s)$ is rapidly increasing in $M$, then a correspondingly large increase in the benefits of successfully patenting is needed for $M$ to increase (particularly if $M$ is restricted to whole numbers). Second, since not all of the $M$ innovations will be submitted to the patent office, this could result in a limited increase in applications. Third, given the time it takes between development and application, a potential increase in the number of applications may take several years to materialize in the data.

# 3 Data and Estimation Strategy

In this section, we first describe our data which combines two main components: patent application data (which drives the country and year coverage in our data) and country

[39] In addition Balasubramanian and Sivadasan (2011) find that firms grow after patenting. Agiakloglou, Drivas, and Karamanis (2016) find that larger firms are also more likely to renew an existing patent whereas smaller firms are more apt to transfer ownership.

data (including tax information, especially patent boxes). We then lay out our strategy for estimating the probability a given application is granted.

## 3.1 Patent Data

We use bibliographic patent data from the European Patent Office (EPO) PATSTAT database for EPO patent applications and grants filed between 1978 and 2019, which we use to construct our control variables used in an estimation window spanning 2000 to 2012. For each application we have the name and country of the applicant(s), inventor(s), and representative(s), the application filing date, the date the application was granted (if it has been), and the technology codes assigned to the application by the EPO (more on these below). This leaves us with 3,601,939 "A"-kind patent applications, of which 46.3% were granted at some point during the sample period (the success rate).

Our goal is to construct the cleanest sample we can to improve identification. With this in mind, we restrict ourselves to those patents where all applicants come from the same country.[40] We do so to eliminate noise arising from patents where the ownership, and thus the tax jurisdiction, may cross borders adding to difficulties in interpreting which tax policies are important for application behaviour.[41] This eliminates 75,796 patents (or 2.1% of the sample).[42] In order to further eliminate excess noise from the sample, we restrict ourselves to only those applicants from EPO member countries.[43] This reduces our number of applications by 1,878,760 or 53.3%. This is a large reduction, but as is well known

[40] Note that the applicants are the owner of the innovation (many times a firm) and therefore often differ from the inventors (who are humans). This also avoids the need for fractional apportionment of cross-country applications as was done by Bradley, et al. (2015) when calculating the total number of applications by country-year. It should be noted that while the bulk of the literature, ourselves included, uses the applicant to assign an application to a country. Since income from an innovation arguably accrues to the applicant rather than the inventor, this seems apt when examining taxation. That said, Bösenberg and Egger identify country by the inventor rather than the applicant.

[41] Ernst and Spengel (2011) and Schwab and Todtenhaupt (2016) find evidence consistent with multinational firms shifting innovation activities across borders for tax purposes, further bolstering our reasons for this restriction.

[42] Note that the success rate of cross-country applications is 47.4%, slightly higher than for single country applications.

[43] This includes the EU member states during any point of our sample period, Switzerland, Croatia, Monaco, Macedonia, Norway, Turkey, Albania, Bosnia and Herzegovina, Serbia, and Montenegro.

there is a significant home bias in terms of patenting (i.e. applicants are far more likely to apply in their own country than in others). In addition, as discussed above, there is a significant home bias in terms of the success rates.[44] Indeed, in our data, the success rate of EPO member applications is 51.6% whereas that for non-members is only 41.6%.[45] Due to missing tax data (described below), we also drop six EPO members, resulting in a loss of 693 additional applications.[46] This leaves us with a total of 1,646,712 applications. Out of these, 96.1% of applications have a single applicant (with another 3.2% having two applicants). As the success rate for multi-applicant applications is markedly lower (46.3% as opposed to 51.8% for solo-applicant ones) we restrict ourselves to the 1,581,841 solo applications. Finally, we have information on the nature of the applicant, e.g. whether the applicant is a company, individual, university, hospital, and so forth.[47] We use this information to restrict ourselves to applications coming from companies, doing so for two reasons. First, the motivation for patenting may differ between categories, i.e. universities and non-profits may be less inspired to patent due to profit-generating considerations. Second, as patent boxes work within corporate tax regulations, we exclude the 105,993 applications coming from individuals because patent boxes may be irrelevant for their tax burdens. This leaves us with 1,387,534 applications from companies (a 12.3% reduction in the sample size).[48]

We construct several pieces of information from these applications. First, for each applicant, we generate the total number of applications they made during the data period (1978-2019).[49] We do so using the entire time span of 1978 to 2019, not only during our

[44] Home bias in patenting extends even further to include a bias in citations (Bacchiocchi and Montobbio, 2010).

[45] Note that this is unlikely driven by differences in when applications are occurring as the average filing date of non-member applications is less than a year after that of member applications.

[46] These were Albania (8 applications), Bosnia and Herzegovenia (17), Macedonia (5), Monaco (582), Montenegro (6), and Serbia (75).

[47] See Eurostat (2011) for a description of the methodology used in this classification.

[48] It should also be noted that the applications from companies are successful 52.9% of the time, the highest of any category. By way of comparison, applications by individuals are successful only 47.4% of the time.

[49] Note that the applications do not assign specific identification numbers to applicants or inventors. In order to match an applicant or inventor across applications, they were matched when the name, address, and country were the same. When this was not possible, we employed the Massacrator 2.0 algorithm, as described in Pezzoni, Lissoni, and Tarasconi (2013).

estimation window of 2000-2012. Even though the sample includes nearly 1.4 million applications, these are made by only 149,202 applicants. As one might expect, the number of applications is dominated by a small number of very active applicants. Although the average number of applications by a single applicant is 9.3, 52.4% of applicants make a single application over the 42 years of data and 90.3% make fewer than ten.[50] The top 5% most active applicants make nineteen or more applications during the sample. This group of 7,854 applicants accounts for 73.7% of the total number of applications with an average of 130.1 applications each. Furthermore, the top 5% are on average more successful, with an average success rate of 54.3% relative to 48.9% for other applicants.[51,52] Thus, experience appears to have a significant effect on success. With this in mind, for each applicant-year $at$, we construct the success rate over the prior three years.[53]

Second, we use information on the inventor team from the application.[54] Note that unlike the applicants where we restricted the sample to single-authored applicants from EPO member countries, we place no such restrictions on the inventor team. Indeed, following Drivas and Kaplanis (2020), we include dummy variables indicating if the inventor team crosses borders ($Intl\ Team_a$) and whether there is an inventor in a different country than the applicant ($Intl\ App\text{-}Inv_a$). Based on Drivas and Kaplanis (2020), we anticipate positive effects for these variables.[55] Across the applications, there are a total of 1,537,807 inventors.

[50]Even when an applicant makes numerous applications across years, multiple applications in a single year is not especially frequent. For non-top 5% applicants, only about 20% of applicant-years involve multiple applications. For those in the top 5%, 71% of applicant-years involve multiple applications and 46% involve just one or two applications.

[51]This mirrors the evidence of Carley, et al. (2015) for US applications.

[52]Focusing on the 653,359 applications during our estimation window of 2000-2012, 491,320 or 75.2%, come from our top 5% group. During this period, applications from the top 5% were successful 55.6% of the time whereas those outside the top 5% were successful 49.8% of the time. Combined with the downward trend in applications and success discussed below, this indicates that the applications used in estimation are not out of line with the overall trends in the full sample.

[53]47.3% of applicants made their first recorded application during this period. In particular, 71.8% of top 5% applications had their first recorded application during this period. Thus, given that our application data starts in 1978, we believe that we do a reasonable job of capturing an applicant's prior application history. In the appendix, we instead use the success rates over the prior five and ten years with no difference from the reported results.

[54]Note that, due to missing inventor data on 6,543 applications, we do not use these applications in our estimations.

[55]Note that the correlation coefficient between these is 0.33. Overall, 57,714 applications have only a cross

On a given application, on average, there are 2.38 inventors.[56] Overall, 36.8% of applications have a single inventor and another 27.6% have only two; 99.1% have eight or fewer. Similarly, 68.2% of inventors are listed on a single application, another 14.0% are listed on two, and 95% are party to seven or fewer applications. For inventors listed on more than one application, the average success rate is 56.7%. In contrast, the success rate of one-time inventors is only 47.6%, i.e. those that are party to multiple applications are on average more successful in line with Drivas and Kaplanis (2020).[57] We therefore control for the number of inventors on the application as in Guellec and van Pottelsburghe (2000).[58] For each inventor-year, we also construct the average success rate of applications they were listed on over the prior three years.[59] This is comparable to Webster, et al. (2014) who control for the number of successful applications by a given inventor prior to the start of the estimation sample. This inventor success rate then used to create the average success rate for the inventor team on an application.[60]

Third, for each application, we have disambiguated information on the representatives (patent attorneys) used in preparation of the application.[61] In total, across the 1.3 million applications, there are 13,723 representatives. On average 1.4 representatives are used on a given application, with 69.3% of applications having a single representative and another 22% having two. As with the inventors, for each representative, we construct a moving average success rate over a three year window and then, for each application, calculate

border team, 98,209 only a cross-border applicant/inventor combination, and 49,214 have both. Using one variable or the other has no marked impact on the results.

[56] This is slightly higher, 2.56, for applications from the top 5%.

[57] When calculating these success rates for the applications used in estimation, the distribution was very similar.

[58] Guellec and van Pottelsburghe (2000) also control for the number of applicants which, given our sample choice, is always one in our data.

[59] If the inventor was not on any applications during the three year window, their success rate was zero. In the appendix, we also construct this window for the prior five and ten years. These alternatives have no qualitative impact on the results. Note that when making these variables, as well as the number of applications by a given applicant, we use the full single-applicant panel running from 1978-2019, not just that for our estimation window.

[60] In unreported results, we use the prior success of the inventor in the team with the highest prior success rate. This has no appreciable effect on the results.

[61] This information is missing for 240,909 applications. The representative names were disambiguated using the same process as the applicant and inventor information.

the average success rates for the representatives on the application.[62] Our expectation is that applications using legal teams that have been more successful in the past will be more successful themselves.[63]

Fourth, we make use of the technology classes (Cooperative Patent Classification or CPC codes) listed on the applications.[64] These CPCs are assigned by the EPO after receiving the application and indicate specific technology areas related to the application. Much like product or industry codes, CPCs can be grouped into broad or narrow categories with the narrowest in our data at the ten digit level. These CPCs are used by the EPO to search for prior art and assess the novelty, and thus the patentability, of the application in question. It is no surprise that the success rate and the time it takes for successful decisions to be made can vary across CPCs. For each application, we add up the number of ten digit CPCs within a given three digit CPC.[65] The average application has 5.3 ten digit CPCs which span an average of 1.65 three digit codes.[66] From this, for each application $a$ and for each three-digit CPC $c$, we construct a dummy variable equal to 1 if any of $a$'s ten digit CPCs fall under $c$.[67] We also keep track of the number of ten digit CPCs ($Codes$) each application covers. This mirrors Bösenberg and Egger (2017), Guellec and van Pottelsberghe (2000), and Lerner (1994) who use the number of technology codes as a proxy for patent quality.[68]

Fifth, we also know whether each of the applications submitted to the EPO were also

[62] In the appendix, we use five and ten year windows with little difference. In further results available on request, we used the maximum prior success rate from the representative team rather than the mean with essentially identical results.

