Policies to Promote Innovation: Insights from Global AI Policies*

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Abstract

By constructing novel datasets on AI innovation policies and global AI patent data, this paper provides the first comprehensive review of AI promotion policies across 48 countries and examines their impact on the AI innovation landscape. We find that AI scientists experience a decrease in productivity after the introduction of national AI strategies. Our evidence suggests that while expanded support incentivizes scientists to pursue more novel and exploratory inventions, many of these projects frequently require longer development timelines and encounter a higher risk of failure. However, a select few projects have better chances of success, resulting in a drop in average quality. Furthermore, we find that AI policies are associated with increased cross-country knowledge spillovers.

Keywords: Innovation, Patents, Artificial Intelligence, Public Policy, Scientists

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1 Introduction

Innovation drives economic growth (Schumpeter, 1947; Solow, 1957; Kogan, Papanikolaou, Seru, and Stoffman, 2017; Klette and Kortum, 2004) and is, arguably, the only means of sustaining long-term growth. Given its importance and the possible underinvestment by firms in developing technologies with significant positive externalities and knowledge spillovers, governments have occasionally implemented policies with the objective of promoting innovation. However, research on whether these government policies are effective in stimulating innovation is limited and its findings have been mixed (Bloom, Van Reenen, and Williams, 2019). Much of the existing evidence is based on data from the United States, with a systematic lack of international evidence. Only recently has there been a surge in innovation policies specifically designed to foster Artificial Intelligence (AI), which provides researchers an opportunity to better gauge the role of governments in stimulating innovation. These policies might be particularly significant, since AI is believed to have the potential to transform societies and be a key driver of the global economy in the 21st century. Since 2000, more than 200 AI-related government policies have been introduced in 69 countries to support AI development. This paper evaluates the impact of these AI policies on innovation.

Our primary finding is that AI scientists intriguingly experience a *decline* in innovation productivity following the introduction of national AI support policies. Specifically, we document a reduction in the number of patents filed by scientists, coupled with a decline in the average quality of these patents, indicated by a drop in subsequent citations. A plausible explanation for our finding is that national-level

support may incentivize scientists to pursue novel projects in an attempt to achieve radical innovation. However, these projects, while holding the potential for significant impact, have longer development time and a substantially higher probability of failure. Given the "winner-take-all" dynamics prevalent in AI — where the number of unsuccessful innovations far exceeds the few that achieve market dominance — this pattern aligns with the real-life observations.[1] Our findings suggest that policymakers should be aware of potential short-term productivity trade-offs when designing and implementing such support measures.

Our initial sample of AI policies comes from the OECD AI Policy Observatory,[2] which we refine to include only national-level AI policies.[3] For example, in 2019, the United States launched the "American AI Initiative" under Executive Order 13859, prioritizing AI R&D, improving access to federal data and computing resources, setting AI governance standards, and promoting workforce development. This initiative was later codified into law through the 2020 National AI Initiative Act, which establishes the National Artificial Intelligence Initiative Office to coordinate federal AI efforts. Subsequent actions, such as the 2025 Strategic AI Initiative, further aimed to remove barriers to AI innovation and strengthen US leadership in AI.

To measure innovation, particularly AI innovation, we utilize a global patent database from Google Patents, extending an established dataset of US AI patents to a global context to assess AI development across countries. The data show significant heterogeneity in AI development worldwide. While the US and China lead in AI

[1] For instance, in the case of innovations related to large language models (LLMs), only the top-performing models capture substantial market share.

[2] Available at https://oecd.ai.

[3] The OECD database contains regional policies, some of which target specific groups or are unrelated to AI. We manually review each policy to ensure that it is (1) directly relevant to AI, (2) national in scope, and (3) supports innovation across all entities.

innovation, each recording millions of AI patents, they are followed by Japan, South Korea, and the United Kingdom. Japan was the largest AI innovator by the number of patent filings in the 1990s, followed by the US, but both have since been overtaken by China in recent decades, which now leads as the largest AI innovator by number of AI patents.

National innovation strategies vary considerably, reflecting differing technological strengths and development levels. Technologically advanced economies like Japan, the US, and China often limit international scientific collaboration, strategically minimizing knowledge spillovers to protect their competitive advantage. Conversely, nations further behind the technological curve tend to pursue extensive cross-border partnerships. This approach accelerates knowledge acquisition and fosters technological progress. These divergent strategies are reflected in national policies. The US, for example, prioritizes infrastructure development and strategic public investments to guide corporate activity, aiming to maintain global AI leadership. Many other nations, seeking to close the gap, emphasize international scientific collaboration and attracting top talent. Despite these differences, understanding the overall impact of AI initiatives holds considerable interest.

We employ a stacked Difference-in-Difference (DID) framework[4] using the AI scientist (inventor) as our unit of analysis to investigate the average treatment effects of national AI policies. After the implementation of national AI policies, we observe that AI scientists file fewer patent applications, both in terms of raw counts and citation-

[4]See Baker, Larcker, and Wang (2022) for recent advances in DID analysis. Following Gormley and Matsa (2011), a stacked DID is often recommended as a straightforward implementation. Our results remain robust to the structural approaches in Callaway and Sant'Anna (2021); Sant'Anna and Zhao (2020).

weighted counts.[5] These patents also exhibit fewer backward citations (references to prior patents), suggesting that inventions rely less on established knowledge and may represent more exploratory and/or "venturing" efforts.

To investigate this possibility more rigorously, we employ a text-similarity approach.[6] We find that post-policy patents are more dissimilar to those filed in the same year, suggesting increased novelty. However, novelty does not necessarily translate into higher average quality; in fact, some of these patents may represent trial-and-error efforts. Consistent with this, we observe a decrease in their average quality, measured by forward citations. In a rapidly evolving field such as AI, a certain level of trial and error can be vital for long-term progress. Additionally, we find that AI scientists are increasingly concentrating on a narrower set of AI domains, potentially indicating a deeper focus on select areas in pursuit of novelty.

Novel patents, unconditional on policies, show a significant positive correlation with longer development times (as measured by backward citation timing) and greater variance in quality — first, these projects are more likely to receive zero forward citations, indicating a higher probability of failure or lower-quality outcomes; second, they are also more likely to achieve extremely high impact, as measured by forward citations.

When considering the effect of policy, we find limited evidence directly linking policies to an increase in radical innovation. In fact, our analysis shows that the variance in innovation quality increases after the implementation of policies. Specifically, novel patents (those without similar applications filed in the same year) exhibit nearly

[5] Forward citations (the number of future citations a patent receives) serve as a commonly used measure of innovation quality. The count is therefore quality-weighted.

[6] On the use of text similarity to evaluate innovation novelty, see Kelly, Papanikolaou, Seru, and Taddy (2021).

double the citation variance of non-novel patents (those with at least one similar concurrent application). This increased variance highlight the inherent uncertainty of novel projects: they are more prone to both significant breakthroughs and complete failures. These findings align with our broader, aggregate-level results. Consequently, these transitional dynamics and associated risks suggest that AI policies may not yield immediate effectiveness in the short run, as a proportion of novel attempts are likely to fail.

Although the total amount of knowledge spillovers, measured by citations, appear to decline, we find that AI policies nonetheless promote greater *international* knowledge exchange. Specifically, a larger proportion of both backward and forward citations for a focal country's patents originate from researchers in other countries post-policy. This suggests that while the absolute volume of spillovers may decrease, policies enhance the relative share of cross-border knowledge exchange.

Lastly, drawing on OECD definitions, we classify AI policies into four categories: Governance, Financial Support, Guidance and Regulation, and Collaboration, and analyze them separately. We do not detect strong heterogeneity across these policy categories, possibly because many policies are multifaceted, making it difficult to isolate category-specific effects. However, the 'Governance' category appears to have the weakest overall influence among the four.

To provide a theoretical underpinning for these findings, we develop a simple general equilibrium model following the endogenous growth literature (e.g. Romer, 1990; Aghion and Howitt, 1992; Acemoglu, Akcigit, Alp, Bloom, and Kerr, 2018). The model posits that government policies mitigate risks and provide support for novel innovation attempts, correcting market failures related to underinvestment

in radical innovation due to payoff uncertainty and the fact that the innovators cannot internalize the full benefits of innovation due to knowledge spillovers to the rest of the economy. While radical innovation increases expected long-term productivity growth, it also introduces transitional risks with increased investment in radical innovation, leading to higher volatility in innovation outcomes and potentially lower average innovation quality in the short term if many novel attempts fail. This theoretical framework supports our empirical observations, suggesting that short-term declines in patent metrics may be part of the long-term breakthroughs.

Our study makes three key contributions. First, we contribute to the literature on policy and innovation (see Bloom, Van Reenen, and Williams (2019) for a review and Aghion, Bergeaud, and Van Reenen (2023) for recent discussions), much of which focuses on the United States and a few other advanced economies. By examining a broader international sample, including major emerging economies such as China, we address an important gap in global evidence. Economic theory suggests that market economies underprovide innovation given the nature of knowledge as a public good, justifying government intervention to generate otherwise unrealized positive externalities. our findings suggest a potential trade-off. Policies designed to stimulate innovation may induce short-term fluctuations in innovation quality, highlighting the need to balance long-term growth objectives with potential short-term volatility.

Second, we contribute to the growing literature on AI in economics and finance. Existing studies largely examine the impact of AI on various outcomes, such as labor and productivity (Acemoglu and Restrepo, 2018), firm growth and product innovation (Babina, Fedyk, He, and Hodson, 2024), or asset prices (Kelly, Kuznetsov, Malamud,

and Xu, 2025). However, relatively few studies explore the drivers of AI innovation itself. We add to this literature by analyzing the effects of national AI policies on innovation outcomes.

Third, we build and introduce two new datasets. The first is a global AI patent dataset that extends the USPTO AI patent classification system to multiple jurisdictions, enhancing cross-national comparisons and providing deeper insights into worldwide AI innovation trends (Arora, Belenzon, Patacconi, and Suh, 2020). Given the increasingly borderless nature of AI development, such comprehensive data are essential for tracking international collaborations and competitive dynamics. The second dataset refines the OECD's catalog of AI policies. While the OECD's initial database provides a useful foundation, some policies are only marginally related to AI, and their scope varies considerably. Our refined datasets mitigate these limitations, making it more suitable for empirical analyses of how national policies shape AI innovation.

2 Sample and Data

2.1 Constructing Global AI Patent Database

The first step in constructing our dataset was to develop a methodology to identify AI-related patent filings globally. We began by focusing on US AI patent filings using the Artificial Intelligence Patent Dataset (AIPD),[7] as provided by the USPTO

[7]The 2023 update of the AIPD identifies which of 15.4 million US patent documents (both patents and pre-grant publications, or PGPubs) published from 1976 through 2023 contain AI. These documents are separately categorized into eight AI component technologies from the AIPD: machine learning, vision, natural language processing, speech, evolutionary computation, AI hardware, knowledge processing, and planning and control.

(Pairolero, Giczy, Torres, Erana, Finlayson, and Toole, 2024).[8] In accordance with the USPTO guidelines, we classified a patent application as AI related if its predictive AI score on AIPD was at least 50%.[9]

Next, we used US AI patents from the AIPD to identify international AI patent applications by measuring their semantic text similarity. We used text vectors[10] provided by Google Patents and computed the pairwise cosine similarity[11] between each international patent application and the US AI patents. If the cosine similarity score exceeded 0.9 for any comparison, we classified that international patent application as AI-related. The rationale for this method is that the USPTO attracts inventors from around the world who seek IP protection for significant technological innovations. Consequently, a bona fide AI invention should be semantically similar to at least a subset of AI patents filed with the USPTO. It is unlikely that a genuine AI invention would show no overlap with *all* AI patents in the USPTO. Therefore, while this method may exclude a small number of edge cases or less critical inventions, it is expected to capture the vast majority of important AI patents.

