Why Governments Grow “Lemons” in the Market for Technology

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Abstract

Governments around the world spend enormous amount of money on R&D. A large part of this investment is wasted, flooding the system with patents that never result in any actual innovation. This effect is especially pronounced in countries with low level of government accountability. To reconcile the growth of “lemon patents” with genuine desire of the government to spur innovation, we offer a game-theoretic model, in which the government has a significant stake in technological development and invests in R&D, even if this simultaneously encourages growth of “lemons”. We illustrate the mechanism by demonstrating the causal impact of Russia’s government policy, which resulted in a simultaneous increase in the number of high-quality patents and a decrease in the share of such patents in the patent pool.

Keywords: patents, corruption, government R&D policy
JEL Classification: O34, O32, H2

1 Introduction

Government investment in research and development (R&D) is a vital input into creation of new technologies, which is in turn an important determinant of sustained economic growth (Romer, 1990; Aghion et al., 1998; Acemoglu et al., 2018). Well-documented positive externalities from the development of new technologies further justify government support for innovation (Jaffe, 1986; Griliches, 1991; Audretsch and Feldman, 1996; Bloom, Schankerman and Van Reenen, 2013). Not surprisingly, governments around the world spend large amount of money on R&D.[1]

In this paper, we study government investment in R&D in a weakly institutionalized environment. Given that the success of government R&D policy is hard to evaluate in the short term (Bloom, Van Reenen and Williams, 2019), investment in R&D is an attractive vehicle for rent-seeking. In the absence of independent expertise and strong corruption deterrence, strong incentives for innovation such as patent prizes or state grants allows bureaucrats to extract bribes for awarding patents with little, if any, quality control. This in turn incentives agents to file low-quality patents with the sole aim of getting government grants (Arutyunov, 2008). Instead of investing in strengthening institutions, even a benevolent government might rely on KPIs such as the total number of new patents or the *efficiency of government R&D expenditures* measured by the ratio of the number of patents to the amount spent (Tijssen and Winnink, 2018).

Still, even in the absence of strong institutions, politicians' behavior is constrained by the market response: if buyers of patented technology know that all patents are "lemons" (Akerlof, 1970; Wilson, 1991), the would not pay buy patents. Our theoretical model explains how the opportunity to take bribes granting patents for "lemons" leads to the following em-

[1] In 2010, the EU outlined five main long-run goals for the 2020 Strategy and pledged to devote 3% of GDP to R&D support. In the US, the government spent \$39.9 billion on R&D in 2017 (Sargent, 2018), which is comparable to the \$44.3 billion budgeted for elementary and secondary education

pirical observation: an increase in government funding does lead to an increase in the number of patents, yet, in the presence of a corrupt motive, is accompanied by the proliferation of "lemon" patents. Though the number of good patents grow, their share in the total pool of granted patents decrease.

The setting in which the bureaucrats verify the quality of the product, but can also be influenced by bribes, is somewhat similar to the problem of government procurement under corruption, explored in Celentani and Ganuza (2002) and Burguet (2017). The key difference from our work is that procurement agent allocates the realization of a project. In our setting, the approved patent enters the market, and private companies decide whether to purchase it or not.

Russia is an excellent field laboratory to study the impact of government policy in the presence of weak institutions (Wengle, 2015, 2018; Markus, 2016; Gans-Morse, 2017; Frye, 2017). Starting in 2008, Russia has dramatically increased the government support for R&D in the field of nanotechnology. Using difference-in-difference approach, we compare changes in quality of patents, measured by citations, in the field of nanotechnology to changes in other fields. This allows us to establish a causal link between availability of the government R&D support and the quality of patents in the affected field. We find that the drop in probability of being cited for nanotechnology-related patents filed after the onset of the policy was 4.5% compared to patents filed before and after policy onset in other fields. Quantitatively, this is a large decrease, since only 2% of all Russian patents are cited at all.[2]

While difference-in-difference approach mitigates the potential omitted variable problem, the estimated average treatment effect on the treated can still be biased if there exists an omitted variable (or a group of variables) that varies by time and patent type and affects patent citations. We perform sensitivity analysis to assess the vulnerability of the average

[2] A different measure of patent citations suggests a decrease of 1%. They are also less likely to obtain 10 or more citations by 1%.

treatment effect to omitted variable bias and find the robustness value to be rather low - in most specifications, the unobserved confounders (orthogonal to the covariates) that explain more than one percent of the residual variance of both the treatment and the outcome to reduce the absolute value of the effect size by 100. Hence, we supplement our difference-in-difference analysis with additional comparison of the quality of Russian patents to quality of US patents. This triple-difference approach eliminates the potential impact of omitted variable (or a group of such variables) that could vary by time and patent class and affect patent citations that could occur due to natural trends in technological development and that is equally biasing US and Russian case (Berck and Villas-Boas, 2016; Olden and Møen, 2020). The results of triple-difference estimation are consistent with conclusion that the average quality of nanotechnology patents decreased after the rise of government funding for this technological field.

This paper contributes, first, to our understanding of effects of rent-seeking and corruption on economic growth. In their book Rowley, Tollison and Tullock (2013) outline the different facets of rent-seeking and its effect on the economy and politics. They argue that an incumbent maximizes his or her chances to stay in power, as well as the amount of collected rents, in the spirit of Downs (1957); Buchanan and Tullock (1962); Peltzman (1972) and other public choice literature. Appelbaum and Katz (1987) presents an outlook where regulators endogenously set the rents and firms and consumers respond to rent-setting in a self-motivated manner. Grundler and Potrafke (2019) investigate the effect of corruption on growth and find that real per capita GDP decreased by around 17% when the reversed CPI increased by one standard deviation. Treisman (2007) shows that reported corruption experiences correlate with lower development, and possibly with dependence on fuel exports, lower trade openness, and more intrusive regulations. This paper illustrates how the rent-seeking in associated with distribution of government R&D grants can have a detrimental effect on the market for technology transfer.

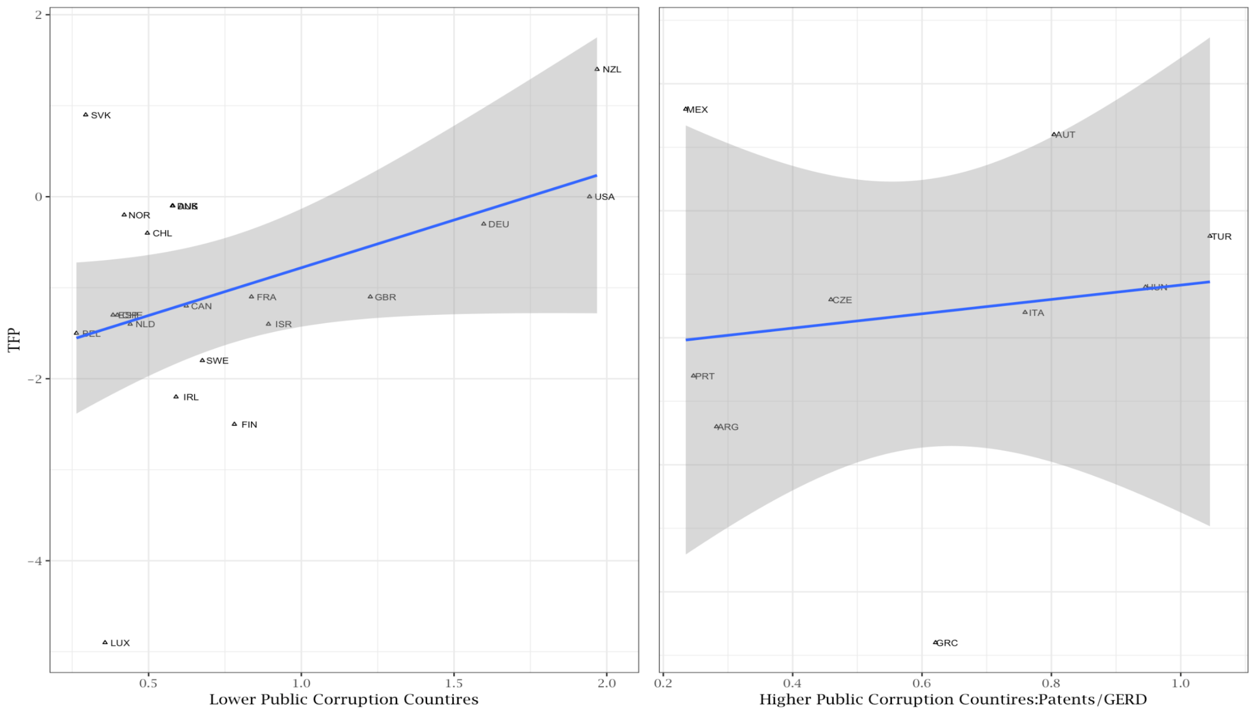
This work is also related to the investigation of the broader effects of government pro-R&D policies on the economic development of countries. Azoulay et al. (2019) show that NIH funding spurs the development of private-sector patents: A $10 million boost in National Institutes of Health (NIH) funding spurs the development of private-sector patents. A $10 million boost in NIH funding led to a net increase of 2.7 patents, citing NIH-funded research. Investigating data drawn from Italy, Akcigit, Baslandze and Lotti (2018) found that government R&D subsidies led to greater profits for politically-connected firms with no change in their efforts to produce new technologies. They interpret this finding as a substitution between a legal monopoly on new technology derived from patents and protection from competition due to political connections.