[63] Note that our approach slightly differs from de Rassenfosse, et al. (2018). They take their sample of applications and use half of it to estimate success rates for representatives which are then used as a control when estimating the success of the other half of the sample. We instead use rolling averages so that the success rate of a representative can vary over time.

[64] CPC data was missing for 532 applications.

[65] In unreported results, we instead use the 647 different four digit categories.This resulted in a very sparse set of data populated mainly by zeros. We therefore use the somewhat less sparse three digit classification where there are 128 different categories.

[66] Again, numbers are comparable for those applications used in estimation.

[67] In alternative results, we use the share of ten digit CPC codes in a given three digit code rather than dummies. Since for 56.4% of applications, all ten digit CPCs fall under a single three digit one, it is no surprise that these are quite similar and gave comparable results. We present the estimates using dummies here to ease interpretation of the CPC sub-sample results. These alternate results are available on request.

[68] Grimaldi and Cricelli (forthcoming) describe alternative approaches to measuring quality.

submitted to the patent offices of the United States, Japan, China, and/or Korea.[69] These, along with the EPO, constitute the five main patent offices globally. From this information, we construct *Family Size* which is the number of the five patent offices to which the application was submitted.[70] In addition, we identify two sets of patents, triadic ones for which an application is made to at least three of these patent offices (of which the EPO is one) and pentadic applications which are submitted to all five. Because applications are costly, firms will only submit to multiple offices when an invention is more valuable. Thus, family size acts as a proxy for the applicant's private information on an innovation's value. If innovation value is correlated with novelty, then family size should have a positive effect on success, a standard result in the literature on the probability of success. Finally, as per Ernst, et al. (2014), Böhm, et al. (2015), and others we control for the number of forward and backward citations (with forward citations for the first five years post-filing). Forward citations are presumed indicative of a more novel innovation and thus a higher probability of application success.[71] More backward citations, on the other hand, may indicate a large existing stock of prior art, indicating lower novelty and less success. Note that due to missing data in PATSTAT, we lose 5,646 applications when doing so. Finally, for each application, we have the number of independent and dependent claims. Due to missing data, we lose 2,576 patents in our estimations. We include these as another standard control for patent quality.

Figure 1 Panel a plots the number of applications per year for our 1,380,381 applications. There is a significant drop-off starting around 2017, a well-known pattern evidencing end-of-sample truncation in PATSTAT. Furthermore, whereas applications from applicants outside the top 5% were a growing share of total applications up to this time, they almost

[69] In unreported results, we included a dummy equal to one if the EPO was the priority office for the application. This was insignificant and affected none of our other results. Although Guellec and van Pottelsburghe (2000) find that success is higher at the priority office, their sample differs from ours in many dimensions including time coverage.

[70] Martinez (2010) discusses different approaches to defining family size.

[71] In the appendix, we omitted this out of concern for potential endogeneity, i.e. granted patents may generate more citations. This had no significant impact on our results.

completely disappear after this truncation begins. Panel b of Figure 1 plots the success rate of applications filed in a given year for all applicants, those in the top 5% and those outside the top 5%. Like the truncation in total applications, there is again a change towards the end of the sample, beginning around 2013. It is unsurprising that this change in trend happens earlier than that found in the number of applications, since applications filed in later years have yet to fully work their way through the examination process and are therefore not considered successful in our data. Applications submitted from 2000 to 2012 that were ultimately successful took on average 1897.5 days, or approximately five years, to work their way through the application process. Since our data ends in 2019, this reinforces the idea that end-of-sample issues are contributing to the decline in success rates after 2012. With this in mind, we restrict the data used in estimation to include only those applications submitted up to and including 2012 and discuss this further below.[72] One last feature of these two graphs is that the number of applications began to flat-line in 2008, coinciding with the financial crisis. At the same time, the average success rate momentarily paused in its downward trend.[73] If the financial crisis of 2008 reduced inventors' willingness to submit marginal patents during those years, these aggregate shifts may well be in line with the above discussion. An important issue for our estimation is that the financial crisis coincides with four of the five patent boxes introduced during our estimation window, which we discuss further below.

## 3.2 Country Data

In addition to controls derived from the patent applications, we include a number of country-level controls, including several key tax variables. These tax data come from Alstadsaeter, et al. (2018) and are supplemented with data from the OECD and PWC *Worldwide Tax*

[72]In the appendix we examine whether, for applications from 2000-2012 that were granted by the end of our data, there was a link between the introduction of a patent box and the length of time required for a decision. We find an insignificant coefficient which suggests that, post-patent box, successful applications took eight days less to be approved, i.e. there was no appreciable difference in days to granting. Thus, we feel confident that the introduction of a patent box is not contributing to the end-of-sample truncation issue.

[73]The overall decline in success rates is in line with the observations of Carley, et al. (2015) in US data.

*Summaries*.[74] First, we use the highest corporate income tax of country $i$ in year $t$, $CIT_{it}$. Second, we include a dummy variable for whether $i$ has a patent box in place in year $t$, $Box_{it}$, as well as the difference between the standard tax rate and that charged under the patent box, $TaxReduction_{it}$. Note that if there is no patent box, then $TaxReduction_{it} = 0$.[75] We also distinguish between patent boxes in two ways. First, boxes are categorized according to whether they are narrow or broad. Narrow boxes provide the preferential rate only to patents registered after the box is in effect, whereas broad boxes extend the tax benefits to prexisting patents.[76] Second, we include a flag for patent boxes which have nexus requirements under which innovation must be done locally in order to qualify for the tax reduction.

Table 1 lists the EPO member countries using patent boxes, the dates of patent box effectiveness, and patent box conditions. Note that excepting the French and Irish boxes, both of which began well before the start of the sample, the boxes become effective after 2000. Thus, following Alstadsaeter, et al. (2018) we restrict our attention to applications submitted from 2000 on. This, combined with the truncation in success rates observed in Figure 1, results in an estimation window from 2000 to 2012 for a total of 646,022 applications. We also control for the b-index obtained from Bösenberg and Egger (2017). Although we direct the reader to their paper for details on the variable's construction, in short, it compares R&D tax incentives to the corporate income tax, with higher values translating to higher after-tax costs for R&D.

Table 1 also lists the number of applications and success rates by country during the estimation window.[77] The average success rate was 54.5%, which varied significantly across countries ranging from a Finnish and Dutch low of 42.6% to a Maltese high of 62.8%. Of the countries with patent boxes active during the estimation period, only France had a success

[74]These can be found at `https://stats.oecd.org/Index.aspx?DataSetCode=CTS_CIT` and `https://www.pwc.com/gx/en/services/tax/worldwide-tax-summaries.html` respectively.

[75]Evers, et al. (2015) provide a useful discussion of how patent boxes in Europe operate. Klemens (2016) also reviews patent boxes and provides a model suggesting that by allowing for separate taxes on mobile intellectual property and immobile fixed capital, patent boxes can increase tax competition.

[76]See Koethenbuerger, Liberini, and Stimmelmayr (2019) for discussion.

[77]Note that Estonia, Liechtenstein, and Monaco do not appear as they had no single-country, single-applicant applications during the estimation window.

rate better than the EPO average (55.6% versus the 54.5% mean). Digging deeper, Figure 2 plots the annual average success rates for the five countries which introduced patent boxes in the interior of our estimation window (i.e. no closer than three years to the ends of the sample). As with Figure 1, this is for the applications filed in a given year, i.e. those filed in period 0 are those filed in the year the patent box takes effect. Excepting Luxembourg, all experienced a rise in success rates in the patent applications following the box's introduction.

Looking across the success rates in Table 1, there is no clear pattern for why some countries have higher success rates. That said, large, wealthy countries submit more applications. Thus, in addition to the tax data, we include real GDP and GDP per capita for country $i$ in year $t$. Both are measured in logs and are obtained from the World Development Indicators.[78] We also include R&D spending relative to GDP, also from the World Development Indicators. Webster, et al. (2014) and others find that applications from countries with more R&D spending in a given field tend to have lower success rates, suggesting declining marginal returns to spending.[79] While it would be desirable to have R&D expenditures at the applicant level, doing so would force us to drop small inventors due to lack of data.[80]

Finally, we include a full complement of country, applicant, and year dummies. In particular, if technological advantages are fairly stable over our thirteen year estimation window, we hope that the country dummies capture the impact of local advantages.[81] Likewise, inclusion of year dummies will help to filter out effects of common shocks such as the financial crisis. Table 2 lists the number of observations and average success rates for the different technology classes while Table 3 presents the summary statistics for the observations used in our estimation window.

[78] These can be found at `https://databank.worldbank.org/source/world-development-indicators`. Note that as both are in logs this is equivalent to controlling for population and GDP per capita as in Gaessler, et al. (2019).

[79] This would be consistent with our assumptions on effort and success above.

[80] As found in Alstadsaeter, et al. (2018) and others, firms which spend more have more innovations. Falk (2007) estimates the aggregate number of patents in a country-year and investigates how this is influenced by where the total R&D spending comes from with private sector expenditures having a larger effect than public money.

[81] See Webster, et al. (2014) for alternative approaches based on spending and exports.

## 3.3 Estimation Strategy

Our goal is to estimate the probability of success of application $a$ from applicant $i$ in country $c$ published in year $t$ that contains CPC codes $k$. To this end, we estimate the following linear probability model:

$$Success_{aictk} = \beta_1 Box_{ct} + \beta_2 X_{aict} + \alpha_{ictk} + \varepsilon_{aictk} \tag{9}$$

$Success_{aictk}$ is a dummy equal to one if the application is granted. Our variable of interest, $Box_{ct}$, indicates whether country $c$ has a patent in place during the year application $a$ is submitted. In some specifications, this is instead altered to measure the tax savings offered by the patent box (where, in the absence of a box, the savings is zero). $X_{aict}$ is a set of additional controls such as the number of offices the application is filed in, the prior success rate of the applicant, and the (non-patent box) corporate tax rate of country $c$ in $t$. The $\alpha_{ictk}$ term represents a set of fixed effects for year, CPC, and either country or applicant fixed effects. Finally, $\varepsilon_{aictk}$ is the error term which we two-way cluster by country and by year.[82] As discussed in Section 2 the patent box impact via the various channels may evolve over time, particularly when the research effort effect is important. Therefore in some specifications we explore time varying effects of the patent box (including looking for pre-trends) using a dynamic difference-in-differences approach. In a similar vein, we explore whether broad boxes, where the benefits apply to pre-existing patents, differ from narrow boxes where tax savings are enjoyed only by new patents.[83] We do the same for nexus requirements. Our use of a linear probability model follows Drivas and Kaplanis (2020) and others with its main advantage being ease of interpreting the magnitude of coefficients. In robustness checks found below, we instead follow Guellec and van Pottelsburghe (2000) and employ a probit

[82]Specifically, we use the *reghdfe* command in Stata to allow for two-way clustering (Correia, 2017). Note, this estimator drops observations where the fixed effects perfectly explain the dependent variable, thus the number of observations can vary depending on the fixed effects used.