Furthermore, we categorized these patents into eight domains (machine learning, vision, natural language processing, speech, evolutionary computation, AI hardware, knowledge processing, planning, and control) based on the highest prediction scores for these domains from AIPD. Finally, we identified a total of 5,344,324 AI patent filings from 1907 to 2023, comprising 1,247,433 US filings and the remainder from

[8] Note that this paper is written by Chief Economists at the USPTO.

[9] AIPD labels documents with a prediction of at least 50% as AI-related, while those below 50% are not considered AI-related.

[10] In the field of natural language processing, these vectors are known as text embeddings. Google provides 64-dimensional representations to capture the semantic meaning of a patent document

[11] Cosine similarity measures how similar two text vectors (embeddings) are in direction; a higher score (close to 1) indicates stronger semantic overlap, whereas 0 indicates orthogonality (no semantic overlap).

various international jurisdictions.

2.2 Measuring Scientist-level AI Productivity

After identifying global AI patent filings, we constructed a set of metrics for each patent application, including forward and backward citations.[12] We further classified these citations as within- or cross-country based on the domiciled country of the lead inventor. Specifically, a citation is classified as within-country if the domiciled country of the lead inventor for both the citing and cited filings is the same; otherwise, it is classified as cross-country. To measure the novelty of a patent application, we constructed an annual count of 'similar' patent applications for each filing - identified by semantic text similarity — within the same year.

Following the innovation literature (e.g. Moretti, 2021), we use scientists (inventors) as the unit of analysis, as they are the cornerstone of innovation. Patent-level data were aggregated to the inventor level by matching each inventor's name and address from Google Patents Public Data, which facilitates the identification of countries of domicile of inventors. Using this dataset, we developed productivity metrics for each inventor, including annual patent filings, backward citations, forward citations, average backward citations, and average forward citations. Finally, to gauge the degree of innovation focus of each inventor, we calculated the annual number of AI domains in which they file patents, as well as the Herfindahl-Hirschman Index (HHI) of these domains.

[12] Forward citations refer to the number of times a focal patent is cited by subsequent patents, whereas backward citations refer to the number of references to prior art.

2.3 National AI-Related Strategies and Policies Data

Our primary data source for analyzing national AI strategies and policies is the OECD AI Policy Database. This comprehensive dataset offers detailed information on global national AI-related policies, including average annual budgets, policy types, and their implementation periods. AI policies are categorized into four main types: governance, financial support, guidance & regulation, and AI enablers & other incentives. Each category has several subtypes.[13] For instance, the governance category has four subtypes: national AI policies & strategies, AI coordination & monitoring bodies, public consultations of stakeholders or experts, and AI use in the public sector. For our main analysis, we create a treat-post dummy variable for these policies and their categories to serve as independent variables in our analysis, assigning a value of 1 during the periods they are implemented and 0 otherwise. In our robustness analysis, we also consider the average annual budget of each policy. We assume that the budget for each detailed category is distributed evenly due to the difficulty in determining the specific financial allocations to each category.

The original dataset contains over 1,000 unique policies from 69 countries, spanning 1969 to 2024. Since some policies are general innovation policies, rather than specifically AI-focused, we use ChatGPT GPT-4o to analyze each policy description and identify those related to AI. Each description was evaluated ten times, and we retained only policies that were confirmed in at least seven out of ten evaluations as:

[13] Governance includes national AI policies & strategies, AI coordination & monitoring bodies, public consultations with stakeholders or experts, and AI usage in the public sector. Guidance and Regulation covers standards and certification for technology development and adoption, labor mobility regulation and incentives, regulatory oversight and ethical advice bodies, and emerging AI-related regulation. AI Enablers and Other Incentives comprise science and innovation challenges, prizes and awards, knowledge transfers and business advisory services, networking and collaborative platforms, AI computing and research infrastructure, data access and sharing, public awareness campaigns and civic participation activities, labor market policies, and AI skills and education.

(1) AI-related, (2) national in scope, and (3) applicable to all entity groups. Point (2) and (3) are to ensure that the selected policies align with our dependent variable, which includes all inventors.

This process yielded a refined dataset of 188 AI-specific policies from 48 countries and regions, spanning 2011 to 2022. We further enhanced data quality by employing a team of research assistants to incorporate reliable government budget disclosures and reports, including information from social media sources. For example, many US AI policies lacked explicit budget information; therefore, we gathered data on annual federal non-defense AI R&D investments from the Networking and Information Technology Research and Development Program (NITRD). Since the FY2020 budget request, NITRD has reported these investments annually in response to Executive Order 13859, "Maintaining American Leadership in Artificial Intelligence."

3 Empirical Results

3.1 Descriptive Statistics of AI Policies

We begin our empirical analysis by providing an overview of national AI-related policies in our dataset. Our analysis includes 188 national AI-related policies from 41 countries, covering the period 2011 to 2019. Figure 1 displays a word cloud derived from the descriptions of the policies examined. The key terms include "artificial intelligence," "development", "research," "government," and "national". More statistics of those national AI-related policies is provided in Table 1, which details the average annual budgets across categories including governance, guidance & regulation, financial support, and AI enablers & other incentives. In particular, the

United States and Saudi Arabia allocate the largest budgets, with figures standing at 6,546 million and 4,936 million USD, respectively.

3.1.1 National AI-Related Policies in the United States

Among these national AI-related policies, we identify the United States' National Robotics Initiative (NRI), launched in 2011, as the first major national-level AI policy in our analysis. According to the National Artificial Intelligence Research and Development Strategic Plan (2016), the NRI is explicitly highlighted as one of the earliest strategic R&D initiatives relevant to AI.[14] Although the plan does not explicitly label the NRI as the first AI-related policy, it documents the NRI's start date as earlier than other AI initiatives, suggesting its foundational role in shaping subsequent national AI policy frameworks.

Additional evidence further supports identifying the NRI as an initial policy shock. The National Artificial Intelligence Research and Development Strategic Plan (2016) documents a notable increase in AI-related publications and patents—particularly in deep learning—following the initiative's introduction,[15] implying a stimulative effect on AI innovation. Complementing this finding, we also document a significant increase in AI-specific research funding provided by the National Science Foundation (NSF) after the NRI's launch. Figure 3 clearly illustrates this pattern, showing that the proportion of NSF awards dedicated to AI research rose from approximately 7% in 2010 to around 10% in 2012, with a sharper increase immediately after the 2011 introduction of the NRI. This structural shift provides empirical support for

[14] See National Artificial Intelligence Research and Development Strategic Plan (2016) is available at https://www.nitrd.gov/pubs/national_ai_rd_strategic_plan.pdf. The relevant discussion is from page 6 to page 7.

[15] See the relevant discussion is available at https://www.nitrd.gov/pubs/national_ai_rd_strategic_plan.pdf from page 13 to page 14.

treating the NRI as the initial national-level AI policy shock, marking the increased governmental commitment and public investment in AI research and development.

Building on this foundation, Figure A1 outlines the evolution of major U.S. AI-related policies. Following the NRI, the next pivotal policy was the National Artificial Intelligence Research and Development Strategic Plan (2016), which explicitly guided government investment toward underfunded research areas and aimed to strengthen the AI talent pipeline. Since 2016, numerous policies have emerged, including the Executive Order on Maintaining American Leadership in AI, reinforcing the government's strategic commitment to AI.

Additionally, the National Artificial Intelligence Research and Development Strategic Plan (2016) highlights various complementary initiatives targeting specialized AI applications, such as the Brain Research through Advancing Innovative Neurotechnologies (BRAIN) Initiative and the National Nanotechnology Initiative. These initiatives focus on subfields such as health information technology, image analytics, robotics, and intelligent systems. Collectively, these policies establish a comprehensive framework that fosters synergies, broadens AI research, and accelerates the development of specialized AI technologies and applications.

3.1.2 Discussion of National AI-Related Policies Examples

Expanding on AI-related policies, we examine key examples from the United States and other major AI-active countries. One of the examples from the United States is the *National AI R&D Strategic Plan* initiated in 2016. It sets a clear agenda for R&D, focusing federal investments in areas less likely to attract private sector funding. This plan specifically aims to fill critical gaps in AI development while expanding

and sustaining a skilled AI R&D talent pool. Complementing this, the *Executive Order on Maintaining American Leadership in AI*, enacted in 2019, mandates significant advancements in AI across federal agencies, industry and academia, boosting scientific research, economic growth and improving national security. The aim is to establish technical standards and simplify AI testing and deployment processes, fostering the growth of AI-focused industries.

The most recent example at the time of writing, although outside our sample period, is President Trump's Executive Order 'Removing Barriers to American Leadership in Artificial Intelligence', which creates a supportive environment for initiatives like Stargate by prioritizing deregulation and strengthening the leadership of American AI. Stargate is a $500 billion public-private partnership funded by a combination of government and private investment.

Another one is China's *National New Generation AI Plan*, launched in 2017, outlines ambitious targets for AI R&D and aims to establish China as a global leader in AI by 2030. This plan is not only advancing R&D but also accelerating industrialization and talent development. Meanwhile, Canada's *Pan-Canadian AI Strategy* of 2017, with a CAD 125 million investment, focuses on retaining and attracting top academic talent, improving research capacity and fostering commercialization. Additionally, Singapore's *AI Research Program* in 2018 launched high-quality research in fundamental AI technologies, encouraging national collaborations and nurturing local AI talents. Similarly, Japan's *High Performance Computing Infrastructure Project*, featuring the Fugaku supercomputer since 2012, supports extensive AI research capabilities.

One of the primary objectives of this research study is to evaluate the impact of these policies. However, it is important to recognize their substantial differences in

scope, design, and implementation. Consequently, our analysis focuses on estimating the *Average Treatment Effects (ATE)* across the sample, offering a broad understanding of their overall influence. In later sections, we complement this aggregate analysis by examining the effects of individual countries' policies where feasible.

3.2 Descriptive Statistics of AI Patent Applications

In analyzing global AI patent applications, we provide a detailed breakdown at the country level in Table 5. The data show that the United States, Japan, China, and South Korea are among the most prolific, with approximately 1 million, 960,000, 730,000, and 300,000 applications, respectively. Furthermore, Figure 2 illustrates the time series variation in AI patent applications in 48 countries from 1990 to 2022. We find divergent trends between China and the United States: after 2018, China surpassed the United States to become the leading AI innovation by the number of AI patent applications, accounting for approximately 50% of global applications by 2019, compared to 20% for the United States. Historically, Japan led AI patent applications throughout much of the twentieth century, but experienced a decline from 1990 to 2022, with the United States surpassing it around 2002.

Furthermore, we examine the domain-specific distribution of AI patent applications, categorized into eight classifications by the AI Patent Database (AIPD), as shown in Table 4. The majority of patents from the United States (30%), China (28%), Germany (35%), and the United Kingdom (33%) fall under "Planning and Control."[16]

[16]AIPD classifies AI patents into eight categories: Planning & Control—processes for identifying, creating, and executing activities to achieve specified goals; Knowledge Processing—representing and deriving facts about the world for use in automated systems; AI Hardware—physical computing components designed for increased processing efficiency and speed; Computer Vision—extracting and interpreting information from images and videos; Machine Learning—computational models that learn from data; Natural Language Processing—understanding and processing written language data; Speech Recognition—techniques for interpreting spoken language, including responding to commands; Evolutionary Computation—computational routines inspired by natural evolution.

In contrast, Japan and South Korea primarily focus on "Vision" technologies, which account for 36% and 28% of their respective applications.

We present additional details in Table 5. The initial four columns of this table enumerate the total AI patent applications, the number of collaborative patents, the number of non-collaborative patents, and the percentage of collaborative AI patents. Here, non-collaborative patents are defined as those whose inventors are within the same country, whereas collaborative patents involve inventors from multiple countries. An interesting observation is that Japan (1%), Korea (3%), China (3%), Australia (7%), Taiwan (10%) and the United States (12%) have the lowest percentages of collaborative AI patents. In contrast, the highest percentages are observed in Mexico (81%), Luxembourg (65%), and Egypt (61%). It suggests a reluctance among leading AI innovating countries to collaborate internationally.