This paper relies heavily on the body of literature focusing on corporate patenting activity. Patents are a main measure of output of innovative activity[3], as they are the most important form in which industrial innovation is protected. Schmookler (1953) pioneered the use of patent statistics for the assessment of the rate of American inventing. Gilfillan (1960) suggested that it is necessary to differentiate patents by quality. Griliches (1979) conducted the first large sample work using computerized United States Patent and Trademark Office (USPTO) data. His work emphasized the varied quality of patents, and stressed the use of patent citations as an important adjustment criterion. Kwon, Lee and Lee (2017) provide a discussion of varying qualities of patents registered at the USPTO in different countries, as well as the overview of the literature on this topic. There are costs of obtaining even a low-quality patent associated with filing fees and the cost of filing the paperwork.

This rest of the paper is organized as follows. Section 2 illustrates the scope of the problem using cross-country correlations. Section 3 offers a simple model of corrupt patent promotion policy. Section 4 contains empirical analysis of R&D policy in Russia. Section 5

[3]Patents are strongly related to R&D across firms, with elasticity close to one, but controlling for unobserved differences across firms, the elasticity is lower (about 0.3)

Figure 1: Patenting Efficiency (Patents/GERD and TFP by Public Corruption, 2012)



concludes.

2 R&D Efficiency and Government Accountability

This section provides cross-country evidence that relates growth in inefficient patents to country's corruption. The starting point is that not all patents are created equal (Griliches, 1979; Zaller, 1992). While some represent superstar technologies responsible for substantial technological breakthroughs, most go unutilized or uncited (Hall, Jaffe and Trajtenberg, 2005). Countries differ widely in the average quality of patents; they also differ in the patenting efficiency, the number of patents per dollar of government R&D expenditures. The problem is that the patenting efficiency does not necessarily result in fast technological development.

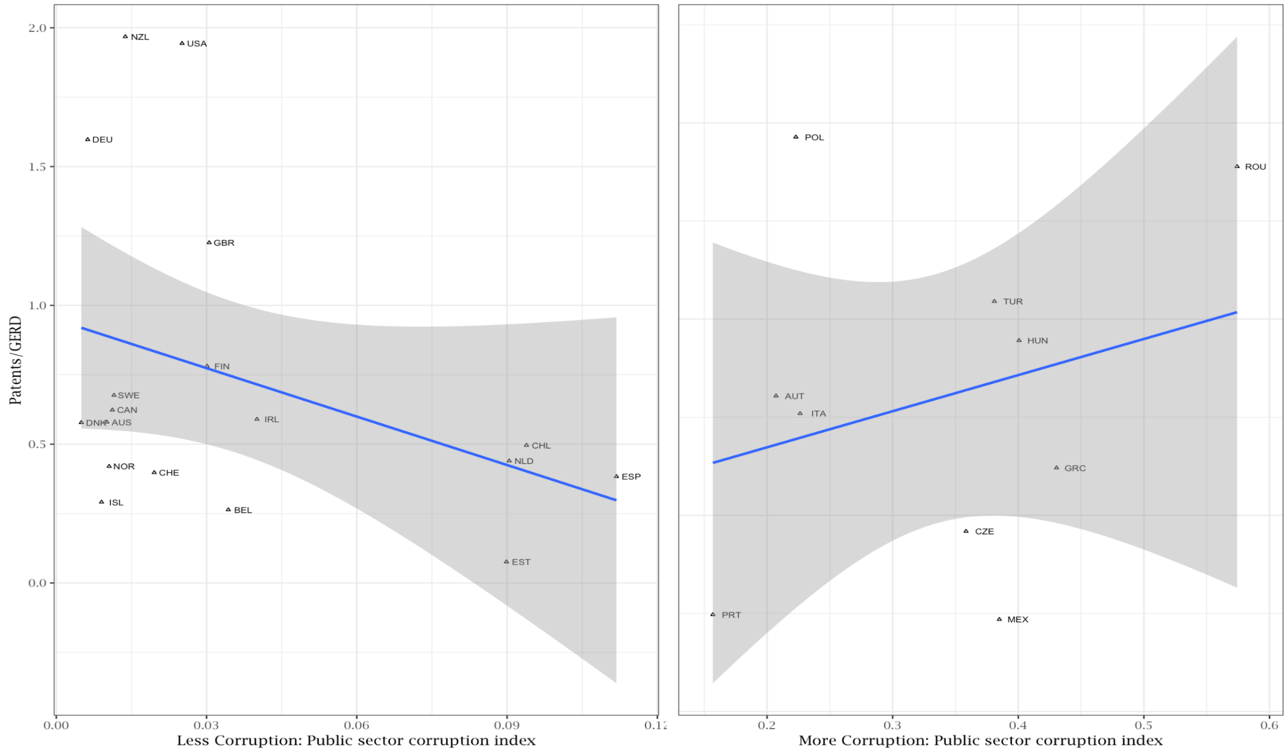
Figure 1 suggests that for countries with low level of corruption in the public sector, greater patenting efficiency is associated with higher Total Factor Productivity (TFP). By contrast, in countries with high level of corruption in public sector, this association no longer holds. Using data for 1995-2015, Table A-3 shows that in countries with low government accountability the efficiency of government investments in R&D in patent production has no significant relationship with the TFP. The measure was obtained from Total Economy Database.[4] Countries are denoted as having low government accountability if the Accountability Transparency Index (ATI) introduced in (Williams, 2015) and comprised of the existence of free and independent media, fiscal (budgetary) transparency, and political constraints is below the median. The Informational Transparency Index (ITI) is comprised of three parts: the quantum of information released by governments; the quality of that information; and the information infrastructure of countries that enables dissemination of that information. Thus, the efficiency in production of new technologies (measured by patents) spills over to the level of technology employed in production only in countries with high level of government accountability.

Next, government R&D efficiency is positively related to Public Corruption (as measured by Quality of Government Data (Teorell et al., 2019)) in more corrupt countries, and negatively related to it in less corrupt ones (Figure 2). Figure 2 presents a cross-section of countries in 2012. (Conditional correlations provided in Table A-4 of the Appendix cover years 1995-2012.) It shows that R&D efficiency, as measured by the number of patents produced by government R&D expenditures (standardized at 2010 USD), is negatively correlated with accountability transparency and the transparency index introduced by Williams (2015). Taken at its face value, this correlation suggests that countries with high public corruption or low accountability are more efficient in production of new technologies per dollar of government investment.[5] As we will see, the more plausible explanation is that when the

[4]https://www.conference-board.org/data/economydatabase/index.cfm?id=27722.

[5]An alternative explanation would be that these countries have low initial level of technological development, and thus are able to catch up by investing in the low-hanging fruit. However, this would contradict

Figure 2: Patenting Efficiency (Patents/GERD) and Public Corruption, 2012



government accountability is low, the patent efficiency becomes a poor indicator of creation of functional technology, and, under certain conditions, can stifle technological development.

3 Theory

This section introduces a model that demonstrates the effect of political rent-seeking on the patent markets and the incentives rent-seeking creates to file cheap but empty patents. It explains how government support for innovation can lead to the deterioration of patent quality with negative implications for the technology market. Importantly, this is a general equilibrium model: the politician chooses a policy, researchers optimize their efforts, and then a competitive market determines the value of patents in the market.

the relationship found in Table A-3, as the impact of such technologies is still expected to improve TFP.

3.1 Setup

There are two types of strategic players in the game, a politician and researchers, and non-strategic profit-maximizing firms. Researchers differ in their talent: there are $\overline{R}$ of talented researchers that can either produce a valuable innovation at cost c and produce a high-quality patent, or choose to do nothing. There is also a pool of size 1 of non-talented researchers that can imitate research; the idiosyncratic cost of producing a "lemon" for non-talented researcher i is a_i, $a_i \in [0, 1]$. These researchers could also choose to do nothing at all.

As it is standard in the literature, the politician cares about both the economic benefits from creation of a new technology, and rents he is able to collect from sub-par patents. The controlling policy parameter that the politician is choosing is the level of bribe b to be paid by an author of a "lemon". In equilibrium, this choice determines the market price for a patent, and thus the incentives of talented researchers to produce valuable innovations.

Making their individual decisions, all researchers observe the levels of bribe, b, and available research grants, π. If a talented researcher engages in patent production, her utility is $U^T(P) = \pi + p - c$, where π is the award, p is the market-determined price that she can get for selling a patent, and c is the cost of research. Otherwise, she gets 0.