[83]As discussed by Ernst, et al. (2014), the introduction of a box is announced well ahead of its actual implementation.

estimator. As shown there, the results are consistent across these models.

# 4 Results

In this section, we build up to our preferred specification before exploring subsets of the data, alternative estimators, and other robustness checks.

## 4.1 Baseline Results

Table 4 presents our baseline results. In Column 1, we include all applicants, those from the bottom 95% and the top 5%, and exclude the representative prior success variable which as mentioned above is missing for a number of applications. This specification does, however, include our three taxation variables (the patent box dummy, the corporate income tax (CIT), and the b-index), all other applicant and application variables, our time-varying country variables, and the country, year, and CPC dummies. Starting with our tax variables, we see that the patent box is associated with a 3.8 percentage point increase in the likelihood of the patent being granted.[84] Given that the average success rate is 54.5%, this 3.8 percentage point boost would translate into a 7.0% increase in the probability of success.[85] Neither the CIT nor the b-index have a significant effect on the success rate. The first of these is as expected from the model.

Turning next to application-specific controls, a larger family is correlated to a higher probability of granting. Similarly, more complex applications, i.e. those covering more CPC codes and with more independent claims, are less likely to be granted. Looking to the composition of the inventor team, somewhat surprisingly, we find no significant effect.

[84] As the success outcome is either zero or one, a coefficient of .1 would mean a 10 percentage point increase in the expected probability of success. If the mean success rate is 50%, that would then anticipate a 20% increase in the expected success rate. Throughout our discussion, we indicate whether we are talking about a percentage point change (10) or a percent change (20%).

[85] That is, the 3.8 percentage point increase is added to a base of 54.5 percent, or an increase of $\frac{3.8}{54.5} = 7.0\%$. Throughout, we endeavor to distinguish between the point estimate which is in percentage points and its economic magnitude which is in percent.

In terms of citations, applications which are themselves cited more are more likely to be granted whereas the number of backwards citations is unimportant.[86,87] While applications from more frequent applicants are less likely to be granted, this effect is extremely small. As expected, applicants and inventor teams which have been more successful in the past are more likely to have current success. Looking at our time-varying country controls, we see that applications from larger countries have less success, with average income having no impact.[88] Finally, we find that although the point estimate suggests that more aggregate R&D spending lowers the average success rate, as in Webster, et al. (2014), the coefficient is not significant in this specification.

In Column 2, we introduce the prior success rate of the legal team preparing the application. Doing so reduces our sample significantly, however as shown this is a significant predictor of success where, as with the applicant and inventor team, greater prior success points to more current success. As noted above, despite the sample size decrease, controlling for quality of the representative is important because the patent box introduction can give rise to representative upgrading, potentially biasing the patent box coefficient upwards if it is omitted. Indeed, when controlling for prior representative success the coefficient on the patent box declines slightly although the difference is not statistically significant. Before we attribute this change wholly to controlling for prior representative success, we must remember that the sample has also changed. Therefore in Column 3, we omit this variable but restrict ourselves to the sample in Column 2. This results in a coefficient on the patent box which is comparable to Column 1, further suggesting the potential for some slight representative upgrading. While the estimates suggest that representative upgrading may occur following the introduction of a patent box, this alone cannot explain the increased success rate of applications following such a policy change, hinting at a possible research effort effect.

[86] Recall that the CPC dummies would control for the mean number of citations within a given technology class.

[87] In the appendix, we show the results when omitting forward citations out of concerns for potential endogeneity, i.e. granting generates forward citations. Doing so has no impact on our overall results.

[88] Recalling that as both are in logs, including these is equivalent to including both GDP and population.

With this in mind, we proceed with the smaller sample that includes the representative information for the remainder of the paper noting that, in results available on request, omitting it in favor of a larger sample has little impact on the results.

As discussed above, the data indicates clear differences in the patenting activity of frequent applicants (those in the top 5%) and infrequent ones. This is found both in the number of applications and their success rates. Furthermore, given that the patent box is a corporate tax policy with potential costs associated with using it, we would expect that its effects are more visible in large, active innovators than in firms who may patent just once or twice. With this in mind, in Columns 4 and 5, we split our sample with Column 4 presenting estimates using just the bottom 95% and Column 5 showing those for the top 5%.[89] Focusing on the patent box dummy, we find that patent boxes only have a significant effect in the top 5% where the coefficient suggests a 4.47 percentage point increase in the success rate (a 7.9% increase relative to the average success rate of 56.5% in this subsample). Because the top 5% submit many more applications than the bottom 95%, this subsample is over twice as large, introducing the possibility that the strong significance of the patent box variable is driven by a greater number of observations rather than a difference in responses. To test this, we create 1000 random subsamples from the top 5% with 158,773 observations each to match the sample size of the bottom 95%. In each case, the estimated coefficient for the patent box variable was positive, with an average value of 0.0447, the same as found in Column 5. This coefficient was significant at the 1% level in 227 of the subsamples, at the 5% level for 641 subsamples, at the 10% level in 116 subsamples, and insignificant in only 16 subsamples.[90] Therefore we are confident that the difference in significance is due to a different response by the top 5% of applicants rather than sample size. In contrast to the tax variables, the other controls are largely similar in the two subsamples. One exception is the total number of applications where, for the bottom 95%, more frequent applications are

[89]In the appendix, we explore alternatives to the 95/5 sample split. As found there, in each case, the estimates point to insignificant patent box effects for infrequent applicants but significantly increases in the average success rates for frequent applicants.

[90]A histogram of the point estimates is in the appendix.

associated with more success, a result that fits with the overall higher success rate for more frequent applicants.

Finally, in Columns 6 through 8, we include applicant fixed effects.[91] We only introduce these here because 56.9% of the applicants made a single application during the estimation window (with another 16.3% doing so only twice). When using all applicants in Column 6, the patent box variable continues to be significantly positive. Furthermore, it roughly doubles in size. Including applicant fixed effects and splitting the sample in Columns 7 and 8 between the bottom 95% and the top 5%, we again find that the patent box is significant only for the top 5% where the coefficient suggests a rise in the probability of success of 6.9 percentage points (or 12.3%). Interestingly, the b-index is now significant, but only for the bottom 95%. This suggests that ex-ante tax incentives may be particularly important for infrequent applicants, as might be the case if these innovators are more credit-constrained when compared to their larger counterparts as posited by the OECD (2016). An additional difference we wish to point out is that the coefficient on prior applicant success differs across the two subsamples and is somewhat surprisingly negative for the bottom 95% of applicants. One potential reason for this is the small number of applications in this subsample means most applicants may not have submitted anything in the prior three years. As a result, 68.1% of the subsample has a prior success of zero. Similarly, 19.1% have a prior success of 100% (i.e. the only other application submitted in the prior three years was successful). In contrast, for the top 5%, only 3.5% of observations have a prior success of zero and just 8.6% have a prior success of 100%. Finally, after controlling for applicant fixed effects, we now find the anticipated positive effect for the number of inventors when using the top 5%.

The above then suggests that patent boxes are linked to an increase in the success rate of applications, that this result is not driven by representative upgrading, and that it occurs only in the most frequent innovators. Two questions, however, still remain. First, are

[91] Note that this absorbs both the total number of applications and the country dummies. Further, since the *reghdfe* command drops applicants with no variation in the outcome variable, this reduces the total number of observations, primarily for the bottom 95% subsample.

patent boxes introduced during a period where success rates are already rising in a country? Second, is the increase in success due to a change in what is submitted (i.e. the submission of pre-existing innovations) or an increase in the novelty of the innovations that are being generated? To examine these, instead of using a simple dummy equal to one when the patent box is in effect, we generate a set of "period" dummies which run from five years ($t-5$ to $t-1$) before the introduction of a patent box ($t=0$) to five years after ($t+1$ to $t+5$). Thus, for a country that introduces a box in 2007, its $t-5$ period dummy equals one in 2002 and its $t+5$ period dummy equals one in 2012. Note two things here. First, as the French box started well before the sample, these period dummies are all zero. Second, for countries with boxes that start outside the sample period (Cyprus, Italy, Turkey, the UK, and the reintroduction of the Irish patent box) their anticipatory period dummies will equal one as appropriate.

With our period dummies in hand, we rerun the regressions in Table 4's Columns 7 and 8 as a dynamic difference-in-differences and illustrate the estimated coefficients and 95% confidence intervals for the period dummies in Figure 3.[92] Beginning with Panel a and the bottom 95%, we find no significant coefficients. That said, there is a slight rise in the point estimate in periods 0 and 1. Recall that most of our patent boxes are introduced in 2007 and 2008, thus the period 0 and 1 dummies coincide with the financial crisis. Recalling that Figure 1 indicates that success rates overall rose slightly during these years, this illustrates the importance of including even non-box countries in the estimation in order to control for the potential impact of the crisis.

Turning to the top 5% in Panel b, we see four key features. First, prior to the introduction of the box, there is no evidence of a general upward trend. This argues against the notion that patent boxes are being introduced in countries where the top 5% are already becoming more successful and that the baseline results are capturing a pre-existing trend in patent box countries. Second, as in Panel a, there is a slight upward tick in periods 0 and 1, which again

[92]Comparable figures for the combined sample and the results without applicant fixed effects are in the appendix.

happens around the financial crisis. That said, these coefficients are insignificant at the 95% level. Third, in periods 2 and onwards we find coefficients which are significantly positive and in line with the estimated coefficient for the simple patent box dummy in Table 4 Column 8. This argues against a large negative selection effect which should manifest as soon as the box is in place (recall that we are already controlling for representative upgrading). Instead, the estimates point towards the rise in success rates being driven by increased research effort that bears fruit two or more years after the patent box begins.[93] Fourth, if the effect was simply driven by innovators continuing to revise and resubmit applications until they are successful, we would again expect an increase in success rates of applications submitted immediately following the patent box's introduction. To test this last notion further, as shown in the appendix, for granted patents we estimate the effect that patent boxes had on the number of days it took from application submission to success. The estimated effect was never significant and for the top 5% suggested an decrease in grant time of 8.5 days (a drop of 0.4%). This is the opposite of what one might anticipate if greater applicant persistence in revisions was leading to the rise in success rates under a patent box. Finally, the patent box effect levels off in years $t + 4$ and $t + 5$. This could be because the increase in innovation novelty reaches a steady state at that point or it could be influenced by end of sample truncation.

Our baseline results therefore point to a delayed, economically significant effect of patent boxes on the success rate of applications coming from the most frequent applicants. While we cannot rule out some slight representative upgrading, the effect of submission of marginally novel patents or higher persistence in the application process is mitigated by the timing of the effect, which instead strongly suggests that the net impact is driven by the generation of more novel innovations. Given the results up to this point, for the remainder of the paper we focus on estimates for the top 5% of applicants only. In the appendix, we report results using all applicants or the bottom 95% only and here merely note that across the various

[93]Recall that prior public disclosure is novelty-destroying under EPO law, which would make it difficult for firms to re-work old ideas post-patent box.

specifications the full sample results mirror those of the top 5% while the bottom 95% do not seem influenced by patent boxes.

## 4.2 Robustness Checks

Here, we employ several strategies to examine the robustness of our findings.