Further analysis in columns 7, 8 and 9 of Table 5 reveals that countries with a lower percentage of collaborative patents typically exhibit much lower average forward citations compared to their non-collaborative patents. For instance, in Japan, the average forward citation for collaborative patents is 0.12, while it is 5.79 for non-collaborative patents. This indicates that the quality of collaborative AI patents is generally lower than that of non-collaborative AI patents in these countries. Conversely, in countries with high collaboration rates, such as Mexico, the quality of collaborative patents is high; the average forward citation for collaborative patents is 1.79, compared to 0.62 for non-collaborative patents.

3.3 Inventor-Level Analysis

3.3.1 Baseline Estimation

A significant development in "Difference-in-Difference" methods since Bertrand, Duflo, and Mullainathan (2004) is that the two-way fixed effect (TWFE) approach is regarded as potentially biased when early-treated observations serve as a control for later-treated observations (Baker, Larcker, and Wang, 2022; Callaway and Sant'Anna, 2021; Sant'Anna and Zhao, 2020). Hence, we start our baseline analysis by using the recommended stacked "difference-in-differences" (DID) regression (see, e.g., Gormley and Matsa (2011); Cengiz, Dube, Lindner, and Zipperer (2019); Deshpande and Li (2019)):

$$E(Y_{ijct}) = exp(\beta_0 + \beta_1 \text{AI Policy}_{jct} + \phi_{ic} + \lambda_{tc} + \epsilon_{icjt}) \tag{3.1}$$

where y represents one of several dependent variables of interest for inventor i in year t, and *AI Policy* is an indicator variable equal to 1 if inventors in cohort c and country j are subject to a national AI-related policy. Given that our dependent variables are count data, we estimate Poisson regressions (Baker, Larcker, and Wang, 2022).

In the stacked difference-in-differences (DID) approach, each treated country is paired with control countries that are either "yet to treat" or "never treated". These control groups are unaffected by bias from the traditional two-way fixed effects (TWFE) estimator, as discussed above. The treated countries and their corresponding clean controls define a cohort. For an inventor in a treated country, this indicator switches from 0 to 1 when the national AI-related policy is implemented.

We include inventor × cohorts (ϕ_{ic}) fixed effects to control for any fixed differences

between inventors and cohort × year (λ_{tc}) fixed effects to account for time trends at the cohort level. Standard errors are clustered at the country level, following Bertrand, Duflo, and Mullainathan (2004). This clustering is essential because our unit of analysis is at the inventor level with a large number of observations. Clustering at the country level ensures that statistical significance is not driven solely by the large N. Instead, test statistics are computed based on the number of countries. Finally, β_1 is the DID estimator, with fixed effects that absorb individual terms such as $Treat$ and $Post$.

The key identifying assumption for difference-in-differences (DID) analyses is the parallel trends assumption, which requires that the treated and control groups exhibit similar trends in the dependent variable prior to the intervention. For all dependent variables analyzed, we report the trends — specifically, the interaction of the treatment indicator with time periods from t-3 to t+3 — in Table A3. Overall, we do not find any significant pre-treatment trends.

In Table 6, we present results on the effects on AI patent counts, forward citations, average forward citations, backward citations, and average forward citations. Our findings suggest that the implementation of national AI-related policies has a significant negative impact on both the productivity of inventors and the quality of their output. Additionally, it appears that inventors rely less on prior knowledge following the enactment of these policies. Specifically, the estimates reported in column 1 of Table 6 show a reduction of 0.075 in the probability of filing an AI patent by treated inventors after the implementation of the policy, indicating a decrease in their productivity after the implementation of the national AI-related policy. One possibility is that the observed decrease in productivity might reflect an effort by

inventors to enhance the quality of their patents. However, column 2 of Table 6 shows a reduction of 0.35 in the probability of obtaining additional forward citations, indicating a decline in the quality of their output as well. Moreover, columns 4 and 5 document reductions of 0.083 and 0.039, respectively, in the number of backward citations of the AI patent and the average number of backward citations per AI patent. These findings suggest that inventors are increasingly less likely to rely on prior knowledge.

Next, we examine the heterogeneous effects of various policy types on AI innovation, as presented in Panel B. Our findings indicate that these policies generally exert a similar negative impact on AI innovation. This may be attributable to the complex nature of AI policies that often encompass multiple support mechanisms and make it difficult to isolate the effect of individual policies.

Notably, columns 4 and 8 of Panel B suggest that policies related to financial support and guidance & regulation are the primary drivers of reductions in inventor productivity and output quality. Specifically, we document reductions of 0.082 (0.114) in AI patent applications and 0.376 (0.276) in the number of forward citations, respectively. In addition, policies that emphasize governance and financial support predominantly contribute to the decrease in backward citations, as evidenced in columns (1) to (8) of panel C. Furthermore, panels B and C indicate that governance-type policies have a relatively minor effect on the reductions observed in inventor productivity, output quality, and reliance on prior knowledge.

We further investigate changes in the percentage of cross-country backward and forward citations after the implementation of national AI-related policies, as reported in Table 11. The OLS estimates for columns 1 and 6 indicate increases of 4.166%

and 4.973% in the percentages of backward and forward citations from across the country, respectively. These findings suggest a shift toward receiving more cross-country citations and relying more on knowledge sources from other countries. The primary drivers of these effects are policies related to financial support and AI enablers & other incentives, which facilitate knowledge spillovers among inventors by creating international platforms for knowledge transfers, business advisory services, networking, and collaboration, as well as enhanced data access and sharing.

3.3.2 Potential Channel: Pursuit of Innovation Novelty

To explore the decline in inventor productivity, output quality and reliance on prior knowledge, we examine whether national-level support can mitigate scientists' concerns about the risks inherent in pursuing novel innovations, risks that typically involve longer development times and higher failure rates. Government support alleviates these concerns by sharing financial burdens, thus reducing the individual cost of failure in pioneering projects. Moreover, such backing serves as a signal of credibility to the market, reducing uncertainty, and attracting additional private investment. Furthermore, government investment in innovation ecosystems, coupled with appropriate guidance and regulation, fosters an environment that encourages experimentation.

We examine the novelty of post-policy innovation by analyzing the number of similar patent applications associated with each patent. Importantly, we do not equate novelty with higher technological impact; rather, we define it as a measure of distinctiveness relative to other inventions. Unique inventions are particularly significant because they often represent exploratory and venturing efforts. In rapidly

advancing fields such as AI — where a "winner-take-all" dynamic is common — pursuing novel inventions is important to reaching and maintaining a position at the frontier.

To document such risks associated with novel inventions, we examine the relationship between patent novelty and patent quality measured by forward citations by patent-level analysis in Table 12. We found that novel projects often require longer development timelines and face a higher risk of failure. However, a select few projects have better chances of success. Specifically, we find that patent novelty is significantly positively associated with development time and with the likelihood of having zero forward citations in Panel A of Table 12, suggesting that some AI patents may be of lower quality and more likely to be classified as failed AI projects. Additionally, we find that patent novelty is also significantly positively associated with high-impact innovations, as measured by patents in the Top 0.05%, Top 0.1%, and Top 0.5% of forward citations within each filing year from Panel C of Table 12. Additionally, in Table A8, we examine the relationship between quality variance (measured by the variance of forward citations) and our novelty measure. We find that novel patents—defined as those with zero similar patent applications in the same year—exhibit greater variability in forward citations, nearly twice as large as that of non-novel patents, which have at least one similar patent application filed in the same year.

Table 8 indicates that following the implementation of national AI-related policies, inventors tend to file AI patents with fewer textually similar counterparts in the given filing year, as shown in column 1. This finding suggests an increase in the uniqueness of AI patents. Specifically, the Poisson estimates in column 1 suggest a reduction

of 0.137 in the probability that an inventor's AI patent filing will have a similar counterpart in the same year for treated inventors after policy implementation.

Our results further suggest that the drivers of these outcomes are policies related to financial support, guidance and regulation, and AI enablers & other incentives. These forms of support may alleviate concerns about the risks of failure that are typically associated with developing novel inventions. In contrast, governance policies appear to remain largely ineffective in this regard.

Achieving novelty and engaging in exploratory work often require a focused and in-depth investigation within a single innovation area. As supporting evidence for our proposed channel, we find that scientists tend to concentrate on a narrower set of areas after policy implementation. To examine this, we construct a measure of the number of AI patent domains and calculate the Herfindahl-Hirschman Index (HHI) using classifications from the AI Patent Database (AIPD). In Table 10, we observe a significant decline in the total number of AI patent domains, accompanied by a notable increase in the domain HHI, as shown in columns 1 and 11, respectively. Specifically, the coefficient in column 1 indicates a 0.044 reduction in the probability of treated inventors adding an additional AI patent domain post-policy, suggesting a more concentrated focus within specific domains. Moreover, the results consistently highlight AI enablers and other incentives as the most significant driver of this effect, as shown in columns 5 and 10.

3.4 Knowledge Spillover via New Co-Authorship

Standard economic theory posits that, in the absence of market failures, investment decisions should be left to private firms. The primary justification for

government intervention lies in the presence of knowledge spillovers. As Bloom, Van Reenen, and Williams (2019) notes, "ideas are promiscuous." Even under a well-designed intellectual property regime, innovators often fail to capture the full benefits of their inventions because spillovers enable others to benefit without bearing the full R&D costs. Therefore, it is important to examine how these policies influence knowledge diffusion.

Our baseline estimation suggests that knowledge spillovers, as proxied by citations, have declined. However, citations capture only a subset of spillovers, as some occur through informal interactions such as meetings and communications. Policies may facilitate these additional spillovers by fostering collaborative platforms that enhance communication among scientists. Since we do not directly observe these informal interactions, we assess the impact of national policies on the formation of new co-authorships as a proxy for increased collaboration. Overall, we find no significant effect following policy implementation, as reported in column 1 of Table 9. By contrast, policies related to guidance and regulation appear to hinder collaboration with new coauthors, as shown in column 4. Specifically, the coefficient of −0.218 in column 4 suggests a lower likelihood that inventors subject to these policies will acquire an additional new coauthor post-implementation. A plausible explanation is that guidance- and regulation-related policies — which often impose restrictions on labor mobility, set standards and certifications for technology development, and introduce enhanced regulatory oversight and ethical guidelines — may inadvertently constrain the formation of new collaborations among inventors. Policymakers should be mindful that these policies may unintentionally dampen knowledge spillovers, limiting their intended effects.

3.5 Country-Level Analysis

While our scientist-level analysis provides valuable insights, one may question whether these dynamics have contributed to a decline in innovation output at the national level. To examine this, we assess the impact of AI-related national policies on AI innovation. Table A7 reports the effects of these policies on AI patent counts, forward citations, and backward citations (Panel A), alongside a pre-trend analysis (Panel B). We find a significant decline in both the quantity and quality of patents following the introduction of these policies. However, this decline coincides with a pre-existing downward trend in AI innovation output among treated countries. It is plausible that governments adopted these policies in response to an already deteriorating innovation performance, making it challenging to isolate their causal effect. A future version of this paper will seek to address this issue by employing a synthetic difference-in-differences approach (Arkhangelsky, Athey, Hirshberg, Imbens, and Wager, 2021) to better distinguish policy effects from pre-policy trends.

4 Conceptual Framework

In this section, we employ a parsimonious general equilibrium framework to better the understanding of our results. In the endogenous growth literature, innovation is a key driver of economic growth. Classic models, such as Romer (1990), emphasize that technological progress arises from intentional R&D investments by profit-maximizing agents. Similarly, Schumpeterian growth models (e.g. Aghion and Howitt, 1992) highlight the role of creative destruction, where new inventions replace outdated technologies. In such settings, innovation often exhibits a winner-takes-all

dynamic: a marginally superior product or invention can capture a disproportionately large share of market rewards. This "superstar" effect implies that the leading innovator accrues most of the gains, while others receive minimal compensation. This dynamic is particularly pronounced in AI innovation, where consumer switching costs are relatively low — for example, a user can easily cancel a subscription to an existing service and switch to a better-performing LLM model.