If a non-talented researcher engages in patent production, he has to pay the bribe b, after which he can pass the expertise with probability $1 - \theta$, where θ represents the quality of institutions. High θ corresponds to strong institutions (a bad patent application has a low chance to be approved), while low θ proxies the weak ones. In this case, the utility of non-talented researcher i is $U^{NT}(P) = (\pi + p)(1 - \theta) - a_i$; otherwise, he gets 0. Note that the market cannot determine the quality of an individual patent; the market price reflects, in equilibrium, the relative shares of good and bad patents. As a result, a non-talented researcher, after paying a bribe and (if) passing the expertise, receives not only the award π, but also the market price p.

Companies purchasing patents do not observe the quality of individual patents before purchasing them. In equilibrium, they will use shares of high- and low-quality patents in the market to determine the price p. Their expected value for high-quality patents is $H > 0$, and for low-quality patents at 0; they are risk-neutral.

The utility function of the politician that cares both about the public welfare (amount of innovation) and rents he extracts, is as follows:

$$U^P = \alpha RH + (1-\alpha)B,$$

where R is the total amount of research produced, H is the value of new technology for society, α is the weight of economic development in politician's utility, and B is the amount of bribes collected from non-talented researchers.

In our analysis, we will focus on the case $0 < c - \pi < H$. The case $\pi > c$ describes the situation, in which the government prize is so big that it alone induces talented researchers to innovate; they are interested in high efforts even without selling their patents on the market. Similarly, when the costs of efforts, c, are prohibitively high, innovation cannot by incentivized by any policy.

3.2 Analysis

Let λ be the share of high-quality patents in the market. A firm purchases a patent if $\lambda H - p \geq 0$, so the market for technology clears, as in the simplest version of the Akerlof's "lemons" model (Akerlof, 1970), at price $p = \lambda H$.

Suppose that b is the politician's policy choice, the size of the bribe. Then, the number of talented researchers R who engage in innovation is determined as follows:

$$R = \begin{cases} 0 & \text{if } \pi + p(b) < c \\ \overline{R} & \text{if } \pi + p(b) \geq c \end{cases} \tag{1}$$

If $R = 0$, $p = 0$ as firms realize that there are no good patents in the market. Then the number of low-quality patents on the market of technology is

$$P(\pi(1-\theta) - a_i) > b) = \pi(1-\theta) - b,$$

and the total amount of bribes is

$$B = b\left(\pi(1-\theta) - b\right).$$

The politician's utility is $U^P = (1-\alpha)b(\pi(1-\theta)-b)$, which is maximized at $b_0 = \frac{1}{2}\pi(1-\theta)$, which in turn yields $U^P(b_0) = \frac{1}{4}(1-\alpha)\pi^2(1-\theta)^2$. When the market price for patents is zero, the sole purpose of paying a bribe is receiving the award π.[6]

Suppose that $R = \overline{R}$, that is, talented researchers innovate. If the bribe is set at b, and the market price is p, the number of low-quality patents in the market is

$$P((\pi+p)(1-\theta) - a_i > b) = (\pi+p)(1-\theta) - b,$$

The price of the patent in the market is determined by the share of good patents applications in the total pool:

$$p = \frac{\overline{R}}{\overline{R} + (\pi+p)(1-\theta) - b} H. \tag{2}$$

[6]If the politician in question was supervised by a principal, e.g., accountable to the public, the principal would of course realize, observing that $p = 0$, that the only reason why patents were granted and money awarded was bribes. This will not be true in our main case.

Let $p(b)$ be a unique solution of (2) given the politician's choice of b; the existence and uniqueness of the equilibrium price follows from the fact that the left-hand side of (2) is an increasing function of p, and the right-hand side of (2) is decreasing in p. Naturally, the function $p(b)$ depends positively on b : the higher is the bribe that non-innovators pay for the opportunity to get a patent, the lower is the share of false patents, and, consequently, the higher is the price the market is ready to pay for a patented innovation.

The total amount of bribes is

$$B = b\left(\left(\pi + p\right)\left(b\right)\left(1 - \theta\right) - b\right).$$

Let us define b^*, the optimal politician's choice, as

$$\begin{aligned} b^* =& b^*(H, \overline{R}, \alpha, \theta) \\ =& \arg\max_{b \geq 0} \left\{ \alpha \overline{R} H + (1-\alpha) b((\pi + p\left(b\right))(1-\theta) - b) \right\}. \end{aligned}$$

To demonstrate that there exists, for a certain natural range of parameters, an equilibrium, in which talented researchers innovate and the market price is non-zero, we need to show that $\pi + p\left(b^*\right) \geq c$ and $U^P\left(b^*\right) > U^P\left(b_0\right)$, i.e., the politician in equilibrium prefers innovation by talented people to the situation, when low-skill researchers pay bribes to receive state funds, and high-skill researchers do nothing.

Suppose that the bribe is set at the level $b_1 = (\pi + H)(1 - \theta)$. Then $p\left(b_1\right) = H$, $\pi + p \geq c$ by assumption, and the politician's utility is $U^P\left(b_1\right) = \alpha \overline{R} H$. It remains to choose parameters α, $\overline{R}$, θ, and H so that the following equation is satisfied:

$$U^P\left(b_1\right) = \alpha \overline{R} H > U^P\left(b_0\right) = \frac{1}{4}(1-\alpha)\pi^2(1-\theta)^2.$$

By the definition of b^*, we have $U^P\left(b^*\right) \geq U^P\left(b_1\right)$. Thus, for the same set of parameters,

$U^P(b^*) > U^P(b_0)$, and the following Proposition is proved.

Proposition 1 *When parameters α, $\overline{R}$, θ, and H^S are sufficiently large (exceed certain thresholds), the politician prefers to set the optimal bribe at the level that makes, via the impact on the price for patented innovation, the talented researchers to innovate.*

The results of the Proposition are very intuitive. Strong incentives for innovation depend positively on politician's interest in growth, α, the total number of talented researchers, $\overline{R}$, the quality of institutions that make it more difficult to patent a false invention, and the extent of spillovers H^S. When each of these parameters is sufficiently large, the market does not unravel. As a result, it is possible to have an increase in government money to result in, simultaneously, an increase in total number of patents, an increase in number of good patents, and a fall in the share of good patents in the total pool.

Some comparative statics results are of independent interest. If the prize that is independent of the market price, π, is high, then the optimal choice is to have the bribe level at $\frac{1}{2}\pi(1-\theta)$, the market price of patents at 0, and no innovation produced. In other words, in a corrupt environment, there is a risk of overpaying for patents: so much "lemons" are brought in that the market unravels. In contrast, when government grants are absent, the market price for patents would be $p = H\frac{\overline{R}}{\overline{R}} = H$, as only high-quality patents would be produced. The quantity of patents produced would thus be $p - c$. If, on the other hand, $\pi > 0$, the quantity of patents produced would be $\pi(1-\theta)$. So for $\pi > p - c$, the number of patents produced would be greater than in absence of government grants.

In the next section, we illustrate the implications of the model by focusing on Russia, with is its low level of government accountability and dramatic increase in R&D investment since 2010.

4 Evidence

In this Section, we start by providing background information on government R&D policy in Russia and the Russian patent systems. Next, in subsection 4.2, we introduce our data and methods. Subsection 4.3 presents the results, while in Appendix ?? we US data to check robustness of our main results. In subsection 4.4, we establish that the decline in patent quality as measured by patent citations led to a reduction in technology purchases as measured by licenses.

4.1 Background

Russia presents an interesting case for investigating government policy on supporting innovation (Wengle, 2015; Frye, 2017). Initially, after the collapse of the USSR, the funding toward supporting innovation was largely absent, leading to shortages of lab supplies and months of unpaid wages (Woodruff, 1999; Frye, 2000; Ganguli, 2017). In the early 2000s, observers still saw Russia's science and technology as its "major untapped resource" (Sher, 2000; Gianella and Tompson, 2007). Among many determinants of unsatisfactory innovative performance of the country, scholars underscore two: weak demand for R&D in the economy and low government funding for R&D (Makarov and Varshavsky, 2013). After 2007, the dramatically increased state investment and grant programs have been targeting specific areas of research, with the rest affected to a smaller degree. For example, various grant programs prioritized research in spheres of nanotechnology and, more recently, age-related medical research. In 2007, the Russian government created a government-owned joint-stock $10 billion Private Equity and Venture Capital Evergreen Fund called Rusnano aimed at commercializing developments in nanotechnology. Another conglomerate established in 2007, called Rostec, specializes in strategically important companies, mainly in the defense industry. Other sources of government funding, such as the Russian Fund for Basic

Research, prioritize nanotechnology. In many instances, just obtaining a patent was sufficient to claim the successful completion of a project undertaken with government funding. Thus, researchers in the field of nanotechnology were incentivized to produce more patents. We argue that this has led to a disproportionate decline in patent quality and value when compared to other fields.

Sometimes, the nature of the patent and its practical usage can be inferred from the title: US 6368227 patents a "Method of swinging a swing") and US 604596 is "On the method of applying a peanut butter and jelly sandwich". A useless Russian patent typically disguised as something that appears genuine to nonspecialists. Some examples of patent names and associated technological problems are summarized by Arutyunov (2008), and presented in Appendix. Yet, filing even an empty patent is costly. Quotes from the Russian patenting agency patentum.ru[7] suggests that performing a patent search and filing an actual claim amounts to 145 thousand rubles (roughly $2500) excluding the mandatory filing fee. This is about five times the average monthly wage in Russia.