To begin with, in Figure 1 we recognized a decline in the success rate in 2013, likely due to end of sample truncation and the time it takes for applications to be processed. Because patent boxes were introduced over several years, there is a concern that our patent box coefficient may be affected by end-of-sample truncation despite the inclusion of year dummies. In Figure 4 we plot the year dummy coefficients and 95% confidence intervals for Column 8 of Table 4. This figure shows a general downward trend in the average success rate, albeit one that was halted during the years of the financial crisis (again why it is important to include both patent box users and non-users to control for the effect of the crisis). This downward trend appears to accelerate somewhat during the final three years of the estimation window. With these patterns in mind, Table 5 reports results when ending the sample in 2011, 2010, and 2009 to see if truncation is driving our results. As shown, in each case, we continue to find a positive and significant impact of the patent box dummy. Consistent with the pattern found in Figure 3, as we end the sample earlier the point estimate falls in magnitude. This provides additional support that the largest effects are felt some years after the introduction of the patent box. Therefore the results do not seem to be the result of an end of sample truncation issue.

So far we have used the linear probability model in part for its ease of interpretation. Nevertheless, this does not account for the dependent variable's discrete nature. With this in mind, in Table 6 we report the results using a probit estimator.[94] We do so with caution, however, because as discussed by Greene (2004) when probit is combined with a large number of categorical variables, there is the potential for bias. With this in mind, we present

[94]Note that in doing so, we must cluster by country only, not country and year.

two probit specifications. In Column 1, we include country, year, and CPC dummies but not applicant dummies to reduce the number of categorical variables. In Column 2, we include applicant, year, and CPC dummies. Note that in this latter one, a small number of observations are excluded due to insufficient variation in the outcome variable. In both cases, we find results consistent with those obtained from the linear probability estimator. We nevertheless use linear probability in our presentation because of the ease it provides in interpreting the magnitude of the estimated effects.[95]

Next, we omit various countries in Table 7. First, as Ireland is the only country to remove a patent box during the period, Column 1 omits Ireland from the estimation. Column 2, on the other hand, reintroduces Ireland but omits the dozen countries with less than 1,000 applications during the estimation window. These omissions have little impact on the results and, if anything, tend to increase the point estimates for the patent box coefficients suggesting that including small countries may create a lower bound effect.

We next control for the effect of technology-specific patent differences via CPC codes. Table 8 varies the sample across columns, including an application in a given column when at least one of its ten digit CPC codes falls under a given one digit code (A, B, C, D, F, G, H, and Y).[96] We do so based on the observation by Carley, et al. (2015) and others that success rates vary by technology classes. There are two potential explanations for this variation. First, as shown by Cohen, et al. (2000), the propensity to patent varies significantly across industries (and thus potentially across CPCs). Second, if the threshold for novelty varies across technologies, then it may be more difficult for a firm to improve novelty sufficiently following the patent box to have an appreciable effect. Thus, although the average likelihood of success would be captured by the CPC fixed effects, this alone does not permit heterogeneous responses to the tax variables across technologies. As can be seen, the coefficient pattern for the patent box is very consistent across technologies, although the

[95] All presented linear probability results are also available for the probit estimator upon request. Here, we merely note that as in Table 6, the probit results are in line with the linear probability results.

[96] Note that as some applications cross one digit codes, the sum of observations across subsamples exceeds the total number of applications.

significance varies. In particular, the pattern holds up well for CPCs A (Human Necessities), F (Mechanical Engineering), G(Physics), H (Electricity) and Y(Emerging Technologies).[97] For those that are insignificant, B (Operations and Transport) has the highest average success rate, suggesting that in this technology it may be particularly difficult to further increase novelty. Codes D (Textiles) and E (Fixed Construction) meanwhile have the lowest number of applications by some margin. Thus, while patent boxes may lead to greater novelty and higher success, this may be easier to achieve in some technologies than others.

Finally, in Table Table 9 we allow the impact of the patent box to vary according to the number of patent offices in which an application was filed. We do so under the presumption that the number of offices to which an application is submitted is positively related to the firm's perception of the innovation's novelty.[98] As such, a patent box may have a larger impact for applications that are submitted to multiple patent offices. In Column 1, we restrict the sample to applications submitted to three or more offices (traidic applications) whereas in Column 2, the sample consists of those submitted to all five of the main patent offices (pentadic applications). [99] We see that the coefficient in both is positive and significant. In comparison to the baseline results in Table 4 Column 8, we find a larger point estimate for triadic patents (Column 1) and an even larger one for pentadic patents (Column 2). While this matches our expectations, the differences are not significant. In Column 3, we interact the patent box dummy with family size. Again, we see that while the point estimate suggests a larger patent box effect for applications submitted to more offices, this effect is insignificant. It is worth noting, as shown in the appendix, that when restricting ourselves to pentadic applications coming from the bottom 95%, we find that patent boxes significantly increase the success rate of applications even for this group of infrequent applicants. This

[97]In the appendix, we show that these last three technologies yield significantly positive patent box coefficients even for the bottom 95%. As discussed in detail there, since software is commonly assigned CPC codes G and H, a combination of potentially highly profitable innovations and low barriers to entry can lead even small applicants to seek patent box coverage for software.

[98]As discussed by Coelli, et al. (2016), the desire to export is a prime motivation for patenting overseas. Thus, in our data with patents coming from the EPO, applying elsewhere would be correlated with export potential and thus qualifying revenue.

[99]These are the offices for the US, China, Korea, and Japan.

might suggest that when the tax savings are sufficiently large, infrequent applicants may respond to patent boxes similar to their larger counterparts. This would be consistent with fixed costs for using a patent box which would require a sufficiently large scale to make its use worthwhile. Note, this would imply that large firms are most likely to use patent boxes for tax avoidance, a result reminiscent of findings by Davies, et al. (2018) that large firms are most active in transfer pricing to tax havens.

## 4.3 Patent Box Characteristics

We have treated all patent boxes as equal up to this point, however, they differ in three key dimensions: the size of the tax benefit, whether pre-existing patents can avail of the patent box (as occurs in a broad patent box), and whether there is a nexus requirement that requires a significant amount of local R&D to qualify for the tax relief. We explore each of these in turn in Table 10.

In Column 1, we replace the patent box dummy with the size of the reduction in the tax burden. Again, the estimates suggest that a patent box increases the probability of success. These estimates add to that by indicating a larger effect from bigger tax cuts. In the estimation sample, the mean tax reduction under a patent box is 0.20, i.e. a 20 percentage point reduction in the tax rate. Using the coefficient from Column 1, this would imply that a box with an average tax rate reduction would increase the success rate by 6.54 percentage points, a number close to that found in the baseline results.

In Column 2, we include two patent box variables: the original patent box dummy and a second which equals one only when the patent box is a broad one. Recall that broad boxes provide tax reductions for applications filed before the box is in place whereas narrow boxes do not.[100] We expect that while both broad and narrow boxes will increase the success rate, the impact is likely to be more immediate for broad boxes. To understand this, recall

[100] See Alstadsaeter, et al. (2018) for discussion on this and other patent box conditions. Here, we point out that they find that box conditions can also affect the number of patents registered in an EPO country. Table 1 provides information on the conditions of various patent boxes in our sample.

that the EPO generally does not allow patents on previously disclosed inventions. If the box is narrow, the innovator may prefer to delay starting the innovation process in order to ensure they can avail of the patent box's benefits. A broad box, on the other hand, does not provide an incentive to delay innovation. This means a broad box may reach the larger, time-delayed effects shown in Figure 3 sooner when compared to a narrow box starting at the same time. As a result, the overall average effect of a broad box will be greater. As the estimates indicate, this is indeed the case although the significance of this difference is not particularly large. This suggests that, if a policy maker wishes to speed up the change in innovation, broad boxes may be marginally more effective.

Column 3 controls for whether or not the patent box has a nexus requirement where again we use the original patent box dummy and a second one equal to one if the patent box has a nexus requirement. In general, nexus requirements specify that in order to qualify for the tax reductions within the box, a threshold amount of R&D expenses must be performed in the box-using country. Such requirements are favored by those worried about patent boxes providing yet another avenue for income shifting (see, for example, Gaessler, et al., 2019). This may influence success if it encourages the use of local resources, enhancing home bias in favor of the application. Alternatively, and perhaps more nefariously, nexus requirements may provide multinationals with an incentive to shift more novel (and more valuable) R&D projects to nexus countries in order to minimize taxes. As this relocation would increase the average novelty in a country, particularly among the large innovators that comprise our sample, this could boost average success. As shown in the table, we only find an effect for nexus boxes. This could then be evidence of multinationals relocating their most novel (and lucrative) investment projects to nexus box countries. That said, it must be noted that in the estimation sample over 97% of the non-nexus patent box applications are French. Since its box is in place for the entire sample, this may instead be the result of the French applicants' fixed effects absorbing the role of non-nexus boxes.

## 4.4 Number of Applications

Although it is not our main focus, the stated goal of all patent boxes is to increase innovation, something often measured as an increase in the number of patent applications or granted patents. This is indeed one of the predictions of our model, although we caution that the magnitude of the effects may be small due to sizable development costs and time lags. Of particular worry, however, is that one potential driver of additional applications is the submission of marginally novel innovations, as warned of by the OECD (2016) and Bradley, et al. (2015). Thus even if the number of applications rises, the patent box may not be working as planned. In our estimates, the positive effects we find are the combined result of increased focus on novelty and the submission of such marginal applications. If the latter is a significant part of the net effect, then we would anticipate that our documented success rate changes would occur alongside an increase in the overall volume of applications and therefore granted patents.

With this in mind, we conclude with a short examination of the impact of a patent box on the number of applications submitted. We do so using the Poisson estimator with fixed effects. Note that this differs from, e.g. Bösenberg and Egger (2017), who estimate the number of applications using a negative binomial estimator.[101] We do so because of the potential for incidental parameters bias in the negative binomial estimator when using fixed effects (Woolridge, 1999). We do our analysis at two levels, one at the country-year level (comparable to Bösenberg and Egger, 2017) and one at the applicant-year level (mimicking Alstadsaeter, et al., 2018).[102] For both, we consider the number of applications and the number of eventually granted patents that were submitted in that year. For the country-

[101]The negative binomial is also used by Alstadsaeter, et al. (2018) and Schwab and Totenhaupt (2019). Blundell, et al. (1995) and Falk (2007) use a dynamic count data estimator although neither controls for taxes.

[102]Note that there are no country-years in which zero applications occur and that the total is for all applicants, not just the top 5%, in order to be comparable to the rest of the literature. In contrast, 63.5% of observations at the applicant-year level are zero even though we again restrict ourselves to the top 5% of applicants. Note that because of the zero success for some applicants, the number of applicants in Columns 3 and 4 differ slightly.

level results, we follow the literature and include GDP, GDP per capita, R&D spending relative to GDP, country dummies, and year dummies alongside our three tax variables. For the applicant-level results, we replace the country dummies with applicant dummies and also include prior applicant success.[103]

Across the four columns, we reject the notion that patent boxes are leading to an increase in applications. In three of the specifications, the estimated coefficient is significant, although only marginally so. Further, the estimated impact of the patent box is small, with the patent box associated with a 0.12% decrease in aggregate applications and a 0.323% decline in those at the applicant level. These results are similar to those found by Gaessler, et al. (2019) although the data samples differ. Therefore, to the extent that our estimated effect of a patent box on the success of applications is pulled downwards by the submission of marginally novel applications, we believe that this is a fairly small effect. Furthermore, in light of the model's predictions, these estimates suggest that the number of applications may be dominated by the costs of development more so than the tax benefits of patent boxes.