Inventors face a strategic choice between incremental innovation, which is safer with modest returns, and radical innovation (also termed radical or disrupting innovation), characterized by higher risk but potentially substantial returns. While innovation could theoretically be modeled as a continuous incremental steps, binary classifications captures the critical dynamics in innovation, especially in AI innovation — where surpassing key thresholds (e.g., topping a leaderboard[17] for large language models) can generate substantial monopoly rents. Incremental innovations enhance existing technologies gradually, whereas radical innovations can establish entirely new markets or transformative technologies, yielding monopoly-like profits to the first successful innovator. However, radical innovations involve significant uncertainty and high initial costs, leading private incentives to often fall below socially optimal investment levels. This underinvestment arises due to market failures such as knowledge spillovers, financing frictions, and the inability of inventors to fully capture the social value of their innovations. Consequently, governments frequently implement targeted R&D subsidies or grants to stimulate radical innovation (Howell, 2017; Bloom, Van Reenen, and Williams, 2019). Our general equilibrium model integrates heterogeneous inventors, consumers, firms, and government interventions

[17] Famous ones include Chatbot Arena (https://lmarena.ai/)

to evaluate how such incentives influence inventors' strategic decisions and overall economic outcomes.

We proceed by laying out the economic environment with the key agents and their objectives. We then derive the inventors' optimal innovation strategy, firms' profit-maximization and production conditions, consumers' utility maximization, and general equilibrium market-clearing conditions. Using this model, we analyze how government grants targeting radical R&D alter the equilibrium allocation of talent and resources between incremental and radical innovation. We conduct comparative statics to explore policy effects, drawing on insights from the literature on endogenous growth (e.g. Romer, 1990; Aghion and Howitt, 1992) and innovation incentives (e.g. Acemoglu et al., 2018). We also discuss welfare implications.

4.1 Model Framework

The economy is populated by four types of agents: Inventors, Firms, Consumers, and the Government. Each plays a specific role: inventors are a continuum of heterogeneous individuals endowed with ideas and skills to innovate. They are forward-looking and choose between pursuing an incremental innovation or a radical innovation. Heterogeneity can be modeled in terms of different success probabilities, innovation costs, or risk aversion levels across inventors. Their goal is to maximize expected utility or payoff from their innovation activities.

Firms produce output using labor and available technology. Incumbent firms can implement incremental innovations (improving their productivity or product quality gradually), while radical innovations often lead to new firms or new product lines (creative destruction replacing old firms/technologies). Firms seek to maximize

profits, taking wages, prices, and the innovation outcomes as given. In equilibrium, firms' profit-maximization conditions determine factor demands (e.g. labor demand) and, if applicable, pricing of goods.

Consumers (or household) derives utility from consuming the final good. Consumers supply labor (inelastically, for simplicity) and earn income from wages and firm profits. There are two types of labor in the economy, inventors are skilled labor perform R&D functions and unskilled labor produce goods in the goods market. They maximize lifetime utility subject to a budget constraint. For tractability, we assume a unit mass of consumers with utility function U,

$$U = \int_0^\infty e^{-\rho t} \ln C(t)\, dt \tag{4.1}$$

where $C(t)$ is consumption. Consumers' optimization yields standard results: labor supply equals labor available (inelastic in this setup), and consumption follows an Euler equation in a dynamic model. Because we focus on the innovation side, we assume the consumer's problem ensures that all output produced is ultimately consumed (i.e. goods market clears with output $Y = C + G$ if government consumes resources, though here government grants are simply transfers of output).

Governments designs policy to influence innovation. It provides grants/subsidies to incentivize radical R&D. We model a subsidy S (or grant) that effectively lowers the cost or increases the payoff of attempting a radical innovation. While governments wield a variety of tools to shape innovation policy, we will discuss in the data section — for simplicity, we assume polices just involve reallocating output. The government's goal is to maximize social welfare, which depends on consumer utility and possibly

other considerations like knowledge creation.[18] In our model, the government chooses S (the subsidy rate or amount) and takes into account general equilibrium effects when formulating policy.

4.2 Innovation Choices of Inventors

As discussed above, each inventor has an opportunity to undertake an innovation project. They must choose between:

(1) Incremental Innovation: A low-risk, low-return project that incrementally improves existing technology. We assume an incremental innovation succeeds with high probability (potentially almost certain) and yields a small improvement or payoff. For example, an incremental project might improve productivity by a factor $1 + \epsilon$ (with $\epsilon > 0$ but small) or yield a profit V_I to the inventor if successful. Because incremental advances are modest and often quickly competitive, we assume the payoff V_I is relatively low (and can be treated as roughly certain for the inventor, given high success rate and low variance). We denote the utility from choosing incremental innovation as U_I. If the inventor is risk-neutral, U_I is basically the monetary payoff V_I (or the utility of that income).

(2) radical Innovation[19]: A high-risk, high-reward project. The probability of success is lower than for incremental projects. Let p denote the success probability for a given inventor's breakthrough attempt. Later on, we discuss the fact that more breakthrough attempts increase the volatility of innovation outcomes. If successful, the inventor creates a new product or technology that gives a winner-takes-all prize: the inventor (or their startup firm) secures a patent or market monopoly for this

[18] knowledge spillover is considered when extending the baseline model.
[19] We use term breakthrough and radical interchangeably.

breakthrough. This yields a large payoff V_B (e.g. the present value of monopoly profits from the new innovation). If the attempt fails (with probability $1 - p$), the inventor gains nothing (or a very low payoff). Inventors may be risk-averse or risk-neutral; for tractability we first assume risk-neutrality so that expected utility drives the choice. The expected payoff from attempting a breakthrough is:

$$U_B = p \cdot V_B + (1 - p) \cdot 0 - C_B \tag{4.2}$$

where C_B is the cost (in time, effort, or resources) of attempting the breakthrough. The cost includes any opportunity cost (e.g. the income foregone by not doing a safe job). We incorporate the government grant or subsidy S here: suppose the government covers a fraction of the cost or provides a direct grant for attempting a breakthrough. For simplicity, let the grant reduce the private cost to $C_B - S$ (assuming $S \leq C_B$). The expected net payoff becomes:

$$U_B = p \cdot V_B - (C_B - S). \tag{4.3}$$

If the grant is large enough, it can even act as an insurance by covering most costs even if the project fails. Inventors differ in their talent, ideas, or costs. We can model this as variation in the success probability p_i or cost $C_{B,i}$ across inventors i. For example: some inventors have breakthrough ideas with higher chance of success or lower research cost (perhaps due to better skills or access to labs), while others have only costly or low-probability breakthrough opportunities. This heterogeneity is crucial for an interior equilibrium where some, but not all, inventors choose the breakthrough route. We assume each inventor knows their own $(p_i, C_{B,i})$. All

inventors can obtain the baseline payoff V_I from incremental innovation (or working on small improvements).

The inventor's optimization problem is then each inventor chooses the innovation type that maximizes their expected utility. In a risk-neutral case, inventor i will choose breakthrough (B) if $U_{B,i} \geq U_I$, and incremental (I) if $U_{B,i} < U_I$. That is:

$$p_i \cdot V_B - (C_{B,i} - S) \geq V_I \tag{4.4}$$

Inventors with sufficient confidence ($p_i \geq p^*$) will pursue breakthroughs. Since by assumption $V_B \gg V_I$—the winner's prize significantly exceeds incremental gains—yet the success probability p_i is typically less than one, inventors face a clear risk-return tradeoff. In the absence of government intervention ($S = 0$), relatively few inventors may be willing to undertake radical innovation, particularly if they are risk-averse or confronted with high opportunity costs. Introducing a subsidy $S > 0$ relaxes this constraint, thereby incentivizing more inventors to attempt breakthroughs, as a greater variety of inventors (types i) will satisfy the condition $U_{B,i} \geq U_I$.

We define ϕ as the equilibrium fraction (or measure) of inventors selecting the radical innovation path. A key comparative static we will analyze is that ϕ increases with S. Our modeling choice to restrict government grants exclusively to radical innovation mimics a real-world screening process, ensuring that only a selective set of promising projects receive funding.

In expectation, the number of successful radical innovations in the economy (per period) will be $\phi \cdot \bar{p}$ (where $\bar{p}$ is average success probability among those who choose B), and the number of incremental innovations will be $(1 - \phi)$ (assuming an incremental always "succeeds" in the sense of delivering a small improvement). This

drives technological progress as described next.

4.3 Firms, Production, and Profit Maximization

The production side of the economy can be modeled in a standard growth framework augmented to include the effects of both types of innovation. We assume a final consumption good Y is produced by competitive firms using labor and a technology index that reflects cumulative innovations. For concreteness, consider a production function:

$$Y_t = A_t \cdot F(L_{Y,t}) \tag{4.5}$$

where $L_{Y,t}$ is labor employed in production at time t, and A_t is an index of technology (productivity) at time t. $F(\cdot)$ is a neoclassical production function exhibiting diminishing returns (we could use a simple linear form $F(L) = L$ for clarity, in which case A_t directly multiplies labor productivity).

Role of Innovations: Innovations increase the technology index A_t. We can think of A_t as $A_t = A_0 \times (1+\epsilon)^{N_t} \times (\gamma)^{M_t}$, where N_t is the number of incremental innovations up to time t and M_t is the number of radical innovations up to t. Here $(1 + \epsilon)$ is the factor by which each incremental innovation raises productivity (a small increase), and $\gamma > 1$ is the larger factor by which each radical innovation raises productivity (a substantial jump). For example, if time is discrete and each period incremental and radical innovations occur, we could write after one period: - If an incremental innovation occurs, $A_{t+1} = (1 + \epsilon)A_t$ (a slight increase). - If a breakthrough occurs, perhaps it replaces old technology with a better one: $A_{t+1} = \gamma A_t$ (a big jump). In a creative destruction interpretation, γA_t might be the productivity of a new leading-edge firm that replaces an old incumbent.

In expectation, if ϕ fraction of inventors pursue breakthroughs, the expected growth rate of A can be defined. In a large population, if ϕ fraction attempt breakthroughs with success prob. $\bar{p}$, expected radical innovations per period is $\phi\bar{p}$, and incremental successes $\approx (1-\phi)$ (assuming nearly certain success for incremental). Then expected growth in A per period is:

$$E[\Delta \ln A] \approx (1-\phi)\ln(1+\epsilon) + \phi\bar{p}\ \ln(\gamma) \tag{4.6}$$

Breakthroughs contribute $\ln(\gamma)$ each (weighted by success probability), incrementals contribute $\ln(1+\epsilon) \approx \epsilon$ each. Because $\gamma \gg (1+\epsilon)$, breakthroughs have the potential to drive long-run growth much more, but only if they occur.

For firm's production and profit maximization problem, we assume final good production is assumed competitive, so final firms take A_t as given (they cannot themselves change it, it's determined by innovation outcomes). They hire labor until the marginal product equals the wage w_t. For example, if $Y_t = A_t L_{Y,t}$ (assuming linear for simplicity), profit for a final firm is $\Pi = A_t L_{Y,t} - w_t L_{Y,t}$. Maximizing w.r.t. $L_{Y,t}$ gives the first-order condition:

$$A_t - w_t = 0 \implies w_t = A_t. \tag{4.7}$$

Thus, the wage equals the marginal product A_t in this simple case, meaning wage growth tracks productivity growth. (In a more general $Y = AF(L)$, we would get $w_t = A_t F'(L_{Y,t})$ and similarly have factor-price equilibrium conditions.)