Nonetheless, 98% of Russian patents filed after 1996 were never cited, and only 0.02% of Russian patents have 10 citations or more. The time lag between patent publication and its first citation is uncommonly high even for those patents that were cited (six years) compared to usual lag in OECD patents (three years). The market of technology transfer using patents is virtually absent, and more than 90% of Russian patents are held by individuals, and not companies. Why would a researcher file a patent that is likely never be licensed or sold, but looks scientific-like to a non-specialist?

One potential use of such patents is to signal the researcher's competence. Government scientific agencies (RFBR, etc.) decide whether to finance innovative projects with a grant based on several factors. Often the most important of them is the number of patents and publications submitted by the researcher. While it is costly to establish the quality of a

[7] https://patentus.ru/sroki-i-tzeny/patentovanie-izobreteniy/

complex research, governments often rely on patenting criteria: novelty, inventive step and applicability. A research that satisfies these criteria is worthy of support. The existence of a patent does not guarantee that these criteria are met. Still, the researcher is evaluated not on the basis of true patent quality, but by the mere quantity of obtained patents.

Indeed, the relative importance of patents and publications obtained by the researcher in the process of applying for a grant is very high, accounting for 45% of the score a researcher receives during project evaluation. Thus, the costs of increasing one's chances of receiving a government grant decline as the sum of costs of patenting and the costs of research converge to merely the costs of patenting. This gives researchers the incentive to file low-quality patents and, hence, increases the share of low-quality patents in the pool of Russian patents. Indeed, vast majority of Russian patents are only filed in Russian Patent Office, as shown in the Appendix (WIPO, 2018), as they are only intended for domestic use, as they are never filed in any other patent office, which is surprising given relatively small size of Russian market for technology. For example, 50% of Swedish patents are filed in two offices or more. Such patents can be used as a main result of the research financed by the government grants, providing the researchers with an opportunity to forgo the actual innovative activity.

4.2 Data and Methods

We use the complete list of Russian patents for the 1996-2015 time period, including patent classification, year of patent application and patent grant, and number of forward-citations. Unfortunately, there is no readily-available indicator denoting whether the patent covers nanotechnology-related technology. Thus, we rely on two approaches to detect such patents.

First, we compile a dictionary of "nanotechnology"-related terms. We then identify the presence of such words in the name of a patent. We denote the dummy variable $nano\_text$ as equal to 1 if patent name contains at least one nanotechnology-related term and 0 otherwise. We complement this approach with another measure based on pre-existing classification of

Russian 5-letter patent classes. We denote the dummy variable, taking the value 1 if patent belongs to nanotechnology-related field as nano.[8] Figure A-2 of the Appendix presents the histogram of patent applications in the 1998-2015 time period. Colors represent patent section in International Patent Classification - the broadest definition of patent field.[9]

Figure A-1 presents the distribution. of Russian patents over 1998-2015 by status (nanotechnology or not) and citations (cited within first 4 years since publication or not). It is easy to see that patenting increased sharply since the onset of the program, with nanotechnology-related applications affected to a higher degree. The number of cited nanotechnology patents increased in the first year, compared to pre-treatment period, consistent with the fact that incentives to file nanotechnology-related patents mechanically creates a push to cite existing patents in the same area as part of the filing process. However, the share of cited patents falls in the nanotechnology field.

Further, we explore the policy change in the provision of R&D funding that occurred in 2008 and provided large grants to researchers in the fields of nanotechnology. Using patent classification, we determine which research-based patent filings were eligible for government support. We then employ a difference-in-difference approach to demonstrate that the average quality of patents eligible for government grants dropped after the onset of government R&D programs compared to patents in fields where government support for innovation was less pronounced. The non-nanotechnology patents serve as a control group, since they are less likely to receive government support. Treatment period $\in 0, 1$ is 0 before the onset of a massive campaign to support innovation in nanotechnology in 2008, and 1 after the onset of

[8] B82B1/00, B82B3/00, B82B10/00, B82B20/00, B82B30/00, B82B40/00, B82C5/00, B82C15/00, B82C20/00, B82C25/00, B82C30/00, B82C35/00, B82C99/00, B82C, 619/51, B05D1/00, 0131/02, G01B 1/00-15/00, G01N 13/10-13/24, G02F 1/017, G12B 21/00-21/24, H01F 10/32, H01F 41/30, H01L 29/775.

[9] Figure A-2 shows that the number of patent applications has grown after the announcement of large-scale government R&D funding. This growth was especially large in sections B (performing operations), C (chemistry) and G (physics). These are the sections most likely to contain nanotechnology-related patents, and, therefore, be eligible for additional government support. Similar growth in nanotechnology-related patent applications is noticeable using the dictionary-based approach, as demonstrated in Table A-2 of the Appendix

a program. Equation 3 provides the details of the estimation.

$$Y_{it} = program_{it} + nano_{it} + nano_{it} * program_{it} + patent.class_{it} + \epsilon_{it}, \tag{3}$$

Treatment variables are as follows: $program_i$ is an indicator variable, denoting whether the government program subsidizing researchers in the field of nanotechnology was in place in the year the patent was obtained; $nano_i$ is an indicator variable that shows whether the patent fell into patent classification of nanotechnology.

Since less than 2% of Russian patents are ever cited, we focus on the following measures of citations: `citations1` is a dummy variable, that takes the value 1 if the patent received at least 1 citation by 2016, 0 otherwise. citations10 is a dummy variable, that takes the value 1 if the patent received at least 10 citations by 2016, 0 otherwise.

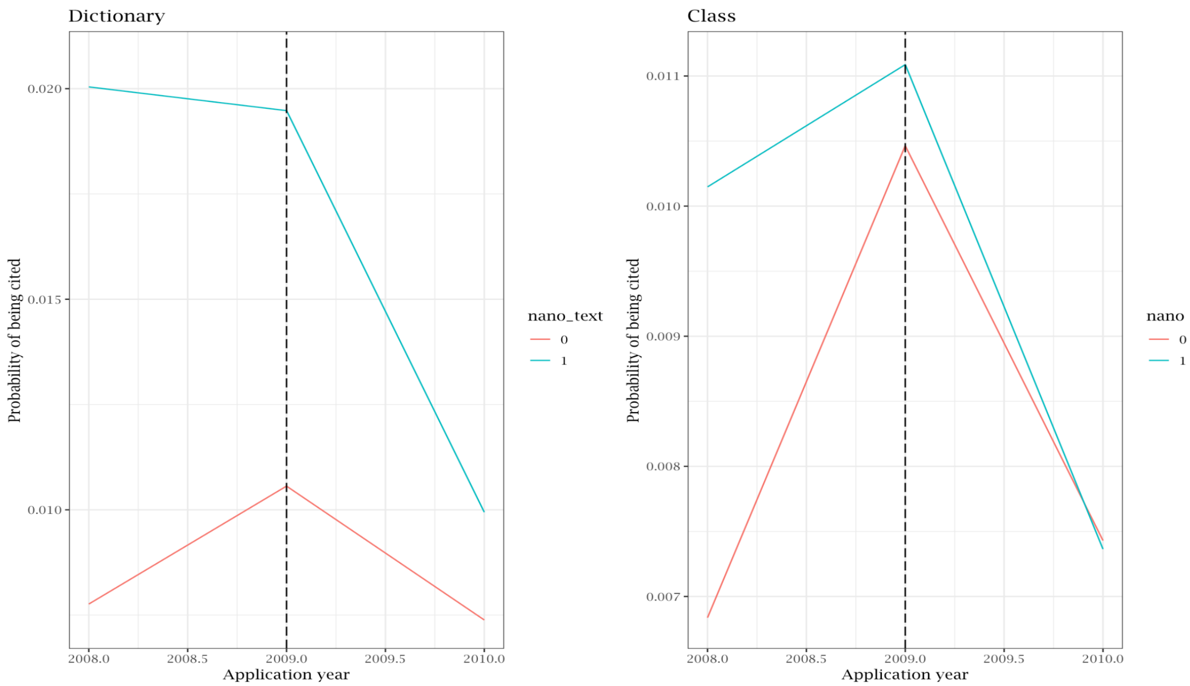
`Control variables`: In order to account for the fact that older patents have more time to be cited, we include year of publication as a control variable. We account for the fact that patents in some fields are more likely to be cited than patents in other fields, by including fixed effects of the first 3 letters of patent classification.

As in any difference-in-difference analysis, we rely on a parallel trends assumption. Figure 3 presents trends for mean age-adjusted patent citations over the first five years of patent existence. Nanotechnology patents are identified via dictionary-based and class-based approaches, respectively. Both dictionary-based and class-based classifications suggest that the decline in patent citations was more pronounced in classes receiving greater government support in nanotechnology-related classes.