# 5 Conclusion

It is undeniable that technological advancement is critical for continued growth. An increasing number of governments are exploring options of encouraging research and development by offering income-based incentives such as patent boxes. Although an increasing body of work finds that these policies increase the number of patents, there is also concern that this is the result of reallocating completed patents and/or R&D activity to low-tax locations. Further, there are concerns that the increase in patents may result from the patenting of mediocre innovations that would otherwise not be submitted for patenting. Finally, all of this must be balanced against the lost tax revenues which, using the estimates of Tørsløv, Wier, and Zucman (2020), could run to over $100 billion annually.

[103]This is the only applicant-level variable that is the same for all applications in a given year. Total applications over the sample is omitted for obvious endogeneity concerns.

With this background in mind, we contribute in several ways. First, we present a model showing that a patent box can indeed lead to the submission of marginal ideas. At the same time, a patent box can encourage additional effort both in the development of innovations and in the preparation of applications. Thus, the overall effect is ambiguous. That said, if the submission of marginal applications is a dominant factor, we should see a negative effect of patent boxes on the success rate of applications in the short run which is at least partially countered by increased research effort in the longer run.

We resolve this ambiguity with data on applications to the EPO from 2000 to 2012. Controlling for a variety of factors, we find that on average a patent box is linked to an increase in average success rates of approximately 6.9 percentage points, or a 12% increase in the probability of success. Further, while we find some slight evidence of applicants using higher quality legal representation in application preparation, the largest effects are felt two years after the patent box is introduced. This result is only found among the most frequent innovators, i.e. those in the best position to take advantage of patent boxes. We therefore find little evidence of patent boxes incentivizing major innovators to flood the patent system with marginal applications in the hopes of obtaining a tax shelter. Instead, we find that introducing patent boxes leads to the development of more novel ideas by those firms who are the driving forces in technological development. This is important given the cost of patent boxes in terms of sacrificed tax revenues, higher R&D costs, and greater patent office administration.

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Figure 1: Aggregate Trends (1978-2019)

(a) Applications by Year

(b) Success Rate by Year

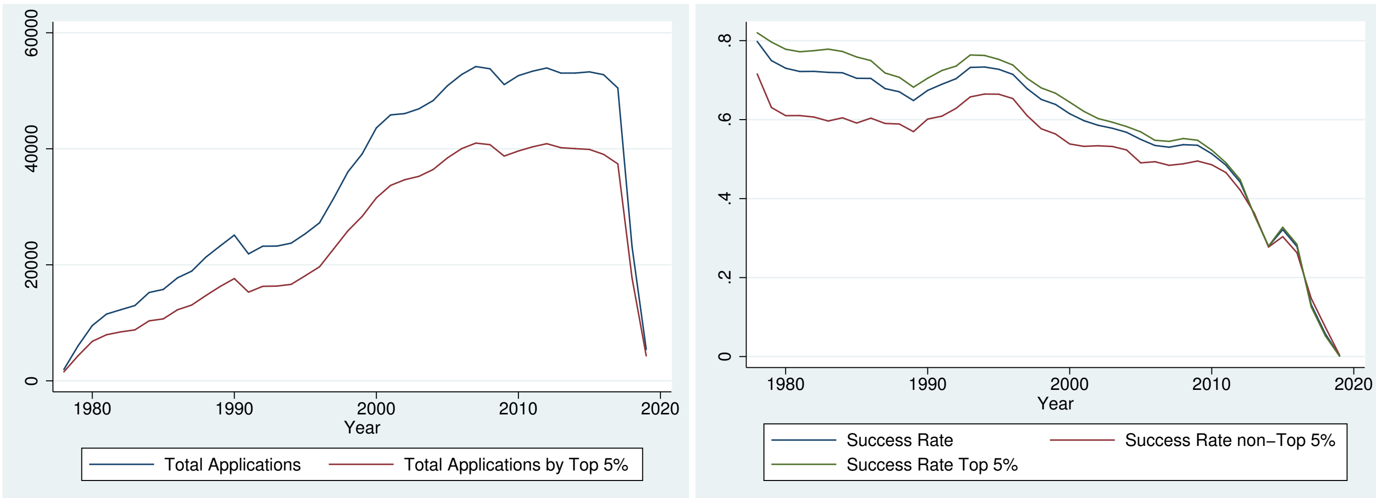



Figure 2: Success Rates Surrounding Patent Box Introduction

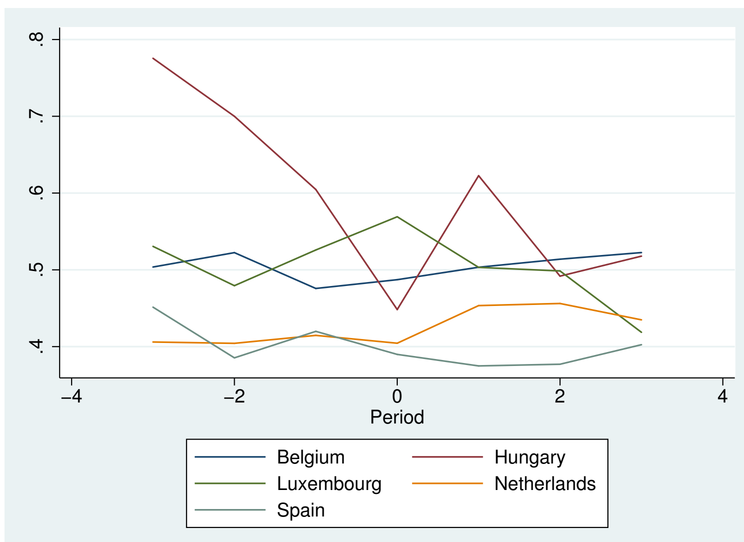
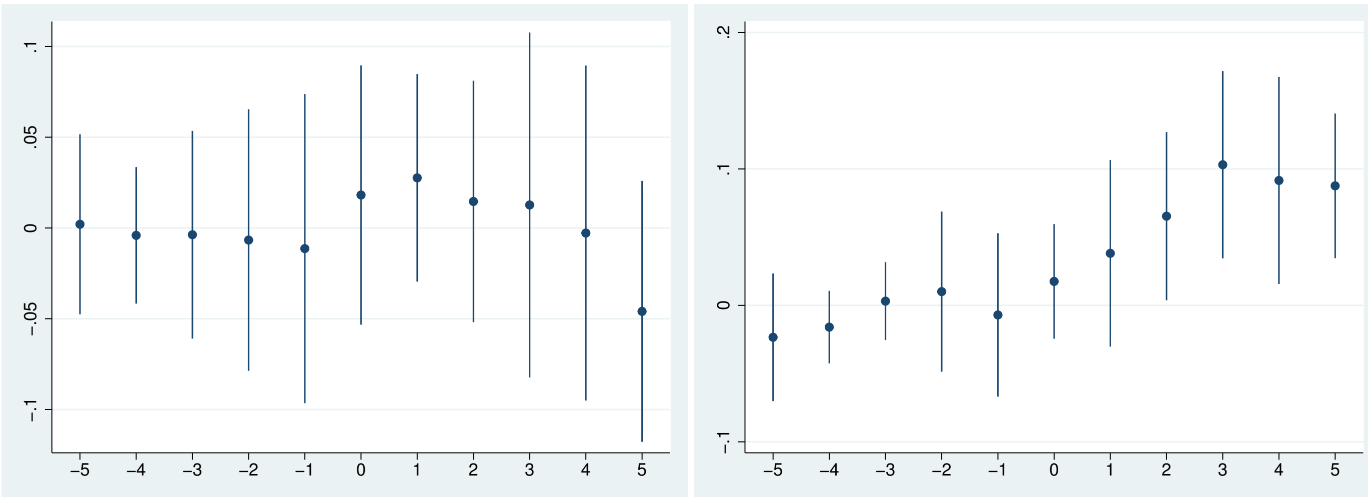


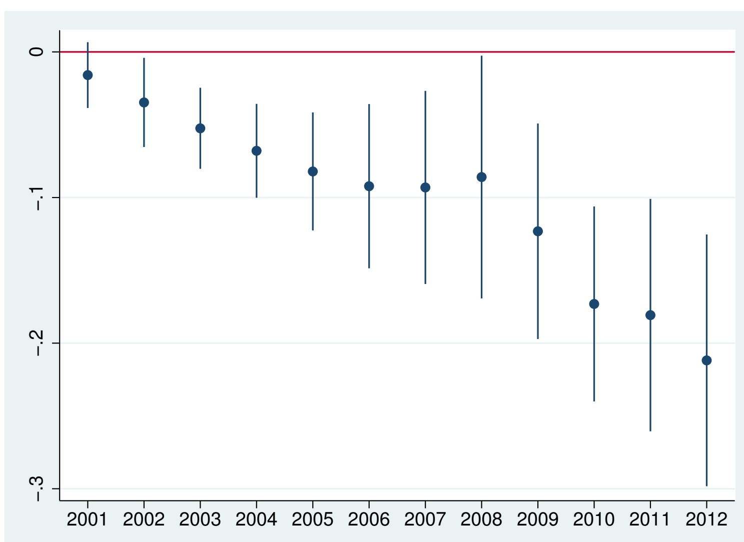
Figure 3: Event Study

(a) Bottom 95% (b) Top 5%




*Note*: 95% confidence intervals illustrated.

Figure 4: Year Dummies




*Note*: 95% confidence intervals illustrated.

Table 1: Countries in the Sample

| Country | Number of Applications | Success Rate | Patent Box Years |
|---|---|---|---|
| Austria | 12,961 | 60.6 | |
| Belgium | 13,789 | 49.5 | 2007-$^{\dagger}$ |
| Bulgaria | 66 | 51.5 | |
| Croatia | 130 | 48.5 | |
| Cyprus | 414 | 47.8 | 2012-$^{*}$ |
| Czech Republic | 781 | 48.3 | |
| Denmark | 13,072 | 49.8 | |
| Finland | 20,039 | 42.6 | |
| France | 83,094 | 55.6 | 1971-$^{*}$ |
| Germany | 254,973 | 59.3 | |
| Greece | 337 | 46.9 | |
| Hungary | 661 | 51.6 | 2003-$^{*}$ |
| Ireland | 4,126 | 47 | 1973-2010; 2016-$^{*,\dagger}$ |
| Italy | 41,305 | 58.2 | 2017- |
| Lithuania | 63 | 55.6 | 2018- |
| Luxembourg | 3,630 | 51.6 | 2008- |
| Malta | 277 | 62.8 | |
| Netherlands | 46,107 | 42.6 | 2007-$^{\dagger}$ |
| Norway | 4,531 | 49.9 | |
| Poland | 830 | 46.5 | 2019- |
| Portugal | 522 | 46.9 | |
| Romania | 60 | 46.7 | |
| Slovak Republic | 141 | 49.6 | 2018- |
| Slovenia | 762 | 51.8 | |
| Spain | 9,046 | 43.8 | 2008-$^{*,\dagger}$ |
| Sweden | 36,774 | 53.2 | |
| Switzerland | 53,241 | 53.5 | 2011-$^{*}$ |
| Turkey | 1,877 | 59.9 | 2015- |
| United Kingdom | 44,989 | 46.3 | 2013-$^{*}$ |

*Notes*: Ireland paused its patent box regime for five years following the financial crisis. The Swiss patent box only applies to the Nidwalden canton. $^{*}$ indicates a broad patent box which applies to prexisting patents. † indicates a patent box with a nexus requirement.