Now consider the innovation sector profits. An incremental innovation typically is minor and may not yield a separate identifiable "profit" stream for a new firm

(often absorbed by an incumbent). We can assume incremental inventors get paid V_I (either as a wage premium or small licensing fee) by firms for their improvement. radical innovations, by contrast, create monopoly rents. In a Schumpeterian fashion, a successful radical innovator obtains a patent and becomes a monopolist in the new product/technology until the next breakthrough arrives. During that period, the innovator's firm earns profit V_B (the present value of which constitutes the prize for the inventor). We can model these profits using a standard monopolistic intermediate sector (as in Aghion and Howitt, 1992): Suppose the new technology is used to produce a differentiated intermediate good essential for final production. The monopolist sets a price above marginal cost, yielding a flow of profit π per period. The present value V_B is π/r in steady state (if the monopoly could last forever with discount rate r), or more accurately $V_B = \pi/(r + \lambda)$ if further innovation arrives with hazard λ (endogenously, λ increases with R&D targeting that product)

In equilibrium, for competitive final good firms, $w_t = \partial Y/\partial L_Y$, which is the Marginal Product of Labor. This gives the wage (factor price) in terms of technology A_t. Monopolistic Intermediate (Innovator) Firms: Price p^* and quantity q^* are chosen to maximize

$$\pi = (p - w)q \tag{4.8}$$

where w is the marginal cost of producing the intermediate good using labor. The first-order condition yields the standard markup. For example, if final good production follows a Cobb-Douglas form:

$$Y = Aq^{\alpha}L^{1-\alpha} \tag{4.9}$$

as in expanding-variety models, then the pricing rule and optimal quantity will depend on the elasticity of demand and the market power of intermediate producers. The intermediate monopolist's optimal price is $p^* = \frac{w}{\alpha}$ and profit $\pi = (1-\alpha)p^q$ These profits π feed into V_B. Note that higher A_t or bigger quality jumps (γ) generally increase the monopoly profit V_B of breakthroughs, since a better product can capture more market share or command a higher price. This creates a positive feedback: bigger potential breakthroughs yield larger V_B, attracting more R&D effort into breakthroughs.

4.4 Consumers' Utility Maximization

The representative consumer chooses consumption (and possibly savings or asset accumulation if dynamic) to maximize utility. In a static one-period model, this is trivial: consume all income. In a dynamic setting, consumers equate the intertemporal marginal rate of substitution to the interest rate. For completeness, assume consumers supply labor L inelastically and receive wage income wL and any profit dividends Π from firms (minus taxes T). The budget constraint is $\dot{A}_t = 0$ here (no asset accumulation if we assume firms' innovation costs are labor costs already accounted). So consumption each period $C_t = w_t L + \Pi_t - T_t$. We normalize $L = 1$ for convenience. Utility maximization yields standard Euler equation: $\frac{\dot{Y}}{Y} = \frac{\dot{C}}{C} = r - \rho$, e.g. We will primarily focus on steady-state or balanced-growth equilibrium, where consumption grows at the same rate as output (driven by innovation).

For our purposes, the crucial part is that consumer welfare increases with higher consumption levels and growth rates, and consumers bear the financing cost of government subsidies via taxes T. If the government uses lump-sum taxes, the

consumer's work and consumption decisions aren't distorted, making it easier to assess welfare changes from innovation policy.

4.5 Equilibrium

In equilibrium, factor and goods markets clear, and expectations are fulfilled:

Labor Market Clearing: The economy's total labor (normalized to 1 or L) is allocated between unskilled and skilled (R&D) activities. Let $L^{R\&D}$ be labor engaged as inventors, and L^Y be labor in final production. We have

$$L^Y + L^{R\&D} = L \tag{4.10}$$

If all inventors are drawn from the labor force, then $L^{R\&D}$ equals the measure of inventors who choose either innovation path. In equilibrium, $L^{R\&D}$ is endogenously determined by how many people find it worthwhile to pursue innovation instead of working in production. In our setup, if V_I (the payoff to incremental innovation) is roughly equal to a normal wage job, then anyone who does not do breakthrough essentially works (either on incremental innovation within a firm or directly in production). We can simplify by saying all labor is used, either in production or innovation. The wage adjusts such that an inventor indifferent between a safe job and incremental innovation is happy either way. We assume $V_I = w$, then incremental innovation is like a job that pays wage w. So effectively, those not chasing breakthroughs just earn w (doing incremental work that yields minor improvements as part of their job). Thus L^Y can be interpreted as including those doing incremental innovation for firms (since it's a paid job yielding output improvement). Meanwhile, those attempting breakthroughs might not contribute to current output (their work is

experimental). So as ϕ (the fraction in breakthroughs) rises, current production labor L^Y falls. The wage w will tend to rise if labor for production is scarce, which in turn raises the opportunity cost of doing R&D. This feedback will influence ϕ: equilibrium ϕ is where inventors are indifferent at the margin given the wage. In formal terms, the marginal inventor satisfies Equation 4.3 with $V_I = w$. So the labor market clearing condition and inventor indifference condition together pin down w and ϕ.

Goods Market Clearing: In each period, total output is allocated between consumption and, potentially, R&D expenditures. Since we model R&D expenditures explicitly as labor costs, which have already been accounted for within the labor market equilibrium, the entire output is effectively consumed—either directly by consumers or indirectly through government transfers in the form of research subsidies. Specifically, if the government provides a grant of S per breakthrough attempt to n_B inventors, the total subsidy expenditure amounts to Sn_B, funded via lump-sum taxation imposed on consumers. Resource feasibility in equilibrium mandates that the real costs associated with R&D (i.e., output forgone by employing researchers in innovation rather than production) plus total consumption equal total production. Since these labor allocations have already been explicitly considered, consistency is ensured. Consequently, the goods market equilibrium condition simplifies to $Y_t = C_t$ + (government and R&D resource use).

Under lump-sum taxation, however, government subsidies represent purely redistributive transfers, as the government collects exactly the amount disbursed to inventors from consumers. Thus, no physical output is wasted, and resources merely shift hands. For simplicity, we therefore focus on the equilibrium condition:$Y_t = C_t$

Factor Price Equilibria: The wage w_t adjusts to clear the labor market as above.

If there were other factors (capital, etc.), their rental rates would similarly adjust. We assume no physical capital for simplicity (one could include it without changing the qualitative results). The interest rate r in a dynamic model would equal the consumer's time preference plus growth if on a balanced path (via the Euler equation). Also, free-entry conditions in innovation might drive some equilibrium conditions: e.g. in many endogenous growth models, free entry of R&D drives the expected net profit of engaging in research to zero in equilibrium. Here, because individuals decide, a similar condition holds: the marginal inventor is indifferent (zero excess expected profit) between breakthrough and safe activities. That condition Equation 4.3 is effectively a free-entry/arbitrage condition for the marginal case.

Innovation Market Equilibrium: An equilibrium allocation of inventors between I and B must satisfy that all inventors who choose a path prefer it. Typically, we will have a cutoff type where $U_B = U_I$ (indifference), such that all higher types choose B and lower types choose I. In equilibrium, the fraction ϕ and the wage w (which influences U_I and possibly V_I) adjust so that this cutoff is consistent. We solve these simultaneously. This gives an endogenous ϕ^* as a function of parameters such as the distribution of p_i and $C_{B,i}$, as well as V_B, S, etc. (We do not derive the closed form due to generality, but conceptually, it is found by equating the payoff for the marginal inventor and using the measure of those above/below that margin given the distribution of heterogeneity.)

Technology Evolution: Over time, A_t evolves as innovations occur. In a balanced growth equilibrium, the arrival rates of incremental and breakthrough innovations are such that on average A_t grows at a constant rate g. This g will be determined by the equilibrium ϕ: more breakthrough effort (higher ϕ) tends to raise g by increasing

the frequency of large jumps, while too low ϕ yields slow growth. The economy may settle in a steady state fraction ϕ that yields an equilibrium growth rate. Government policy can shift this g by shifting ϕ.

In summary, a general equilibrium for this economy is a set of $\{w_t, r_t, \phi, L^Y, L^{R\&D}, C_t, Y_t\}$ such that (i) inventors maximize expected utility (choosing I or B) given w_t and S, (ii) firms maximize profits given A_t and w_t, (iii) consumers maximize utility given their budget, (iv) markets clear (labor and goods), and (v) A_t evolves according to innovation outcomes. This setup encapsulates the strategic interaction between inventors (R&D supply), firms (R&D demand or usage, and production), and government (policy), in a winner-takes-all innovation environment.

The core trade-off in equilibrium is captured by condition Equation 4.3 for the marginal inventor. Using a simple specification for heterogeneity, suppose inventors differ by the cost C_B required for their breakthrough project (which could include effort disutility or opportunity cost). Let $F(C_B)$ be the distribution of inventor types by cost (lower C_B means a more efficient or better-prepared inventor for breakthroughs). For algebraic simplicity, assume $p_i = \bar{p}$ is the same for all (heterogeneity exists only in cost). Then cutoff case in Equation 4.3 becomes:

$$\bar{p} \cdot V_B - C_B + S = V_I = w \tag{4.11}$$

Solving for the cutoff cost:

$$C_B^* = \bar{p} V_B + S - w \tag{4.12}$$

All inventors with $C_B \leq C_B^*$ pursue breakthroughs, while those with higher costs do

not. The fraction of breakthrough inventors is $\phi = F(C_B^*)$ (the cumulative distribution up to C_B^*). For instance, if C_B is uniformly distributed on $[0, \bar{C}]$, then $\phi = C_B^*/\bar{C}$ (for $C_B^* < \bar{C}$). Equation 4.12 shows how equilibrium ϕ is determined jointly with the wage w.

The wage w is linked to ϕ via labor market clearing and production. If more people engage in R&D (higher ϕ), fewer workers are available for production, pushing w up (since $w = A_t$ in our simple production model). To keep the marginal inventor indifferent, an increase in w (which raises the safe payoff) must be offset by either a higher subsidy S or a higher cutoff C_B^* (i.e., only lower-cost inventors pursue breakthroughs). In equilibrium, w adjusts such that equation Equation 4.12 holds with ϕ remaining consistent.

We can solve this conceptually. Using the uniform example: $\phi = C_B^*/\bar{C}$. Plugging Equation 4.12:

$$\phi = \frac{\bar{p}\, V_B + S - w}{\bar{C}} \tag{4.13}$$

One can solve for ϕ in terms of S. For example, if $C_B \sim U[0, \bar{C}]$ and without general equilibrium feedback on w (taking w as roughly exogenous or treating small open economy with fixed wage), then $\phi = (\bar{p}V_B + S - w)/\bar{C}$ as above. This clearly gives $\partial\phi/\partial S = 1/\bar{C} > 0$. So subsidies raise the fraction of breakthrough innovators. If S is large enough (exceeding $w - \bar{p}V_B$), then ϕ hits 1 (everyone goes for breakthroughs). On the other hand, if S is zero or very small, ϕ might be quite low, possibly 0 if $\bar{p}V_B < w$ (meaning even the best project barely breaks even). Thus, the economy without intervention may end up stuck in an equilibrium with primarily incremental innovation, especially if V_B (private reward) is not extremely high or w is high due to other opportunities.

This model thus captures a possible market failure: private market might under-provide breakthrough innovation because individual inventors compare $\bar{p}V_B$ to w (or V_I), and if $\bar{p}V_B < w$ no one attempts breakthroughs, even though one breakthrough could raise A_t substantially and benefit society. This under-investment can occur due to externalities (knowledge created by a breakthrough benefits others, not fully captured in V_B) and risk/coordination issues (each inventor alone may not capture the full social value, and multiple inventors racing dissipate returns). Aghion and Howitt (1992) identified various effects in such innovation races — appropriability effect (innovators don't get full social surplus), business-stealing effect (breakthroughs steal profits from incumbents, which is a private gain but not a social gain), etc.—leading the decentralized equilibrium growth to be potentially too low or too high relative to optimum. Importantly, the winner-takes-all nature can create excessive duplication (too many racing for the prize, which from a social view is wasteful effort) or insufficient investment (if risk or externalities deter inventors). Our equilibrium condition (for marginal inventor indifference) is the knife-edge where private returns equal opportunity cost; a social planner would weigh success probability times social value of innovation (which could be larger than V_B if there are spillovers to other sectors or consumers beyond monopoly profits).

4.5.1 Effects of Government Grants: Comparative Statics

We now analyze how changes in the subsidy S (government grant for breakthroughs) affect the equilibrium outcomes. The key endogenous variables of interest are the fraction of breakthrough innovators ϕ, the innovation rate (frequency of breakthroughs vs incrementals), the long-run growth rate g, and welfare.