4.3 Results

Table A-5 demonstrates the decline in the probability of being cited for nanotechnology patents during years of additional government support for nanotechnology when compared

Figure 3: Parallel trends assumption:Probability of being cited within first 5 years (by dictionary and class classifications)



to other fields. Specifically, a dictionary-based approach suggests a 4.6% decline in the probability of being cited at least once by 2016 for nanotechnology-related patents as a result of increased government support. A classification-based approach suggests a 1% decline in the probability of being cited by 2016. These results are robust for two ways of classifying patents as belonging to nanotechnology with either text analysis of the patent name or the five-letter patent class it belongs to.

Omitted variable bias can seriously impact any analysis of social phenomena. A difference-in-difference approach relies on a parallel trends assumption to mitigate the effects of extraneous factors and selection bias, but it can still be subject to the omitted variable bias. There are multiple approaches to sensitivity analysis (Rosenbaum and Rubin, 1983; Heckman et al., 1998; Imbens, 2003; Hosman et al., 2010; Imai, Keele and Yamamoto, 2010; VanderWeele and Arah, 2011; Blackwell, 2014; Frank et al., 2013; Dorie et al., 2016; Middleton et al., 2016).

We choose the approach ÑÐ° Cinelli and Hazlett (2020) for the following reasons. First, it relaxes some strong assumptions required for the majority of these methods. Second, it provides readily-available statistics that illustrate the sensitivity of the analysis to omitted variable bias.

Cinelli and Hazlett (2020) suggested an approach to quantify the confounding that would be required to nullify the observed regression results. To do so, we report the "robustness value" measure of sensitivity that illustrates the overall robustness of a coefficient to unobserved confounding. If the confounders' association to the treatment and to the outcome (measured in terms of partial R^2) are both assumed to be less than the robustness value, then such confounders cannot "explain away" the observed effect. This measure is a function of the estimate's t-value and the degrees of freedom.

Omitted variable bias can be decomposed as follows (**?**):

$$|\hat{bias}| = se(\hat{\alpha})\sqrt{\frac{R^2_{Y\sim Z|X,D}R^2_{D\sim Z|X}}{1-R^2_{D\sim Z|X}}(df)}$$

where $se(\hat{\alpha})$ is the standard error of the main coefficient of interest $\hat{\alpha}$, Y is the outcome of interest, D is the main explanatory variable, X is a vector of covariates, Z is the omitted variable, and df is degrees of freedom of the regression.

The absolute value of the bias thus depends upon the strength of association of the outcome with the omitted variable (measured by the partial R^2:$R^2_{Y\sim Z|X,D}$)[10], and the strength of association of the main explanatory variable with the omitted variable ($R^2_{D\sim Z|X}$).

An intuitive way to interpret the results is by comparing them to observed variables. The core assumption here is that confounding explains less of the residual variation in treatment

[10]Note that $R^2_{Y\sim Z|X,D}$ has a direct one-to -one association with $R_{max} = R^2_{Y\ D+X+Z}$ proposed in (Oster, 2019):$R^2_{Y\sim Z|X,D} = \frac{R_{max}-R^2_{Y\ D+X}}{1-R^2_{Y\ D+X}}$. However, the second sensitivity parameter, required by Oster (2019) - δ_{Oster} - is not easily interpretable in substantive terms, as it captures both the relative influence of X and Z over the treatment, but also their association with the outcome because $W1$ and $W2$ have been defined through association with the outcome

and in the outcome than the observed covariate.

We choose publication year as the strongest predictor of citations received by the patent since it is widely accepted in the literature that there is a strong positive relationship between the age of the patent and its forward citations. The robustness values for the four main models are reported in Table A-5.

For model 1, unobserved confounders (orthogonal to the covariates) that explain more than 0.62 % of the residual variance of both the treatment and the outcome are enough to reduce the absolute value of the effect size by 100 %. Conversely, unobserved confounders that do not explain more than 0.62 % of the residual variance of both the treatment and the outcome are not strong enough to reduce the absolute value of the effect size by 100 %. Similarly, unobserved confounders should explain at least 0.36 %, 0.49 % and 0.49 % of the residual variance of both the treatment and the outcome in models 2-4 to reduce the absolute value of the effect size by 100 %. The observed robustness values are rather low, yet the citation data of Russian patents exhibits rare events characteristics, meaning that the predictive power of most variables would be rather low. Benchmarking the effect of the difference-in-difference coefficient against the publication year suggests that omitted variable at least three times as influential as it will reduce the effect to zero (Figure **??**).

Table A-6 presents similar results for age-adjusted patents. The outcome variable in this case is the number of citations received by patent i by year t, divided by the number of years since patent publication. The results suggest that disproportional government support of nanotechnology-related patents had a negative effect on their quality.

While class-based nanotechnology classification is negative and significant, suggesting 7% decline in probability of being cited (adjusted for patent age) is negative and statistically significant, it is still sensitive to omitted variable bias. Unobserved confounders (orthogonal to the covariates) that explain more than 0.18% of the residual variance of both the treatment and the outcome are enough to reduce the absolute value of the effect size by 100 % at the significance level of alpha = 0.05 . Conversely, unobserved confounders that do not explain more than 0.18 % of the residual variance of both the treatment and the probability of being cited are not strong enough to reduce the absolute value of the effect size by 100 % at the significance level of alpha = 0.05 . Benchmarking the effect of the difference-in-difference coefficient against the publication year suggests that omitted variable at least as influential as it will reduce the effect to zero (Figure A-5).

The difference-in-differences approach employed in subsection 4.3 measures the effect of government funding on patent citations in the treated group (nanotechnology), relative to changes in the patent citations in the control group (other patents). However, it suffers from high sensitivity to omitted variable bias. In this section, we employ US patent data to pursue the triple difference approach by comparing the double differences in nanotechnology citations with the double difference in non-nanotechnology citations, allowing the control of more factors that could bias the average treatment effect.

It is possible that there exists an omitted variable (or a group of variables) that varies by time and patent type and affects patent citations. The double-difference approach eliminates the effect of such a variable if both nanotechnology patents and non-nanotechnology patents experience the same change in it. The differential advances in the technology can be such a factor. Yet it is hard to measure and therefore cannot be easily controlled. Thus, we remove the effect of such an omitted variable with a triple-differencing strategy, allowing an additional comparison between Russian and US patent citations.

New and growing fields, such as nanotechnology, can exhibit different patterns of development, compared to more established fields[11]. Thus, one might suggest the presence of a time-varying confounder that changes differently across nanotechnology and non-nanotechnology

[11] Nanotechnology became a specialized field in the 1980s after two major breakthroughs: the invention of the scanning tunneling microscope in 1981 which provided unprecedented visualization of individual atoms and bonds, and the discovery of fullerenes in 1985. Nanotechnology-related patent classification - Class 977 - was created in January 2011.

patent fields. A time-varying confounder that is not class-invariant violates the common trend assumption of difference-in-difference. We address the problem with a DDD design, using Russian and US patent data. The assumption is that nanotechnology patents in both countries are exposed to time-varying counfounders related to the relative novelty of the field. However, US patents are not influenced by Russian policy aimed at nanotechnology funding. Thus, we aim to remove the bias from the confounder and isolate the treatment effect by estimating the triple difference model of the following form:

$$\begin{aligned} Y = program + nano + rus + nano * program + nano * rus + \\ + program * rus + nano * program * rus + broad.patent.class + publication + \epsilon, \end{aligned} \tag{4}$$

where the outcome variable are citations - a count of citations received by the patent by 2016; `citations1` - a dummy variable that takes the value 1 if the patent received at least one citation by 2016, and 0 otherwise and citations10 - a dummy variable, that takes the value 1 if the patent received at least 10 citation by 2016, 0 otherwise.

As before, in order to account for the fact that older patents have more time to be cited, we include the year of patent publication. In order to account for the fact that patents in some fields are more likely to be cited than patents in other fields, we include the fixed effects of the first 3 letters of patent classification.

We rely on pre-existing classification of patent classes that are more likely to include nanotechnology patents for construction of our `Explanatory Variable`. We denote the dummy variable, taking the value 1 if the patent belongs to nanotechnology-related field as `nano`. The results of triple-difference estimation are presented in Table A-7.

The results of models 2 and 3 suggest that after the implementation of government support for nanotechnology in Russia, the patents in this area received fewer total citations, and fewer of them reached at least 10 citations. At the same time, the probability of Russian nanotechnology patents receiving at least one citation increased compared to US patents.

This may reflect the fact that when applying for a patent, researchers are expected to cite existing relevant patents when producing patents that have few citations.

The results of this subsection serve as an additional robustness check for our main results. In subsection 4.3, we demonstrated that both quality (as measured by citations) and market attractiveness (as measured by licenses) of nanotechnology-related patents have declined in the aftermath of government support for innovation in this field. There are possible alternative explanations for these results. First, if government support triggers growth in fundamental research, companies may become interested in resulting technologies later on, while the present-day positive impact on licensing could be negative.

Yet this hypothesis would fail to explain the fall of patent quality, as measured by citations, since the comparison is drawn between patents of the same publication year. If anything, government support for RD should prompt the increase in citations since patenting requires citing relevant research. Thus, citations in the affected fields should not decline, especially if government agencies highlight the importance of patenting for both selection of grantees and successful completion of the grant contract. For example, Azoulay et al. (2019) show that NIH funding by the United States government spurs the development of private-sector patents that cite NIH-funded research.