Table 2: CPC Codes

| | All Applicants | | Top 5% Only | |
|---|---|---|---|---|
| CPC code | Obs. | Success Rate | Obs. | Success Rate |
| A: Human Necessities | 110,349 | 54.7 | 71,442 | 56.8 |
| B: Operations and Transport | 149,172 | 63 | 99,239 | 66.4 |
| C: Chemistry and Metallurgy | 14,531 | 62.5 | 68,676 | 53.7 |
| D: Textiles | 91,151 | 52.3 | 10,502 | 65.1 |
| E: Fixed Constructions | 33,018 | 56.3 | 17,011 | 62.3 |
| F: Mechanical Engineering | 79,348 | 60.7 | 55,294 | 64.3 |
| G: Physics | 109,706 | 44.1 | 80,037 | 45.5 |
| H: Electricity | 125,191 | 48.6 | 103,634 | 49.5 |
| Y: Emerging Cross-Sectional Technologies | 80,098 | 59.2 | 57,926 | 61.3 |

*Notes*: Observations are the number of applications in the estimation window with a given CPC code listed. 65.3% of applications contain only one; 98.4% contain three or less. Thus, the sum of observations across rows exceeds the number of applications.

Table 3: Summary Statistics

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Granted | 646,022 | 0.5450325 | 0.4979683 | 0 | 1 |
| Filing Date | 646,022 | 2006.206 | 3.689671 | 2000 | 2012 |
| Patent Box | 646,022 | 0.1848466 | 0.3881734 | 0 | 1 |
| CIT | 646,022 | 0.3227945 | 0.0662948 | 0.1 | 0.5161155 |
| b-index | 646,022 | 0.9631331 | 0.1070114 | 0.5058044 | 1.042012 |
| Tax Reduction | 646,022 | .0366621 | .0777964 | 0 | .27192 |
| Nexus | 646,022 | .0529951 | .2240239 | 0 | 1 |
| Broad | 646,022 | .1552997 | .3621904 | 0 | 1 |
| Offices | 646,022 | 2.593006 | 1.370755 | 0 | 5 |
| Codes | 646,022 | 5.356819 | 5.227992 | 1 | 329 |
| Claims | 646,022 | 15.05554 | 21.34444 | 1 | 10677 |
| Ind. Claims | 646,022 | 2.164754 | 2.405841 | 1 | 196 |
| Num. of Inv. | 646,022 | 2.451788 | 1.722909 | 1 | 99 |
| Intl Team | 646,022 | 0.0906625 | 0.2871289 | 0 | 1 |
| Intl App-Inv | 646,022 | 0.1282247 | 0.3343401 | 0 | 1 |
| For. Cites | 646,022 | 1.913029 | 5.973979 | 0 | 596 |
| Back Cites | 646,022 | 5.748228 | 8.951659 | 0 | 1013 |
| Total Apps | 646,022 | 4202.49 | 9751.625 | 1 | 43047 |
| Prior Success (3 yrs) | 646,022 | 0.52206 | 0.326566 | 0 | 1 |
| Mean Inv Success (3 yrs) | 646,022 | 0.2782722 | 0.3370434 | 0 | 1 |
| Mean Rep Success (3 yrs) | 551,810 | 0.5299358 | 0.1615784 | 0 | 1 |
| GDP | 646,022 | 28.07134 | 0.9383021 | 22.69007 | 28.8964 |
| GDP per capita | 646,022 | 10.68314 | 0.2349141 | 8.282806 | 11.62597 |
| R&D | 646,022 | 2.300556 | 0.6159442 | 0.2269 | 3.90785 |
| Triadic | 646,022 | 0.4766448 | 0.4994546 | 0 | 1 |
| Pentadic | 646,022 | 0.129573 | 0.3358333 | 0 | 1 |

Table 4: Baseline Estimates

| Sample: | (1) All | (2) All | (3) All | (4) Bottom 95% | (5) Top 5% | (6) All | (7) Bottom 95% | (8) Top 5% |
|---|---|---|---|---|---|---|---|---|
| Patent Box | 0.0382*** | 0.0363*** | 0.0386*** | 0.0141 | 0.0447** | 0.0658*** | 0.0179 | 0.0693*** |
| | (0.0102) | (0.0114) | (0.0116) | (0.0130) | (0.0158) | (0.0157) | (0.0175) | (0.0175) |
| CIT | -0.0364 | 0.00522 | -0.0719 | -0.134 | 0.0826 | -0.0890 | -0.129 | -0.0425 |
| | (0.104) | (0.0828) | (0.0875) | (0.118) | (0.0879) | (0.121) | (0.125) | (0.122) |
| b-index | -0.0517 | -0.0357 | -0.0513 | -0.0924 | -0.0255 | -0.0156 | -0.169** | 0.00228 |
| | (0.0431) | (0.0420) | (0.0458) | (0.0540) | (0.0409) | (0.0514) | (0.0559) | (0.0468) |
| Family Size | 0.0320*** | 0.0318*** | 0.0307*** | 0.0534*** | 0.0263*** | 0.0405*** | 0.0510*** | 0.0382*** |
| | (0.00365) | (0.00425) | (0.00443) | (0.00557) | (0.00307) | (0.00381) | (0.00449) | (0.00386) |
| Codes | -0.00215*** | -0.00199*** | -0.00211*** | -0.00196*** | -0.00187*** | -0.00194*** | -0.00126* | -0.00202*** |
| | (0.000478) | (0.000500) | (0.000526) | (0.000810) | (0.000441) | (0.000373) | (0.000675) | (0.000405) |
| Claims | -6.67e-05 | -7.89e-05 | -9.61e-05 | -0.000174 | -7.60e-05 | -3.47e-05 | 0.000648** | -6.66e-05 |
| | (7.25e-05) | (6.82e-05) | (8.20e-05) | (0.000243) | (5.77e-05) | (5.90e-05) | (0.000250) | (6.88e-05) |
| Ind. Claims | -0.00386*** | -0.00331*** | -0.00347*** | -0.00364* | -0.00286*** | -0.00134* | -0.000297 | -0.00166** |
| | (0.00114) | (0.000902) | (0.00111) | (0.00168) | (0.000749) | (0.000733) | (0.00130) | (0.000758) |
| Num. Inventors | -0.00181 | -0.000283 | -0.000143 | 0.000448 | 0.000685 | 0.00264*** | 0.00189 | 0.00259*** |
| | (0.00144) | (0.000957) | (0.000974) | (0.00187) | (0.000857) | (0.000712) | (0.00172) | (0.000711) |
| Intl Team | -0.00138 | -0.00436 | -0.00360 | -0.0130* | -0.00186 | 0.000420 | -0.00187 | 0.000940 |
| | (0.00467) | (0.00453) | (0.00494) | (0.00668) | (0.00511) | (0.00392) | (0.00707) | (0.00425) |
| Intl App-Inv | -0.0113 | -0.0107 | -0.0130 | 0.0125 | -0.00862 | -0.00324 | 0.00224 | -0.00258 |
| | (0.0107) | (0.0105) | (0.0121) | (0.0116) | (0.0105) | (0.00797) | (0.0139) | (0.00818) |
| Forward Cites | 0.00290*** | 0.00297*** | 0.00300*** | 0.00457*** | 0.00256*** | 0.00240*** | 0.00260*** | 0.00235*** |
| | (0.000587) | (0.000681) | (0.000673) | (0.000639) | (0.000698) | (0.000519) | (0.000466) | (0.000559) |
| Backward Cites | -0.000153 | -8.98e-05 | -0.000133 | 0.000330 | -3.99e-05 | -4.84e-05 | -0.000423 | -1.34e-05 |
| | (0.000179) | (0.000183) | (0.000194) | (0.000458) | (0.000199) | (0.000208) | (0.000391) | (0.000218) |
| Total Apps. | -2.78e-06*** | -3.03e-06** | -2.96e-06* | 0.00328*** | -1.62e-06* | | | |
| | (6.61e-07) | (1.03e-06) | (1.46e-06) | (0.000600) | (7.52e-07) | | | |
| App. Success | 0.241*** | 0.210*** | 0.230*** | 0.0675*** | 0.398*** | -0.103*** | -0.221*** | 0.0493 |
| | (0.0132) | (0.0120) | (0.0127) | (0.00757) | (0.0241) | (0.0235) | (0.0114) | (0.0290) |
| Inv. Success | 0.0670*** | 0.0579*** | 0.0625*** | 0.0440*** | 0.0722*** | 0.0566*** | 0.0130 | 0.0698*** |
| | (0.00610) | (0.00692) | (0.00737) | (0.00713) | (0.00829) | (0.00640) | (0.00732) | (0.00821) |
| Rep. Success | | 0.275*** | | 0.200*** | 0.251*** | 0.190*** | 0.0661** | 0.192*** |
| | | (0.0255) | | (0.0214) | (0.0322) | (0.0311) | (0.0269) | (0.0391) |
| GDP | -0.446*** | -0.302** | -0.373** | -0.583*** | -0.123 | -0.429 | -1.005*** | -0.244 |
| | (0.138) | (0.127) | (0.142) | (0.134) | (0.192) | (0.342) | (0.182) | (0.349) |
| GDP per capita | -0.0347 | -0.274* | -0.251 | 0.0153 | -0.364* | -0.145 | 0.245** | -0.270 |
| | (0.143) | (0.146) | (0.159) | (0.131) | (0.182) | (0.291) | (0.111) | (0.301) |
| R&D | -0.00705 | -0.0193 | -0.0186 | -0.000141 | -0.0147 | -0.0430 | 0.00810 | -0.0399 |
| | (0.0213) | (0.0222) | (0.0226) | (0.0203) | (0.0241) | (0.0326) | (0.0195) | (0.0316) |
| Constant | 13.30*** | 11.66*** | 13.58*** | 16.52*** | 7.479* | 14.08* | 26.13*** | 10.11 |
| | (3.074) | (2.660) | (2.928) | (3.111) | (3.962) | (6.973) | (5.158) | (6.893) |
| Obs. | 646,022 | 551,810 | 551,810 | 158,733 | 393,077 | 510,595 | 117,689 | 392,906 |
| Adj. R-sq. | 0.095 | 0.105 | 0.099 | 0.073 | 0.130 | 0.192 | 0.270 | 0.178 |

*Notes*: Standard errors two-way clustered by country and by year in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Columns 1 through 5 include country, year, and CPC fixed effects. Columns 6 through 8 include applicant, year, and CPC fixed effects.