First, for inventors' response, an increase in S lowers the effective cost of undertaking a breakthrough project, directly making U_B more attractive. This shifts the indifference condition Equation 4.3 in favor of breakthroughs. Mathematically, $\partial C_B^*/\partial S = 1$; from Equation 4.12, C_B^* increases one-for-one with S. Consequently, more inventors find it worthwhile to pursue breakthroughs. As noted, $\frac{\partial \phi}{\partial S} > 0$, meaning the fraction of breakthrough inventors rises. The composition of innovation effort shifts toward high-risk, high-reward projects. If S is small, the effect might be marginal; if S is large, it could trigger a dramatic shift—possibly even multiple equilibria if there are strategic complementarities. However, in our simple setup, there exists a unique ϕ for each S.

Second, for innovation Output: With more breakthrough attempts, the expected number of successful breakthroughs increases. This has two implications: One is Higher *Expected* Growth: Since each breakthrough yields a sizable productivity jump $\ln(\gamma)$, increasing their arrival raises the economy's growth rate g. In a steady state, $g \approx (1-\phi)\epsilon + \phi\bar{p}\ln(\gamma)$ as discussed. $\frac{\partial g}{\partial \phi} = -\epsilon + \bar{p}\ln(\gamma)$ (approximately). Typically $\ln(\gamma)$ is much larger than ϵ, so unless ϕ is extremely high, increasing ϕ via subsidies raises g. Thus, grants targeting radical innovation tend to increase long-run technological progress and output growth. This result aligns with the idea that directing more resources to breakthrough innovation yields faster growth.

It is important to highlight the transitional dynamics and associated risks implied by the model. While average innovation outcomes could improve, the variability of these outcomes may also increase. Specifically, a winner-takes-all structure involving multiple inventors might generate periods without breakthroughs — when all risky projects fail—punctuated by infrequent yet significant innovations. The timing of

such breakthroughs is beyond the scope of the current model. Empirically, the initial adoption of policies designed to promote breakthrough innovations may induce a larger number of ambitious attempts but few actual successes. Simultaneously, reduced incremental innovation could lead to fewer guaranteed small improvements, potentially causing an overall decline in average innovation quality. As a result, the economy might experience more volatile technological progress, characterized by intermittent leaps forward or prolonged stagnation if breakthroughs are delayed. Nevertheless, provided that ϕ is not excessively close to 1, incremental innovation persists, thereby ensuring a continuous stream of minor improvements.

In terms of resource allocation, as ϕ increases, more labor is diverted from immediate production to R&D. In the short run, this can lower current output (since $L^Y = 1 - \phi$ goes down). However, this is an investment in future output via higher A_{t+1}. This trade-off resembles a short-run output loss for long-run gain. A higher S intensifies this effect: more subsidy draws labor into R&D. The marginal cost of public funds here would be the forgone output from those workers plus the tax burden. If ϕ rises a lot, the wage w might increase (because fewer workers produce goods), which raises V_I (opportunity cost) and counteracts some of the subsidy's effect. In a general equilibrium, this feedback tempers ϕ's increase. In fact, one can show $\partial w/\partial S > 0$ in the short run (due to labor scarcity in production), which enters Equation 4.12 negatively, partially offsetting the direct $\partial C_B^*/\partial S = 1$. Nonetheless, unless the production function sharply diminishes returns, the net effect is still more breakthroughs.

Generally, moderate subsidies increase welfare by correcting underinvestment in risky R&D. However, extremely large subsidies might overshoot the optimal ϕ. If too

many resources go into breakthrough attempts, the economy could face diminishing returns: many duplicative R&D projects chasing similar breakthroughs (each with low probability of being the winner) can waste resources. The marginal breakthrough attempt could have a social return below that of an incremental innovation or below the opportunity cost. In such a case, the growth rate might not increase proportionally with ϕ (e.g. if N people independently try the same idea, probability of success might have diminishing increments, or if one success makes others' attempts redundant ex-post). Thus, while $\partial g/\partial \phi$ is positive initially, it could eventually decline if ϕ approaches 1 due to congestion in research or lack of incremental improvements. There is an optimal mix of incremental and radical innovation that balances steady progress with occasional big leaps.

To illustrate comparative statics, consider two extreme cases:

1. No Subsidy (Baseline): Suppose $\bar{p}V_B < w$ so that $\phi = 0$ (no one attempts breakthroughs). The economy relies entirely on incremental innovation, growing at rate $\approx \epsilon$ (very slow). Welfare is lower due to slower growth, though consumption is stable.

2. Very High Subsidy: Now S is so high that even low-probability or high-cost projects are attempted (ϕ close to 1). The economy experiences frequent breakthroughs, potentially growing at an explosive rate $\approx \bar{p}\ln(\gamma)$, but at the cost of large subsidy expenditures and minimal current output (almost everyone is researching). If breakthroughs exhibit diminishing returns or duplication, the marginal utility of another researcher on breakthrough may be low. Also, if inventors are risk-averse, forcing all to gamble could lower their ex-ante expected utility even if the aggregate grows faster (due to risk not accounted in

average growth).

3. Intermediate Optimal Subsidy: The optimal policy S^* balances these considerations by equating the social marginal benefit of directing an additional inventor to breakthrough research with the social marginal cost (foregone incremental innovation and subsidy expenditure).

In our model, this implies subsidizing the breakthrough efforts of the most capable inventors—those with low C_B or high p_i—effectively mirroring the function of a well-designed grant program. A uniform, across-the-board subsidy might induce some lower-productivity inventors to attempt breakthroughs despite having a lower probability of success, which could reduce overall efficiency. Thus, targeted grants can generate more breakthrough successes per dollar spent.

Our results are related to a recent literature examining the possibility that growth could be stimulated by using policies to reallocate innovative investment away from those making small contributions to aggregate productivity growth toward those that do (Lentz and Mortensen, 2016; Acemoglu et al., 2018; Atkeson and Burstein, 2019; Peters, 2020).

4.6 Extension

The baseline models effectively illustrate core concepts but implicitly assume a single market failure—underinvestment in breakthrough innovations due to risk or negative externalities—potentially necessitating government grants. This assumption does not invalidate our analysis; without it, the optimal subsidy $S^* = 0$, and any excess subsidies would distort the market, though this would be a trivial case. In practice, as we will explore in the empirical section, many countries implement innovation-

promoting policies, driven largely by knowledge spillover effects. As highlighted by Bloom, Van Reenen, and Williams (2019), innovators often underinvest because they cannot fully capture the benefits of their work, with spillovers benefiting others, including competitors. Thus, extending the model to explicitly account for spillovers is a valuable exercise.

Following Romer (1990); Atkeson and Burstein (2019), we introduce a stock of knowledge z_t, which accumulates from past innovations and can be interpreted as "research goods" produced by R&D labor. For simplicity, we assume this knowledge is non-rival and accumulative, fueling long-run growth. When an inventor achieves a breakthrough, they earn a private reward and simultaneously augment the economy's technological base, denoted A_t. We capture non-rivalry by assuming new knowledge instantly spills over, enhancing the economy's technological foundation. For example, a breakthrough might boost the productivity of all future R&D or increase economy-wide production efficiency. This aligns with Romer's framework, where the stock of ideas A_t enhances output or facilitates further innovation. We assume incremental innovations contribute negligibly to the knowledge stock for simplicity; allowing a small, non-zero contribution would not yield additional insights. The expected change in the knowledge stock per period (omitting the time subscript t for brevity) is:

$$E[\Delta \ln A] \approx (1-\phi)\ln(1+\epsilon) + \phi\bar{p}\ln(\gamma) + \phi\ln(z), \tag{4.14}$$

where all other terms follow Equation 4.6, and z represents the contribution of breakthroughs to the knowledge stock or research goods. This formulation reflects the idea that breakthroughs significantly advance the technological frontier. Since

knowledge is non-rival, once created, it can be used by any firm or researcher without diminishing its availability. Spillovers imply that even a monopolist's breakthrough—while temporarily conferring private market power—eventually diffuses (e.g., through expired patents, imitation, or others grasping the underlying principles), raising overall economic productivity.

However, the inventor's optimization problem remains unchanged. Inventors do not internalize the full societal benefit of their innovations, such as spillovers to the broader economy. Breakthroughs generate non-rival knowledge z, which inventors cannot fully appropriate. Consequently, the social payoff exceeds the private payoff:

$$U_B^{\text{social}} = p(V_B + z) - C_B > U_B^{\text{private}} = pV_B - C_B. \tag{4.15}$$

From Equation 4.13, the participation rate of breakthrough inventors (ϕ) is suboptimal in the private equilibrium:

$$\phi^{*,\text{social}} = \frac{p(V_B + z) - w}{\bar{C}} > \phi^{*,\text{private}} = \frac{pV_B - w}{\bar{C}}. \tag{4.16}$$

Inventors, operating under the private equilibrium, underestimate the true social return of breakthrough innovations due to uninternalized spillovers. As a result, they favor incremental innovations more often than is socially optimal. To address this market failure, the government can provide a targeted subsidy G, reducing the inventor's effective cost of breakthrough innovation from C_B to $C_B - G$. The optimal subsidy aligns private incentives with the social optimum:

$$G^* = p \cdot z. \tag{4.17}$$

In summary, explicitly incorporating knowledge spillovers into the inventor's optimization problem reveals how the private market equilibrium systematically underinvests in breakthrough innovations. Targeted government subsidies play an important role in correcting this distortion, aligning private incentives with the social optimum and enhancing economic growth and aggregate welfare, as emphasized by Romer (1990); Atkeson and Burstein (2019); Acemoglu and Restrepo (2018).

In the empirical analysis in the following sections, we will explore the comparative statistics of government polices for promoting innovation using global policies and innovation data. focusing on the effects of these policies on innovation outcomes. We first, will introduce the data.

5 Conclusion

Using two novel datasets, we describe the global landscape of national promotion policies and AI innovation. Employing a stacked Difference-in-Differences framework, we observe that for inventor analysis, AI scientists produce fewer patents of lower average quality post-policy, despite an increase in the novelty of their work. This pattern aligns with the high-risk, high-reward dynamics of AI, where policies incentivize exploratory efforts with uncertain outcomes. Moreover, similar patterns are observed at the country level, indicating a consistent decline in both the quantity and quality of patents following the introduction of the policy.

Our findings inform policies and highlight the importance of balancing short-term productivity trade-offs with potential long-term gains when designing AI policies. Policymakers should recognize that nurturing innovation in rapidly evolving areas like AI may require tolerating initial inefficiencies and elevated failure rates.

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6 Figures and Tables

Figure 1
Word Cloud for National AI Strategies and Policies

This figure shows the word cloud of descriptions for National AI-related Strategies and Policies.



Figure 2
Time Variation of Percentage of AI Patent Filings

This figure shows the time variation of percentage of AI patent filings across 48 countries from 1990 to 2022.