A second alternative explanation is that government funding of nanotechnology patents became effective at a time when nanotechnology research experienced a decline, and the patents in the field became less cited. This conjecture is unlikely to hold since an examination of citation trends of nanotechnology and other patent citations suggest that parallel trend assumption was true for the pre-treatment period. Still, one might suspect that there was some fundamental change in the year when government policy took effect, but was independent of this policy. Yet the analysis of the triple-difference model, including US patents, does suggest that no such change took place or that it was Russia-specific.

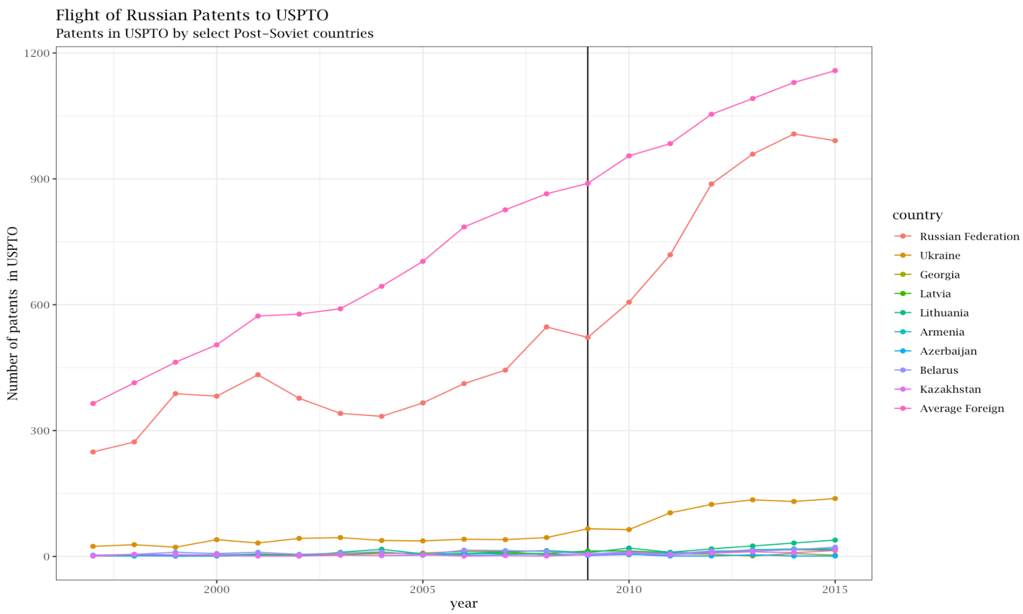
Figure 4: Aggregated licenses per patent by aggregated patent class

4.4 Government R&D support and licensing

Next, we investigate whether the decline in patent quality as measured by patent citations led to a reduction in technology purchases (measured by licenses). Licensing is one of the most common ways of technology transfer, and thus reflects the changes in the market for patents. Since licensing data is not readily available for Russian patents, we rely on government-compiled reports, which provide the total number of licenses of nanotechnology patents, as well as non-nanotechnology patents. This data has several limitations. One cannot observe exact patent class or any other unit-level information. In addition, we were able to collect data only for a limited span of time, from 2000 to 2011. Thus, these results can only serve as illustrative evidence.

Figure 4 suggests that nanotechnology patents affected by government policy receive fewer licences when compared to post-policy implementation, and this decline is especially pronounced when compared to the increase in licensing of non-nanotechnology patents.

Figure 5: Patents filed in USPTO from select countries



If the average quality of Russia falls, reducing the price of technology transfer to companies, inventors should move to other patent offices. We provide another illustrative example, using the data on foreign patents filed in USPTO (Figure 5). “Average Foreign" represents the total number of foreign patents filed in USPTO in a given year, divided by the number of countries that filed patents in USPTO office that year. The figure presents USPTO patents for Russia and select post-soviet countries as comparison. It suggests that soon after the onset of government R&D funding, the number of Russia patents filed in USPTO increased dramatically. There was no comparable jump in USPTO patents for other post-soviet countries.

This observation does not contradict the view that the deterioration of average patent quality in RUPTO pushed inventors to file patents in other patent offices.

5 Conclusion

In a weakly institutionalized environment, government support for R&D can be used as a vehicle for rent-seeking. We document the wide discrepancies in the impact of government funding on the creation of patented technologies and show that countries with higher levels of corruption have a greater patenting efficiency, but that does not translate into actual technological development. Using a game-theoretical approach, we suggest a mechanism that explains how corruption in the public sector creates incentives for polluting the technology market with fake patents and leading to the creation of "Lemons" problem in the market for technology. We further employ a difference-in-difference approach in context of Russian policy to support nanotechnology. We show how government support for innovation can reduce the overall quality of patents in the field that is eligible for such support. These findings help to reconcile various findings regarding the efficiency of government innovation policies in different countries by incorporating political incentives and institutional quality into policy analysis. Furthermore, they provide a theoretical background for evaluating the impact of political incentives for investing in the creation of new technologies in the technological development of countries.

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Appendix

Patent Num	Patent Name	Technology
RU2062143	A rigging for production of methanol	The application of this technology would lead to destruction of the surrounding area of up to hundreds of square kilometers.
RU2265585	Technology of production of methanol and other aliphatic spirits	The production of methanol and other aliphatic spirits with such method is proved impossible
RU2181622	A method of natural gas oxidation	The description of technology doesn't include any numbers or proportions. Essentially, patent claims only that there exists an unspecified method of natural gas oxidation
RU2282612	The method of production of liquid oxygenates by natural gases conversion and the equipment for its' conduction	Implies a technological reaction that is impossible due to physical parameters of mentioned substances
RU2205172	The method of production of methanol	Describes a technology that allows to achieve parameters 5-7 times worse than mentioned in a patent

Table A-1: Government Accountability and Patenting Efficiency

	Dependent variable:			
	Patents/GERD			
	(1)	(2)	(3)	(4)
Public Corruption (I=1)	1.216*			
	(0.693)			
Information Transparency		0.028*		
		(0.016)		
Transparency Index			−0.032*	
			(0.019)	
Accountability Index				−0.064***
				(0.014)
GDP	−0.017	−0.009	−0.017	−0.011
	(0.032)	(0.033)	(0.032)	(0.032)
Constant	1.362***	−0.698	3.707***	5.741***
	(0.138)	(1.240)	(1.341)	(0.989)
Observations	491	491	491	491
R^2	0.007	0.006	0.007	0.039
Adjusted R^2	0.003	0.002	0.003	0.035
Residual Std. Error (df = 488)	2.370	2.371	2.370	2.331
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A-2

	Dependent variable:	
	Patent name contains nanotechnology-related term	
	logistic	*OLS*
	(1)	(2)
Program in place	0.255^{**}	0.002^{***}
	(0.119)	(0.001)
Application year	0.114^{***}	0.0005^{***}
	(0.013)	(0.0001)
Constant	-234.492^{***}	-0.928^{***}
	(25.610)	(0.118)
Observations	191,583	191,583
R^2		0.002
Adjusted R^2		0.002
Log Likelihood	−5,964.383	
Akaike Inf. Crit.	11,934.770	
Residual Std. Error		0.071 (df = 191580)
F Statistic		205.507^{***} (df = 2; 191580)
Note:		*p<0.1; **p<0.05; ***p<0.01

Figure A-1: Patents by status (nanotechnology/not) and citations (cited/not)