Table 5: Early Ending Dates

| | (1) | (2) | (3) |
|---|---|---|---|
| Ending in: | 2011 | 2010 | 2009 |
| Patent Box | 0.0605*** | 0.0542*** | 0.0395** |
| | (0.0165) | (0.0161) | (0.0128) |
| CIT | -0.0480 | -0.0134 | 0.0334 |
| | (0.123) | (0.110) | (0.0927) |
| b-index | 0.0400 | 0.0322 | 0.0444 |
| | (0.0419) | (0.0395) | (0.0479) |
| Family Size | 0.0394*** | 0.0395*** | 0.0412*** |
| | (0.00378) | (0.00403) | (0.00369) |
| Codes | -0.00187*** | -0.00174*** | -0.00175*** |
| | (0.000406) | (0.000420) | (0.000463) |
| Claims | -5.70e-05 | -4.80e-05 | -3.57e-05 |
| | (6.16e-05) | (5.65e-05) | (4.72e-05) |
| Ind. Claims | -0.00143* | -0.00163* | -0.00170* |
| | (0.000755) | (0.000760) | (0.000805) |
| Num. Inventors | 0.00251** | 0.00256** | 0.00274*** |
| | (0.000828) | (0.000836) | (0.000833) |
| Intl Team | 0.00155 | 0.00216 | 0.00205 |
| | (0.00464) | (0.00520) | (0.00599) |
| Intl App-Inv | 0.000398 | 0.000541 | -6.89e-05 |
| | (0.00871) | (0.00889) | (0.00914) |
| Forward Cites | 0.00236*** | 0.00240*** | 0.00240*** |
| | (0.000592) | (0.000568) | (0.000540) |
| Backward Cites | -5.95e-05 | -6.34e-05 | -5.56e-05 |
| | (0.000186) | (0.000247) | (0.000313) |
| App. Success | 0.0357 | 0.0216 | -0.000244 |
| | (0.0320) | (0.0358) | (0.0390) |
| Inv. Success | 0.0691*** | 0.0686*** | 0.0677*** |
| | (0.00822) | (0.00823) | (0.00816) |
| Rep. Success | 0.183*** | 0.168*** | 0.201*** |
| | (0.0407) | (0.0385) | (0.0476) |
| GDP | -0.348 | -0.516 | -1.057*** |
| | (0.349) | (0.422) | (0.246) |
| GDP per capita | -0.258 | -0.0665 | 0.663* |
| | (0.317) | (0.500) | (0.322) |
| R&D | -0.0755** | -0.0755** | -0.0447 |
| | (0.0268) | (0.0332) | (0.0286) |
| Constant | 12.96* | 15.64* | 22.88*** |
| | (6.751) | (7.041) | (4.838) |
| Obs. | 360,561 | 326,846 | 291,125 |
| Adj. R-sq. | 0.179 | 0.183 | 0.190 |

*Notes*: Standard errors clustered by country and by year in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All specifications use only the top 5% applicants and include applicant, year, and CPC fixed effects.

Table 6: Probit Estimator

| | (1) | (2) |
|---|---|---|
| Patent Box | 0.128*** | 0.208*** |
| | (0.0448) | (0.0496) |
| CIT | 0.258 | -0.0813 |
| | (0.241) | (0.365) |
| b-index | -0.0684 | 0.0273 |
| | (0.0769) | (0.107) |
| Family Size | 0.0752*** | 0.115*** |
| | (0.00603) | (0.00825) |
| Codes | -0.00535*** | -0.00600*** |
| | (0.000742) | (0.000808) |
| Claims | -0.000610 | -0.000712 |
| | (0.000609) | (0.000674) |
| Ind. Claims | -0.00728*** | -0.00403* |
| | (0.00248) | (0.00233) |
| Num. Inventors | 0.00188 | 0.00768*** |
| | (0.00175) | (0.00150) |
| Intl Team | -0.00620 | 0.00251 |
| | (0.0114) | (0.00761) |
| Intl App-Inv | -0.0237 | -0.00583 |
| | (0.0258) | (0.0205) |
| Forward Cites | 0.00780*** | 0.00774*** |
| | (0.00243) | (0.00219) |
| Backward Cites | -7.67e-05 | 4.89e-05 |
| | (0.000473) | (0.000525) |
| App. Success | -4.47e-06*** | |
| | (1.72e-06) | |
| Inv. Success | 1.084*** | 0.116** |
| | (0.0662) | (0.0566) |
| Rep. Success | 0.207*** | 0.212*** |
| | (0.0185) | (0.0200) |
| GDP | -0.256 | -0.393 |
| | (0.608) | (1.115) |
| GDP per capita | -1.084** | -1.009 |
| | (0.528) | (0.971) |
| R&D | -0.0472 | -0.147* |
| | (0.0645) | (0.0756) |
| Constant | 16.15 | 20.60 |
| | (12.43) | (22.18) |
| Obs. | 393,077 | 389,443 |

*Notes*: Robust standard errors clustered by country in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All specifications use only the top 5% applicants. Column 1 includes country, year, and CPC fixed effects. Column 2 includes applicant, year, and CPC fixed effects.

Table 7: Omitting Countries

| Sample excludes: | (1) Ireland | (2) Countries with <1000 obs. |
|---|---|---|
| Patent Box | 0.0659*** | 0.0695*** |
| | (0.0185) | (0.0175) |
| CIT | -0.0598 | -0.0473 |
| | (0.123) | (0.126) |
| b-index | 0.00501 | 0.00642 |
| | (0.0479) | (0.0460) |
| Family Size | 0.0382*** | 0.0382*** |
| | (0.00391) | (0.00390) |
| Codes | -0.00201*** | -0.00202*** |
| | (0.000410) | (0.000406) |
| Claims | -7.04e-05 | -6.61e-05 |
| | (7.29e-05) | (6.82e-05) |
| Ind. Claims | -0.00177** | -0.00160* |
| | (0.000778) | (0.000769) |
| Num. Inventors | 0.00265*** | 0.00262*** |
| | (0.000724) | (0.000718) |
| Intl Team | 0.00126 | 0.00117 |
| | (0.00443) | (0.00432) |
| Intl App-Inv | -0.00258 | -0.00265 |
| | (0.00836) | (0.00822) |
| Forward Cites | 0.00234*** | 0.00235*** |
| | (0.000566) | (0.000570) |
| Backward Cites | -1.32e-05 | -1.24e-05 |
| | (0.000220) | (0.000217) |
| App. Success | 0.0501 | 0.0496 |
| | (0.0295) | (0.0292) |
| Inv. Success | 0.0699*** | 0.0699*** |
| | (0.00830) | (0.00829) |
| Rep. Success | 0.193*** | 0.192*** |
| | (0.0389) | (0.0395) |
| GDP | -0.152 | -0.257 |
| | (0.324) | (0.358) |
| GDP per capita | -0.357 | -0.276 |
| | (0.279) | (0.309) |
| R&D | -0.0366 | -0.0426 |
| | (0.0305) | (0.0322) |
| Constant | 8.463 | 10.55 |
| | (6.444) | (7.027) |
| Obs. | 390,797 | 391,312 |
| Adj. R-sq. | 0.178 | 0.178 |

*Notes*: Standard errors clustered by country and by year in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All specifications use only the top 5% applicants and include applicant, year, and CPC fixed effects.

# Table 8: By Technology Class

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| Contains CPC: | (A) Human Necessities | (B) Operations & Transport | (C) Chemistry & Metal | (D) Textiles | (E) Fixed Construction | (F) Mechanical Engineering | (G) Physics | (H) Electricity | (Y) Emerging Tech |
| Patent Box | 0.0484** | 0.00255 | -0.000223 | -0.0163 | 0.0123 | 0.114*** | 0.0784*** | 0.119*** | 0.0664** |
| | (0.0197) | (0.0239) | (0.0161) | (0.0373) | (0.0396) | (0.0353) | (0.0196) | (0.0223) | (0.0225) |
| CIT | -0.00512 | -0.163 | 0.0983 | -0.560 | -0.367 | 0.179 | -0.00915 | 0.191 | 0.0824 |
| | (0.147) | (0.166) | (0.199) | (0.338) | (0.252) | (0.204) | (0.143) | (0.246) | (0.202) |
| b-index | -0.0338 | -0.133* | 0.0219 | -0.341 | -0.243 | -0.124* | 0.0268 | 0.0978 | -0.0442 |
| | (0.0619) | (0.0638) | (0.0811) | (0.202) | (0.140) | (0.0657) | (0.0653) | (0.0719) | (0.0772) |
| Family Size | 0.0406*** | 0.0337*** | 0.0498*** | 0.0381*** | 0.0347*** | 0.0344*** | 0.0358*** | 0.0375*** | 0.0287*** |
| | (0.00392) | (0.00451) | (0.00499) | (0.00504) | (0.00673) | (0.00390) | (0.00373) | (0.00723) | (0.00278) |
| Codes | -6.04e-05 | -0.00273*** | -0.00200*** | -0.00320** | -0.00440** | -0.00199*** | -0.00115* | -0.00273*** | -0.00125** |
| | (0.000713) | (0.000402) | (0.000372) | (0.00120) | (0.00178) | (0.000506) | (0.000578) | (0.000757) | (0.000521) |
| Claims | -3.06e-05 | -0.000240 | -8.13e-05 | -0.000276 | 0.000153 | -0.000721 | -0.000170 | -7.69e-05 | -0.000188 |
| | (2.47e-05) | (0.000282) | (0.000167) | (0.000561) | (0.000586) | (0.000491) | (0.000224) | (0.000362) | (0.000280) |
| Ind. Claims | -0.000328 | -0.000597 | -0.00121 | 0.00159 | 0.00278 | 0.000194 | -0.000269 | -0.00296** | 0.000129 |
| | (0.000955) | (0.00162) | (0.000917) | (0.00285) | (0.00226) | (0.00185) | (0.000949) | (0.00125) | (0.00161) |
| Num. Inventors | 0.00122 | 0.00503*** | 0.00241 | 0.00358 | 0.00392 | 0.000290 | -0.00162 | 0.00311 | 0.000891 |
| | (0.00167) | (0.00106) | (0.00175) | (0.00448) | (0.00427) | (0.00148) | (0.00168) | (0.00250) | (0.00200) |
| Intl Team | -0.0111 | -0.00254 | 0.00642 | 0.0194 | 0.00770 | 0.0115 | 0.00258 | 0.00779 | 0.000409 |
| | (0.00769) | (0.0106) | (0.00693) | (0.0300) | (0.0209) | (0.0125) | (0.0114) | (0.00920) | (0.00900) |
| Intl App-Inv | 0.000266 | 0.0102 | -0.00804 | -0.0425* | 0.000141 | 0.00170 | -0.000121 | -0.00434 | 0.00188 |
| | (0.0111) | (0.0105) | (0.00856) | (0.0199) | (0.0225) | (0.0142) | (0.0122) | (0.0117) | (0.0120) |
| Forward Cites | 0.00127* | 0.00362*** | 0.00166** | 0.00322*** | 0.00516*** | 0.00419*** | 0.00221*** | 0.00231*** | 0.00282*** |
| | (0.000653) | (0.000928) | (0.000708) | (0.000955) | (0.000883) | (0.000714) | (0.000581) | (0.000554) | (0.000463) |
| Backward Cites | -9.27e-06 | -0.000675 | 0.000101 | -0.00105 | 0.000529 | -0.000735 | -0.000117 | -0.00209 | -0.000272 |
| | (0.000298) | (0.000501) | (0.000194) | (0.00125) | (0.00212) | (0.00117) | (0.000683) | (0.00161) | (0.000499) |
| App. Success | 0.00739 | 0.0232 | 0.0614 | 0.122 | -0.0558 | -0.00478 | 0.0593 | 0.147** | 0.0676** |
| | (0.0293) | (0.0229) | (0.0483) | (0.0756) | (0.0316) | (0.0277) | (0.0455) | (0.0571) | (0.0266) |
| Inv. Success | 0.0607*** | 0.0301*** | 0.0872*** | 0.0184 | 0.0300* | 0.0355*** | 0.0763*** | 0.0962*** | 0.0421*** |
| | (0.0114) | (0.00722) | (0.0138) | (0.0229) | (0.0165) | (0.00974) | (0.0158) | (0.0108) | (0.0129) |
| Rep. Success | 0.164*** | 0.185*** | 0.211*** | 0.247*** | 0.108** | 0.200*** | 0.179*** | 0.178** | 0.180*** |
| | (0.0333) | (0.0344) | (0.0457) | (0.0493) | (0.0431) | (0.0511) | (0.0583) | (0.0678) | (0.0444) |
| GDP | -0.0825 | -0.158 | 0.144 | 0.616 | -0.0894 | -0.664*** | -0.253 | -0.506 | -0.0973 |
| | (0.312) | (0.237) | (0.429) | (0.734) | (0.433) | (0.214) | (0.405) | (0.597) | (0.370) |
| GDP per capita | -0.507 | -0.436** | -0.201 | -0.580 | -0.486 | 0.0372 | -0.166 | -0.0747 | -0.433 |
| | (0.306) | (0.196) | (0.370) | (0.623) | (0.329) | (0.297) | (0.366) | (0.516) | (0.419) |
| R&D | -0.0648* | 0.0175 | -0.00510 | -0.222** | 0.101** | 0.000464 | -0.00481 | -0.0548 | -0.0117 |
| | (0.0320) | (0.0241) | (0.0305) | (0.0943) | (0.0423) | (0.0245) | (0.0335) | (0.0562) | (0.0176) |
| Constant | 8.288 | 9.692* | -1.736 | -9.607 | 8.302 | 18.79*** | 9.018 | 15.04 | 7.750 |
| | (5.734) | (5.250) | (8.673) | (15.00) | (9.762) | (3.942) | (7.916) | (11.85) | (6.788) |
| Obs. | 70,849 | 98,468 | 68,081 | 10,220 | 16,484 | 54,494 | 79,173 | 102,965 | 56,880 |
| Adj. R-sq. | 0.159 | 0.165 | 0.156 | 0.194 | 0.151 | 0.170 | 0.190 | 0.155 | 0.180 |