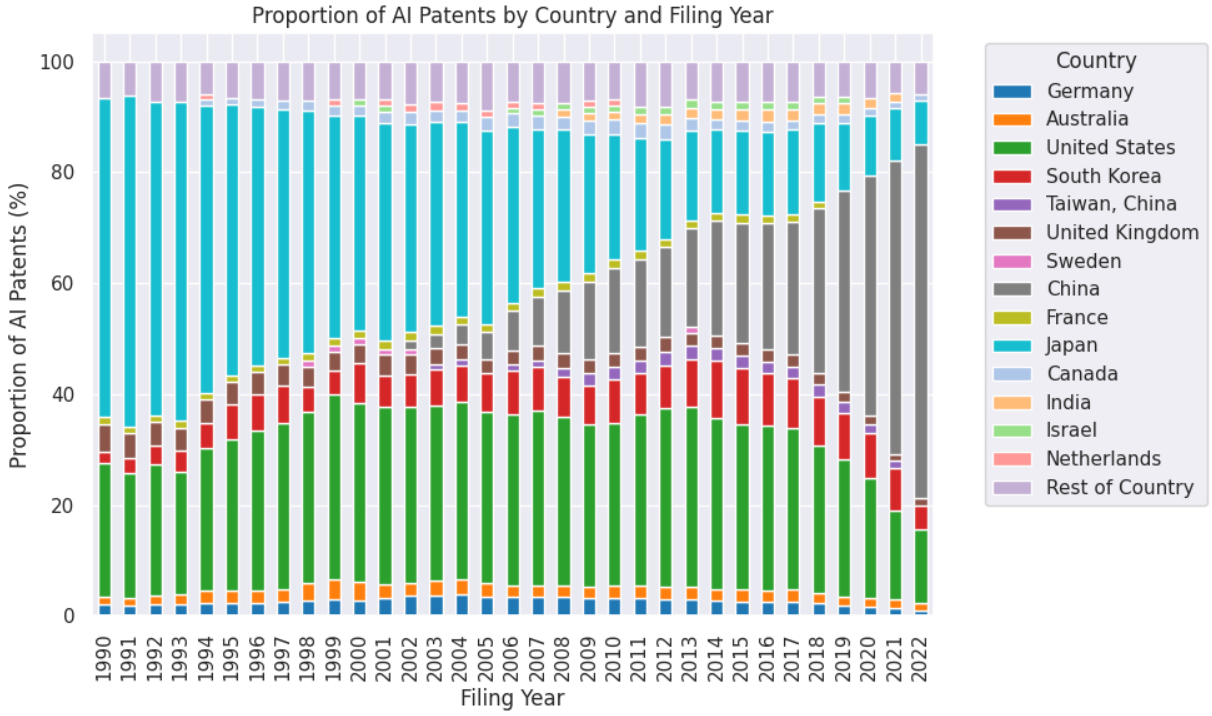
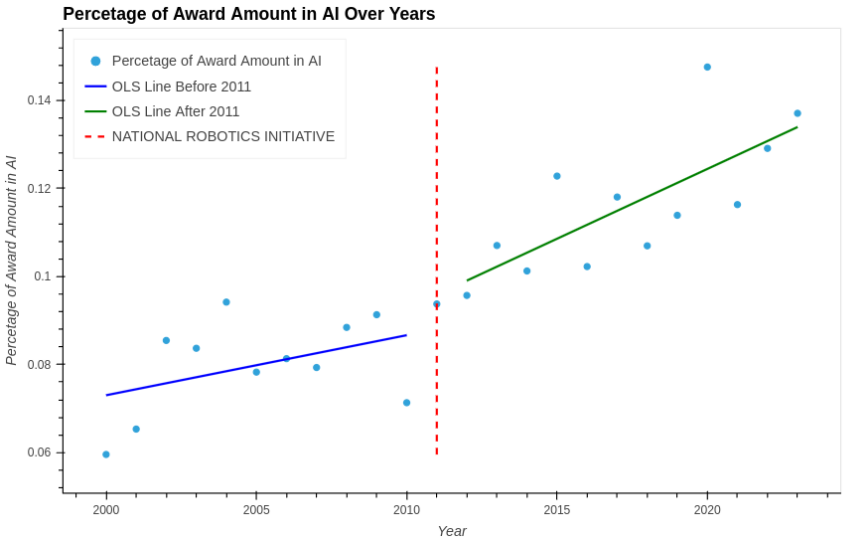
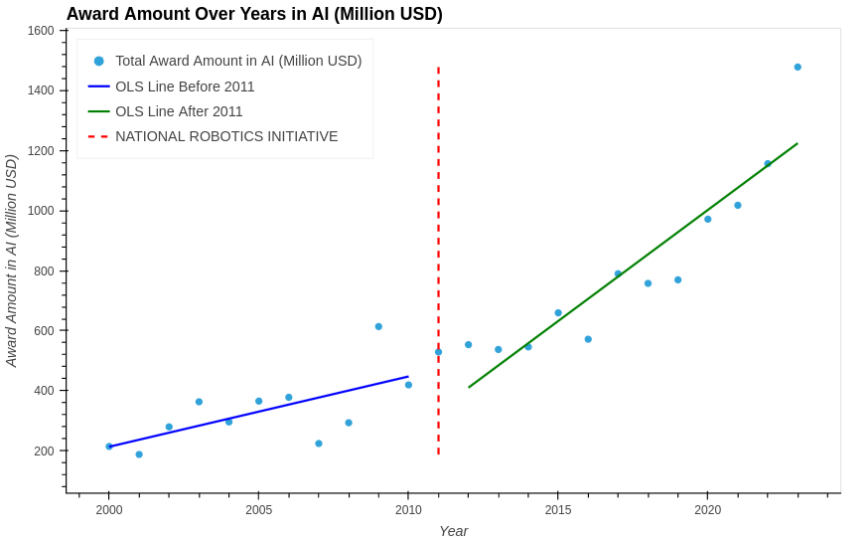


Figure 3
Time Series Variation of Award Amount and percentage of Award Amount in AI from NSF

This figure 3 plots the time-series variation of award amount and percentage of award amount in AI from National Science Foundation (NSF) from 2000 to 2023.



(a) Percentage of Award Amount in AI



(b) Award Amount in AI

Table 1
Summary Statistics for AI Policy Budgets and AI Innovation by Country

This table shows the total budget for AI policy and the budget for the specific categories by country over the sample period from 2006 to 2019.

Country	Average Annual Budget ($M)	Governance ($M)	Financial Support ($M)	Guidance and Regulation ($M)	AI Enablers and Other Incentives ($M)	No. of AI Patents	No. of AI Inventors	No. of AI Academic Publications
Argentina	26.00	25.00	0.30	0.00	0.70	842	8	2285
Australia	213.00	66.83	102.92	1.08	42.17	84362	2348	31439
Austria	15.00	6.50	0.00	8.50	0.00	6742	66	10181
Belgium	25.50	25.25	0.12	0.12	0.00	11459	141	9384
Brazil	53.50	20.50	33.00	0.00	0.00	4931	46	22576
Bulgaria	12.50	5.00	0.00	0.00	7.50	949	8	2751
Canada	36.00	35.25	0.00	0.75	0.00	75388	1294	37465
China	2640.00	2640.00	0.00	0.00	0.00	734246	79011	435418
Czechia	740.50	356.67	13.33	6.92	363.58	2814	71	7035
Denmark	124.50	21.43	10.71	42.14	50.21	9882	290	7308
Egypt	30.00	22.50	0.00	0.00	7.50	668	15	12162
Estonia	121.00	97.50	10.00	0.00	13.50	585	2	1477
Finland	230.50	145.00	35.00	50.00	0.50	20579	287	7467
France	2379.50	742.31	994.71	185.87	456.62	51277	507	41602
Germany	555.00	342.75	150.58	6.25	55.42	109163	1380	65259
Greece	20.00	20.00	0.00	0.00	0.00	1359	26	9472
Hungary	6.00	0.50	0.00	0.50	5.00	2414	39	4844
India	55.50	35.00	10.00	0.00	10.50	52681	1228	147404
Ireland	30.00	20.00	0.00	0.00	10.00	9699	152	5422
Israel	972.50	292.50	365.83	12.50	301.67	43057	1038	6273
Italy	890.00	816.00	52.50	0.00	21.50	24159	451	39980
Japan	803.00	616.75	37.50	0.00	148.75	967756	11167	39420
Korea, Republic of	1895.00	909.52	468.99	122.86	393.63	305639	6188	35951
Luxembourg	0.50	0.33	0.00	0.17	0.00	808	21	1451
Mexico	60.00	40.00	0.00	0.00	20.00	3948	21	8236
Netherlands	797.50	180.00	0.00	0.00	617.50	36689	750	19612
Norway	271.50	181.50	75.00	10.50	4.50	6505	93	8489
Poland	1000.00	1000.00	0.00	0.00	0.00	3611	69	14468
Portugal	119.00	14.50	3.50	101.00	0.00	1158	71	9592
Romania	1.00	1.00	0.00	0.00	0.00	1856	35	6258
Russian Federation	920.00	620.00	300.00	0.00	0.00	24776	128	38579
Saudi Arabia	6800.00	5600.00	133.33	133.33	933.33	2562	92	21237
Singapore	1272.00	777.00	310.00	0.00	185.00	9003	271	14218
South Africa	10.00	10.00	0.00	0.00	0.00	2048	26	5681
Spain	1575.50	931.75	212.50	6.25	425.00	15201	153	28973
Sweden	83.00	1.50	75.00	3.00	3.50	32313	353	11862
Switzerland	250.00	250.00	0.00	0.00	0.00	21074	355	15453
Türkiye	34.04	19.75	3.00	0.00	11.29	2726	126	23574
Ukraine	139.00	139.00	0.00	0.00	0.00	1486	30	9869
United Kingdom	4858.53	4074.14	394.48	219.46	170.46	101299	1356	65331
United States	4936.50	451.50	1535.00	2520.00	430.00	1136918	20432	208374

Table 2
Keywords Describing National AI Strategies and Policies

This table shows the keywords describing national AI-related policies in thirteen principal countries, from 2006 to 2019.

Country	Keywords
Australia	Provide financial incentives, Promote public-private partnerships, Foster AI education and workforce training, Support AI startups, Develop national AI strategies, Establish AI regulatory frameworks, Improve infrastructure, Guide corporate investment, Boost internal R&D, Enhance AI governance, Fund research missions, Support innovative collaborative technologies, Increase transparency and integrity, Encourage adoption and use of AI technologies, Co-fund collaborative projects, Provide access to emerging technologies, Develop ethical AI frameworks, Build international AI relationships, Strengthen AI capability and adoption, Attract and train AI specialists
Canada	risk-based approach, Algorithmic Impact Assessment, regulatory frameworks, public-facing automated decision-making systems, Pan-Canadian Artificial Intelligence Strategy, investments in talent, research capacity, commercialization, standardization, interconnected nodes of scientific excellence, global thought leadership, support national research community, foster co-operation between AI research centres and industry, multi-stakeholder and multi-disciplinary expertise, AI Source List, expedite procurement, establish pre-qualified list of suppliers
China	Enhancing AI hardware capacity, Strengthen platform ecosystems, Develop research and industrial leadership, Build technology parks for AI research, Establish AI governance and regulatory frameworks, Promote AI education and workforce training, Foster international cooperation in AI, Support AI startups and innovation centers, Optimize university infrastructure for AI, Set national standards for AI technologies, Increase R&D spending in AI, Develop national AI strategies, Cultivate AI talent development, Provide financial incentives for AI development, Promote public-private partnerships in AI, Enhance capabilities of data infrastructure, Regulate algorithm security and development, Standard
France	Enhance research ecosystem, Accelerate AI dissemination, Encourage trustworthy AI development, Develop AI educational excellence, Foster interdisciplinary AI research, Support AI startups and SMEs, Create prestigious AI research institutes, Offer high-level AI scientific training, Establish collaborative research platforms, Develop national AI strategies, Promote public-private partnerships, Provide financial incentives, Improve infrastructure (e.g., supercomputers, data hubs), Foster AI education and workforce training, Support the digitalisation of SMEs, Develop embedded and frugal AI solutions, Enhance AI governance, Develop sovereign AI frameworks
Germany	Develop national AI strategies, Establish AI regulatory frameworks, Foster AI education and workforce training, Promote public-private partnerships, Provide financial incentives, Enhance AI governance, Support AI startups, Improve infrastructure, Guide corporate investment, Boost internal R&D, Create ethical rules for AI, Build AI research ecosystem, Develop technology transfer initiatives, Fund AI applications for environmental benefits, Integrate AI in societal sectors, Support demographic and ecological transformation, Foster international research collaboration, Enhance participatory technology design, Develop AI platforms for universal use, Harmonize legislation for AI systems
India	Foster talent and build a community, Encourage research and reduce R&D costs, Reduce import dependency, Position as a provider of end-to-end solutions, Create a policy and legal framework, Issue concrete recommendations for government, industry, and research programs, Standardisation of Artificial Intelligence technology, Establish the National Program on AI, Undertake exploratory proof-of-concept AI projects, Craft a national strategy for AI ecosystem, **Collaborate with experts
Israel	Develop national AI strategies, Improve infrastructure, Support AI startups, Provide financial incentives, Encourage entrepreneurship, **
Japan	Construct high-speed network, Promote R&D for innovative fundamental technology, Accelerate Joint AI R&D with Industries, Academia, and Governments, Establish new governance models, Promote appropriate and proactive implementation of AI
Korea	Provide AI technology development infrastructure, Develop and promote AI R&D strategies, Establish intelligent network, Reform R&D system, Promote cross-ministerial collaboration, Enhance interactions with the general public, Foster data and AI convergence, Establish ethical standards for AI, Build a foundation for social deliberation on AI ethics, Secure world-class AI technology, Promote active use of the data value chain, Create economic surplus through AI
Netherlands	Promote public-private partnerships, Foster AI education and workforce training, Develop national AI strategies, Provide financial incentives, Enhance AI governance
Sweden	Elevate competence about AI, Promote education and competence development, Deliver policy proposals, Adapt regulatory frameworks, Accelerate policy development, Formulate a national roadmap, Recommendations on investment and policy development, Map the use of AI and big data analysis, Accelerate applied AI research and innovations, Develop and provide infrastructure for data management, Support industry-science cooperation, Increase undergraduate AI education
United Kingdom	Develop national AI strategies, Enhance AI governance, Foster AI education and workforce training, Support AI startups, Establish AI regulatory frameworks, Provide financial incentives
United States	advance AI research, develop regulatory frameworks, promote public-private partnerships, foster AI education and workforce training, support AI startups, enhance AI governance, provide financial incentives, develop national AI strategies, guide corporate investment, boost internal R&D, ensure AI safety and security, accelerate AI adoption, cultivate AI workforce, establish AI ethical guidelines, expand AI R&D investments, promote AI in national security, develop AI standards and benchmarks, increase access to AI resources