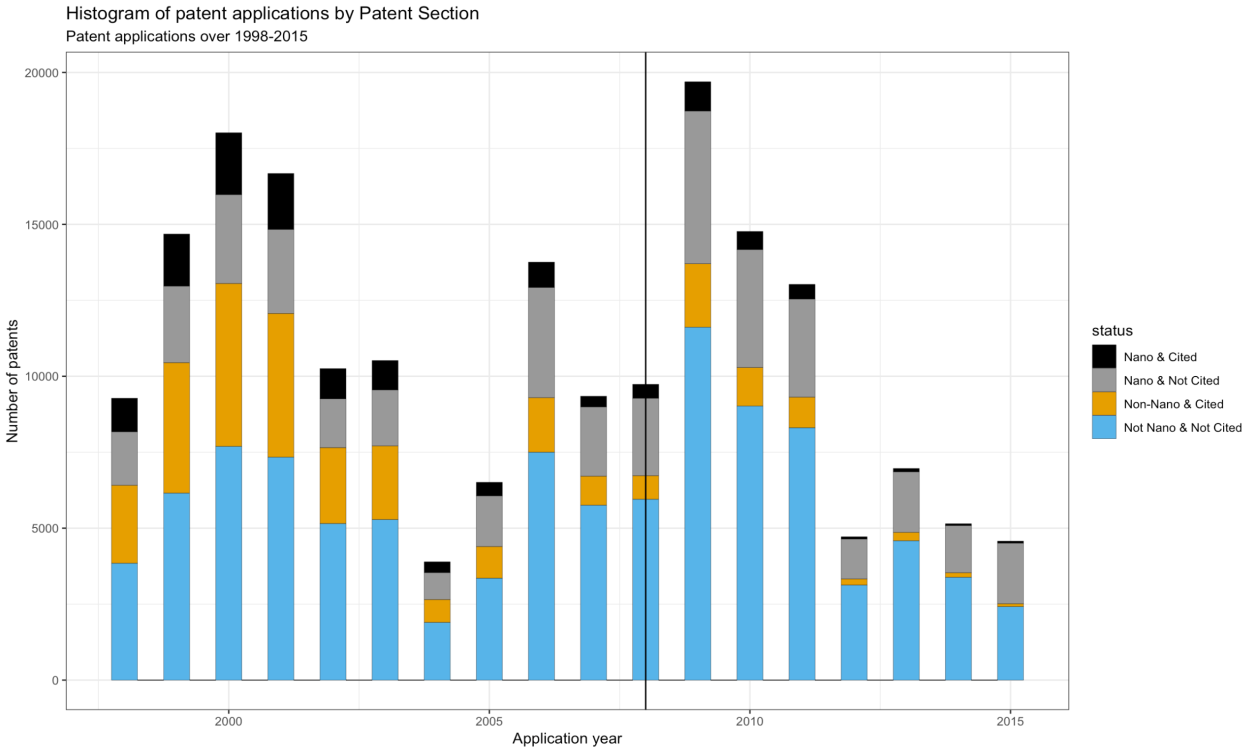

Figure A-2: Number of patents applications per IPC section per year

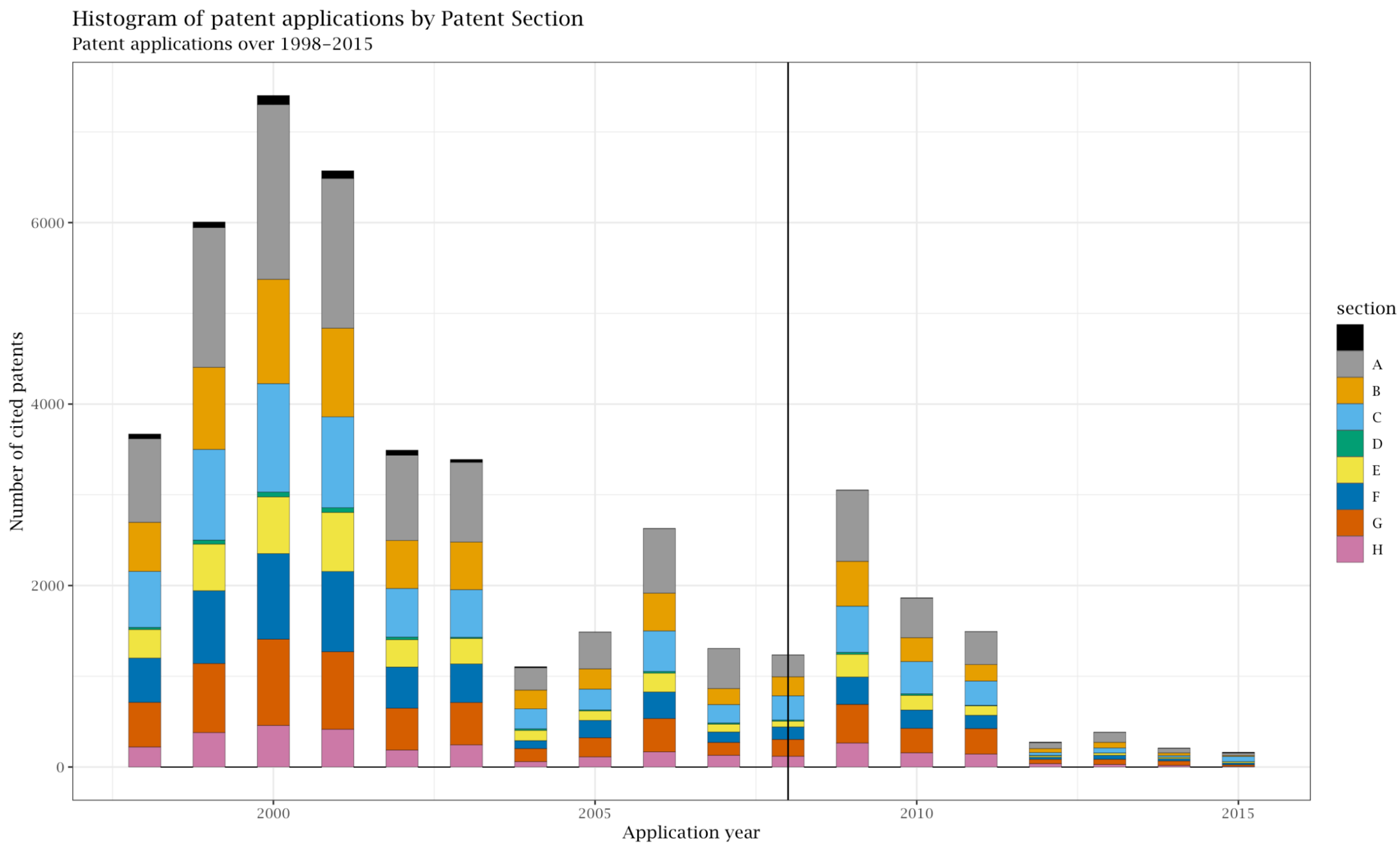

Figure A-3: Distribution of patent families by number of offices for the top 20 origins, 2013-2015. Source:World Intellectual Property Indicators 2018 - WIPO

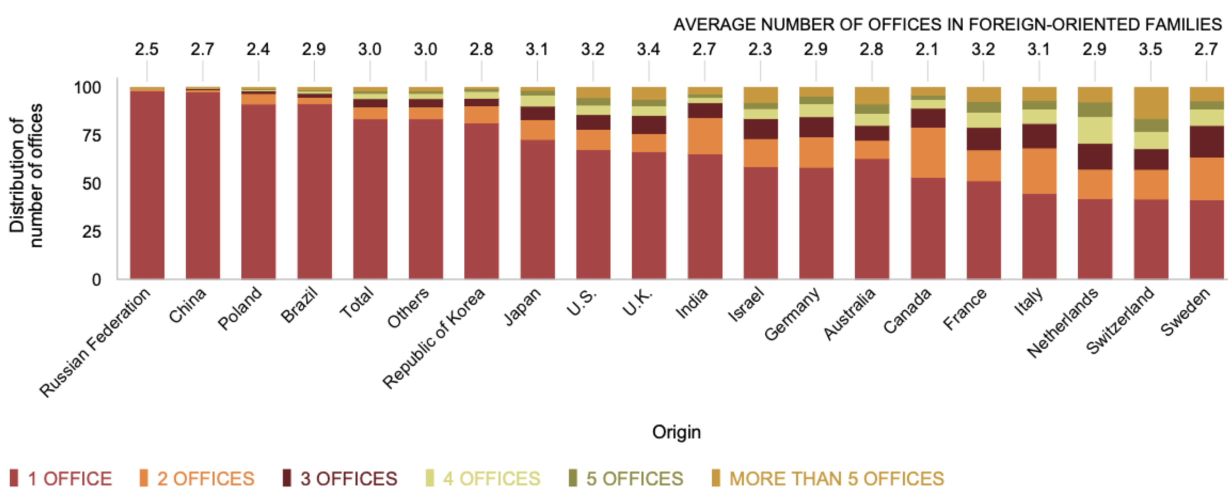

Table A-3: Total Factor Productivity, Government Patenting Efficiency and Low Accountability

	Dependent variable:		
	‘Total Factor Productivity‘		
	(1)	(2)	(3)
R&D efficiency	0.549***	0.554***	1.331***
	(0.199)	(0.200)	(0.436)
Low ATI		−0.129	0.610
		(0.317)	(0.486)
R&D efficiency ×Low ATI			−0.880**
			(0.439)
Constant	0.530	0.655	−0.019
	(0.605)	(0.680)	(0.756)
Observations	491	491	491
R^2	0.155	0.156	0.163
Adjusted R^2	0.092	0.091	0.097
Residual Std. Error	2.367 (df = 456)	2.369 (df = 455)	2.361 (df = 454)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A-4: Public Corruption, Information Transparency and Accountability and Patenting Efficiency

	Dependent variable:			
	Government R&D efficiency in patenting			
	(1)	(2)	(3)	(4)
Public Corruption (I=1)	1.512***			
	(0.311)			
Information Transparency		−0.037***		
		(0.006)		
Transparency Index			−0.064***	
			(0.009)	
Accountability Index				−0.034***
				(0.008)
GDP	0.019**	0.015*	0.018**	0.022***
	(0.008)	(0.008)	(0.008)	(0.008)
Constant	0.587***	3.054***	4.467***	2.372***
	(0.136)	(0.405)	(0.558)	(0.435)
Country FE	+	+	+	+
Observations	491	491	491	491
R^2	0.952	0.954	0.955	0.952
Adjusted R^2	0.948	0.950	0.951	0.948
Residual Std. Error (df = 455)	0.539	0.529	0.524	0.542
Note:	*p<0.1; **p<0.05; ***p<0.01			