*Notes*: Standard errors clustered by country and by year in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All specifications use only the top 5% applicants and include applicant, year, and CPC fixed effects.

Table 9: Triadic and Pentadic Applications

| Sample: | (1) Triadic Only | (2) Pentadic Only | (3) All |
|---|---|---|---|
| Patent Box | 0.0903*** | 0.107*** | 0.0675* |
| | (0.0189) | (0.0327) | (0.0358) |
| Box*Family Size | | | 0.000540 |
| | | | (0.0107) |
| CIT | -0.113 | -0.287* | -0.0422 |
| | (0.180) | (0.156) | (0.123) |
| b-index | 0.0558 | 0.107 | 0.00238 |
| | (0.0575) | (0.0868) | (0.0475) |
| Family Size | 0.0200*** | 0 | 0.0380*** |
| | (0.00379) | (1.19e-05) | (0.00429) |
| Codes | -0.00182*** | -0.00194*** | -0.00202*** |
| | (0.000414) | (0.000584) | (0.000403) |
| Claims | -6.69e-05 | -0.000249 | -6.66e-05 |
| | (7.24e-05) | (0.000430) | (6.93e-05) |
| Ind. Claims | -0.00195** | -0.00110 | -0.00166* |
| | (0.000799) | (0.00138) | (0.000791) |
| Num. Inventors | 0.00191* | 0.00348* | 0.00259*** |
| | (0.00104) | (0.00171) | (0.000717) |
| Intl Team | 0.00322 | 0.000871 | 0.000941 |
| | (0.00519) | (0.00780) | (0.00435) |
| Intl App-Inv | -0.00376 | 4.49e-05 | -0.00259 |
| | (0.0107) | (0.0124) | (0.00829) |
| Forward Cites | 0.00257*** | 0.00243** | 0.00235*** |
| | (0.000691) | (0.000944) | (0.000555) |
| Backward Cites | -0.000272 | -0.000397* | -1.31e-05 |
| | (0.000166) | (0.000203) | (0.000204) |
| App. Success | 0.0684* | 0.0327 | 0.0493 |
| | (0.0361) | (0.0285) | (0.0291) |
| Inv. Success | 0.0764*** | 0.0975*** | 0.0698*** |
| | (0.00996) | (0.0144) | (0.00815) |
| Rep. Success | 0.184*** | 0.170*** | 0.192*** |
| | (0.0425) | (0.0505) | (0.0391) |
| GDP | -0.0482 | -0.0139 | -0.244 |
| | (0.446) | (0.612) | (0.349) |
| GDP per capita | -0.416 | -0.323 | -0.270 |
| | (0.311) | (0.434) | (0.301) |
| R&D | -0.0552 | -0.0701 | -0.0399 |
| | (0.0399) | (0.0551) | (0.0311) |
| Constant | 6.224 | 4.386 | 10.11 |
| | (9.342) | (13.10) | (6.890) |
| Obs. | 214,546 | 62,247 | 392,906 |
| Adj. R-sq. | 0.178 | 0.181 | 0.178 |

*Notes*: Standard errors clustered by country and by year in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All specifications use only the top 5% applicants and include applicant, year, and CPC fixed effects.

Table 10: Patent Box Characteristics

| | (1)<br>Tax Rate<br>Reduction | (2)<br>Covers<br>Existing Patents? | (3)<br>Nexus<br>Requirement? |
|---|---|---|---|
| Tax Reduction | 0.327*** | | |
| | (0.0900) | | |
| Patent Box | | 0.0676*** | -0.0597 |
| | | (0.0182) | (0.0544) |
| Broad Box | | 0.0360* | |
| | | (0.0173) | |
| Nexus Req. | | | 0.135** |
| | | | (0.0556) |
| CIT | -0.0516 | -0.0230 | -0.0368 |
| | (0.129) | (0.109) | (0.123) |
| b-index | -0.00212 | -0.00906 | 0.00672 |
| | (0.0463) | (0.0485) | (0.0462) |
| Family Size | 0.0381*** | 0.0381*** | 0.0382*** |
| | (0.00379) | (0.00390) | (0.00388) |
| Codes | -0.00201*** | -0.00202*** | -0.00203*** |
| | (0.000406) | (0.000406) | (0.000400) |
| Claims | -6.67e-05 | -6.65e-05 | -6.66e-05 |
| | (6.93e-05) | (6.99e-05) | (6.88e-05) |
| Ind. Claims | -0.00166* | -0.00168** | -0.00166** |
| | (0.000761) | (0.000745) | (0.000762) |
| Num. Inventors | 0.00259*** | 0.00261*** | 0.00258*** |
| | (0.000699) | (0.000728) | (0.000700) |
| Intl Team | 0.000931 | 0.000948 | 0.00107 |
| | (0.00425) | (0.00420) | (0.00464) |
| Intl App-Inv | -0.00262 | -0.00256 | -0.00255 |
| | (0.00812) | (0.00815) | (0.00835) |
| Forward Cites | 0.00235*** | 0.00235*** | 0.00235*** |
| | (0.000562) | (0.000565) | (0.000586) |
| Backward Cites | -1.41e-05 | -2.01e-05 | -1.47e-05 |
| | (0.000216) | (0.000223) | (0.000217) |
| App. Success | 0.0490 | 0.0491 | 0.0499 |
| | (0.0290) | (0.0289) | (0.0290) |
| Inv. Success | 0.0697*** | 0.0698*** | 0.0696*** |
| | (0.00814) | (0.00816) | (0.00827) |
| Rep. Success | 0.192*** | 0.192*** | 0.193*** |
| | (0.0389) | (0.0389) | (0.0387) |
| GDP | -0.230 | -0.401 | -0.201 |
| | (0.341) | (0.271) | (0.354) |
| GDP per capita | -0.284 | -0.126 | -0.311 |
| | (0.293) | (0.240) | (0.306) |
| R&D | -0.0412 | -0.0499* | -0.0394 |
| | (0.0318) | (0.0262) | (0.0307) |
| Constant | 9.893 | 12.98** | 9.353 |
| | (6.753) | (5.400) | (6.960) |
| Obs. | 392,906 | 392,906 | 392,906 |
| Adj. R-sq. | 0.178 | 0.178 | 0.178 |

*Notes*: Standard errors clustered by country and by year in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All specifications use only the top 5% applicants and include applicant, year, and CPC fixed effects.

Table 11: Number of Applications

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Country-Level | | Applicant-Level | |
| Number of Apps: | Submitted | Granted | Submitted | Granted |
| Patent Box | -0.125* | -0.0282 | -0.323* | -0.167** |
| | (0.0742) | (0.0572) | (0.186) | (0.0717) |
| CIT | -0.178 | -0.482 | -0.175 | -0.408 |
| | (0.376) | (0.484) | (0.614) | (0.472) |
| b-index | 0.0455 | -0.134 | -0.0578 | -0.136 |
| | (0.149) | (0.170) | (0.331) | (0.268) |
| App. Success | | | 0.151** | 0.419*** |
| | | | (0.0616) | (0.0523) |
| GDP | 3.462*** | 2.490*** | 3.478*** | 2.407*** |
| | (0.656) | (0.698) | (0.912) | (0.928) |
| GDP per capita | -1.670*** | -1.540*** | -1.811** | -1.341* |
| | (0.470) | (0.464) | (0.784) | (0.776) |
| R&D | 0.185* | 0.168* | 0.132 | 0.0834 |
| | (0.0992) | (0.0958) | (0.134) | (0.115) |
| Obs. | 371 | 371 | 50,066 | 49,684 |
| Num. of Countries | 29 | 29 | | |
| Num. of Applicants | | | 6,346 | 6,215 |

*Notes*: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Columns 1 and 2 use the annual number of submitted/granted applications by all applicants in a country and include country and year fixed effects. Columns 3 and 4 use the annual number of submitted/granted applications by a top 5% applicant and include applicant and year fixed effects.

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