Table A-5: Government Policy and Patent Quality

	Dependent variable:			
	text: citations1	text: citations10	class: citations1	class: citations10
	(1)	(2)	(3)	(4)
Nanotechnology	0.070^{***}	0.008^{***}	0.023^{***}	-0.0001
	(0.022)	(0.003)	(0.007)	(0.001)
Program	0.059^{***}	0.0001	0.062^{***}	-0.0001
	(0.003)	(0.0004)	(0.004)	(0.0004)
Nanotechnology×Program	-0.046^{*}	-0.009^{***}	-0.010^{**}	0.001
	(0.027)	(0.003)	(0.004)	(0.0005)
Constant	0.550^{***}	0.007^{***}	0.549^{***}	0.007^{***}
	(0.012)	(0.001)	(0.012)	(0.001)
3-letter IPC FE	+	+	+	+
Publication year FE	+	+	+	+
Observations	191,583	191,583	191,583	191,583
R^2	0.125	0.004	0.125	0.004
Adjusted R^2	0.124	0.004	0.124	0.004
Residual Std. Error	0.399	0.047	0.399	0.047
F Statistic	196.05^{***}	6.06^{***}	196.07^{***}	6^{***}
Robustness Value	0.0062	0.0035	0.0048	0.0049
Note:				*p<0.1; **p<0.05; ***p<0.01

Figure A-4: Benchmarking: baseline models

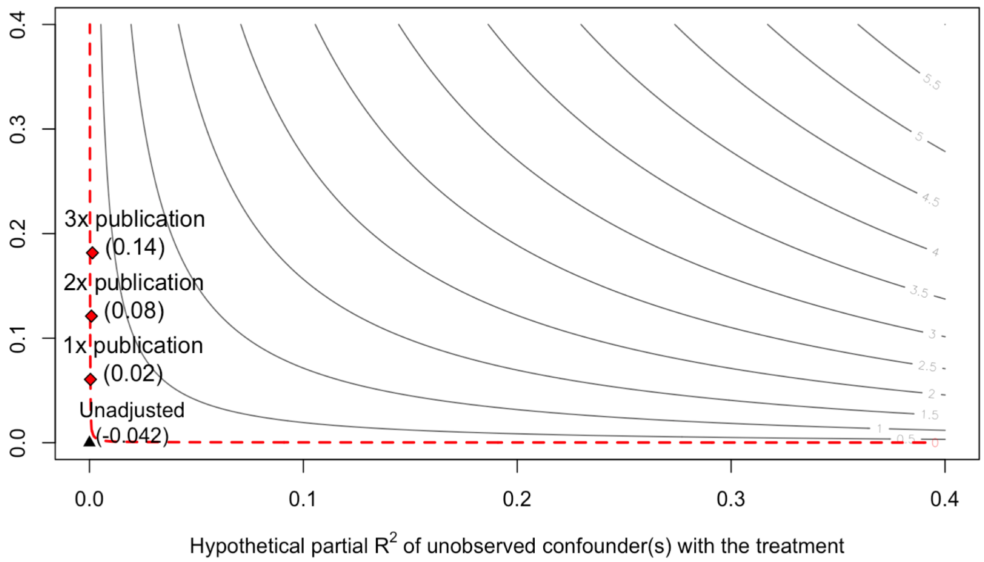

Table A-6: Age-adjusted patent citations

	Dependent variable:	
	citations per age	
	(1)	(2)
Nanotechnology (text)	0.105	
	(0.795)	
Nanotechnology (class)		0.118
		(0.251)
Program	0.358^{***}	0.591^{***}
	(0.092)	(0.110)
Nanotechnology (text) × Program	−0.596	
	(1.150)	
Nanotechnology (class) × Program		-0.787^{***}
		(0.199)
Constant	0.440	0.434
	(0.394)	(0.394)
Observations	1,194,924	1,194,924
R^2	0.0001	0.0001
Adjusted R^2	−0.00005	−0.00003
Residual Std. Error (df = 1194799)	37.585	37.585
F Statistic (df = 124; 1194799)	0.562	0.685
Robustness Value	0.00053	0.0036
Note:	*p<0.1; **p<0.05; ***p<0.01	

Figure A-5: Benchmarking the effect of the difference-in-difference coefficient against the publication year

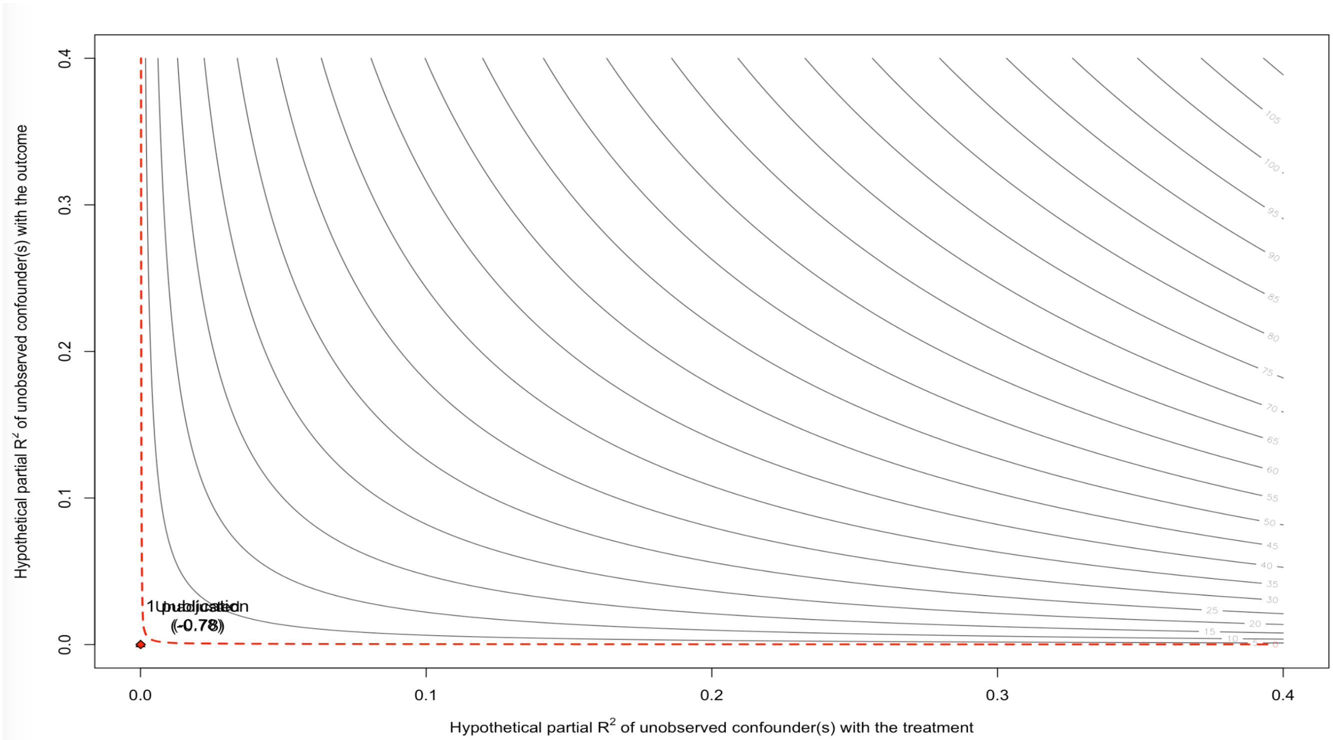

Table A-7: Triple-Difference Approach

	Dependent variable:		
	citations1	citations10	citations
	(1)	(2)	(3)
Russia	-0.549^{***}	-0.312^{***}	-19.529^{***}
	(0.002)	(0.001)	(0.226)
Program	-0.903^{***}	-0.471^{**}	-14.675
	(0.262)	(0.211)	(32.214)
Nanotechnology	0.006	0.003	1.083^{**}
	(0.004)	(0.004)	(0.539)
Russia × Program	0.249^{***}	0.304^{***}	19.211^{***}
	(0.004)	(0.003)	(0.452)
Russia × Nanotechnology	0.044^{***}	0.035^{***}	2.200^{***}
	(0.005)	(0.004)	(0.623)
Program × Nanotechnology	-0.032^{***}	0.015^{***}	1.210^{*}
	(0.006)	(0.005)	(0.717)
Program × Russia × Nanotechnology	0.028^{***}	-0.013^{**}	-2.117^{**}
	(0.007)	(0.006)	(0.851)
Constant	-26.045^{***}	7.290^{***}	296.379^{***}
	(0.649)	(0.521)	(79.705)
Observations	853,974	853,974	853,974
R^2	0.444	0.227	0.049
Adjusted R^2	0.444	0.227	0.048
Residual Std. Error (df = 853548)	0.371	0.298	45.547
F Statistic (df = 425; 853548)	$1,602.422^{***}$	589.407^{***}	102.957^{***}
Robustness value	0.0168	0.0101	0.00261
Note:			*p<0.1; **p<0.05; ***p<0.01