Table 3
Inventor-Level Panel Data Descriptive Statistics

This table reports the overview statistics from 2006 to 2019. The definitions of all variables are reported in the Appendix.

	N	Mean	Std	Min	25%	Median	75%
AI Patent Counts	4,629,555	1.70	2.69	1.00	1.00	1.00	2.00
AI Patent Fcites	4,629,555	6.69	30.14	0.00	0.00	1.00	5.00
Avg AI Fcites	4,629,555	3.80	14.75	0.00	0.00	1.00	3.00
AI Patent Bcites	4,629,555	30.15	247.42	0.00	1.00	5.00	15.00
Avg AI Bcites	4,629,555	15.67	78.18	0.00	0.50	4.00	10.00
Cross Country bcites (%)	3,490,491	44.62	34.98	0.00	16.67	35.29	75.09
Cross Country fcites (%)	2,572,877	34.00	39.92	0.00	0.00	13.33	66.67
Similar AI Patent Counts	4,629,555	4.29	12.40	0.00	1.00	2.00	4.00
New Coauth. Count	3,667,387	4.52	7.46	1.00	2.00	3.00	5.00
Inventor AI Domains	4,629,555	1.26	0.67	1.00	1.00	1.00	1.00
Inventor AI Domains HHI	4,629,555	0.91	0.20	0.14	1.00	1.00	1.00

Table 4
Summary Statistics of Domains for AI Patent Filings

This table reports the overview statistics of domains for AI patent filings by country from 1990 to 2022.

Country	No. of AI Patent Filings	Vision(%)	AI Hardware(%)	Evolutionary Computation(%)	Machine Learning(%)	Planning and Control(%)	Natural Language Processing(%)	Speech(%)	Knowledge Processing(%)	Primary Filings Focus
United States	1136918	18.39	24.24	3.25	3.03	30.31	7.99	3.80	8.99	Planning and Control
Japan	967756	36.05	17.64	4.49	1.59	23.92	6.42	3.44	6.45	Vision
China	734246	26.20	20.32	3.24	3.46	27.85	7.26	3.38	8.28	Planning and Control
Korea, Republic of	305639	27.99	21.75	3.46	2.08	24.73	8.43	4.44	7.12	Vision
Germany	109163	24.70	20.25	3.25	2.42	35.07	4.15	4.02	6.14	Planning and Control
United Kingdom	101299	19.62	23.22	3.41	2.80	32.31	6.11	4.22	8.30	Planning and Control
Australia	84362	18.80	17.44	5.30	2.56	35.45	7.34	4.53	8.58	Planning and Control
Canada	75388	18.10	21.68	3.59	2.83	30.31	9.10	4.29	10.10	Planning and Control
Taiwan, Province of China	63058	36.05	25.02	2.59	1.68	21.57	5.37	3.09	4.62	Vision
India	52681	12.72	25.87	2.63	3.37	30.39	10.99	2.71	11.33	Planning and Control
France	51277	27.02	22.59	3.72	3.36	27.56	5.22	2.92	7.63	Planning and Control
Israel	43057	26.36	26.78	2.78	3.41	21.76	7.00	3.34	8.57	AI Hardware
Netherlands	36689	34.05	19.13	4.25	2.73	24.71	4.34	4.19	6.59	Vision
Sweden	32313	20.15	17.57	3.78	2.55	34.24	4.35	6.43	10.93	Planning and Control
Russian Federation	24776	24.71	21.62	4.33	2.94	30.77	6.42	2.87	6.34	Planning and Control
Italy	24159	19.08	22.48	3.55	2.66	38.81	4.42	2.31	6.68	Planning and Control
Switzerland	21074	23.15	20.76	3.90	3.62	30.47	6.49	5.05	6.57	Planning and Control
Finland	20579	18.00	18.73	3.60	2.92	28.98	7.11	7.96	12.69	Planning and Control
Spain	15201	22.56	19.10	5.04	2.80	33.30	5.10	3.78	8.30	Planning and Control
Belgium	11459	25.48	22.92	3.03	2.72	28.77	4.64	3.02	7.42	Planning and Control
Denmark	9882	15.23	15.03	6.10	2.73	38.10	5.01	12.14	5.66	Planning and Control
Ireland	9699	16.55	20.90	2.62	3.78	32.97	10.77	3.23	9.18	Planning and Control
Singapore	9003	28.25	21.58	2.69	3.63	26.66	5.74	4.70	6.75	Vision
Austria	6742	23.58	23.49	3.46	2.37	33.63	4.12	4.06	5.28	Planning and Control
Norway	6505	20.97	21.66	3.09	2.64	36.02	5.04	3.97	6.61	Planning and Control
Brazil	4931	14.09	19.75	4.83	3.59	38.88	8.15	2.72	7.99	Planning and Control
New Zealand	4467	20.53	16.95	5.22	2.71	35.01	7.48	4.03	8.08	Planning and Control
Mexico	3948	17.35	16.39	4.94	2.56	39.79	7.04	4.20	7.73	Planning and Control
Poland	3611	20.44	22.35	3.13	3.13	29.80	6.59	4.93	9.64	Planning and Control
Czechia	2814	16.38	20.04	2.84	4.09	37.49	7.14	3.34	8.67	Planning and Control
Türkiye	2726	26.96	18.64	3.19	2.64	30.37	5.21	4.77	8.22	Planning and Control
Saudi Arabia	2562	14.48	19.20	3.71	8.67	39.81	5.66	1.13	7.34	Planning and Control
Malaysia	2460	22.80	30.73	3.41	2.60	24.96	6.06	3.21	6.22	AI Hardware
Hungary	2414	22.20	19.51	3.77	3.15	28.09	4.89	3.19	15.20	Planning and Control
Hong Kong	2387	28.61	19.15	2.81	3.77	25.93	7.96	5.74	6.03	Vision
South Africa	2048	14.11	18.90	5.08	2.34	40.09	6.88	3.47	9.13	Planning and Control
Romania	1856	30.82	23.11	1.78	3.77	21.77	7.92	2.26	8.57	Vision
Ukraine	1486	26.65	24.97	3.97	2.36	26.04	6.86	2.29	6.86	Vision
Greece	1359	22.15	21.85	3.38	5.08	25.83	6.11	4.86	10.74	Planning and Control
Portugal	1158	22.11	25.73	4.06	4.75	26.68	4.15	2.50	10.02	Planning and Control
Bulgaria	949	12.96	37.30	1.58	1.37	29.93	5.80	1.37	9.69	AI Hardware
Argentina	842	13.30	24.82	4.04	4.87	31.71	8.19	3.80	9.26	Planning and Control
Luxembourg	808	23.02	16.58	2.72	3.22	38.37	3.71	5.20	7.18	Planning and Control
Egypt	668	14.52	25.00	2.99	5.09	19.91	19.16	2.54	10.78	AI Hardware
United Arab Emirates	650	16.15	16.31	2.92	6.31	39.38	6.15	1.54	11.23	Planning and Control
Philippines	619	14.86	19.06	3.55	2.10	42.16	6.79	3.07	8.40	Planning and Control
Estonia	585	22.74	14.53	4.79	4.27	25.13	6.67	7.35	14.53	Planning and Control
Belarus	533	27.77	23.45	3.75	4.50	23.08	9.01	2.63	5.82	Vision

Table 5
Summary Statistics of AI Innovation Collaboration

This table reports the overview statistics for AI Innovation Collaboration by country from 1990 to 2019.

Country	No. of AI Patents	No. of Colab AI Patents	No. of Non-Colab AI Patents	Percentage of Colab AI Patents	Fcites(Colab AI-Patents)	Fcites(Non-colab AI-Patents)	Avg Fcites(Colab AI-Patents)	Avg Fcites(Non-colab AI-Patents)	Diff Avg Fcites (Colab vs Non-Colab)
United States	1136918	135945	1000973	11.96	1240216	17433158	1.09	15.33	-14.24
Japan	967756	10997	956759	1.14	116037	5605612	0.12	5.79	-5.67
China	734246	22300	711946	3.04	91494	2236040	0.12	3.05	-2.92
Korea, Republic of	305639	8561	297078	2.80	34205	769276	0.11	2.52	-2.41
Germany	109163	27230	81933	24.94	181019	481264	1.66	4.41	-2.75
United Kingdom	101299	26464	74835	26.12	251848	537683	2.49	5.31	-2.82
Australia	84362	5606	78756	6.65	44965	145895	0.53	1.73	-1.20
Canada	75388	23168	52220	30.73	211918	454934	2.81	6.03	-3.22
Taiwan, Province of China	63058	6317	56741	10.02	23169	140470	0.37	2.23	-1.86
India	52681	25389	27292	48.19	127525	95946	2.42	1.82	0.60
France	51277	13209	38068	25.76	103847	213158	2.03	4.16	-2.13
Israel	43057	11050	32007	25.66	104286	326554	2.42	7.58	-5.16
Netherlands	36689	7446	29243	20.29	54481	111125	1.48	3.03	-1.54
Sweden	32313	6850	25463	21.20	37746	122044	1.17	3.78	-2.61
Russian Federation	24776	4259	20517	17.19	34934	57335	1.41	2.31	-0.90
Italy	24159	4972	19187	20.58	30604	72340	1.27	2.99	-1.73
Switzerland	21074	9208	11866	43.69	61683	70582	2.93	3.35	-0.42
Finland	20579	3518	17061	17.10	22102	94258	1.07	4.58	-3.51
Spain	15201	4228	10973	27.81	27550	22392	1.81	1.47	0.34
Belgium	11459	4474	6985	39.04	35592	42195	3.11	3.68	-0.58
Denmark	9882	2582	7300	26.13	19062	34289	1.93	3.47	-1.54
Ireland	9699	4697	5002	48.43	34606	22947	3.57	2.37	1.20
Singapore	9003	4141	4862	46.00	20531	34797	2.28	3.87	-1.58
Austria	6742	2676	4066	39.69	13139	16537	1.95	2.45	-0.50
Norway	6505	1734	4771	26.66	12449	24104	1.91	3.71	-1.79
Brazil	4931	1644	3287	33.34	7744	5282	1.57	1.07	0.50
New Zealand	4467	1099	3368	24.60	9060	15817	2.03	3.54	-1.51
Mexico	3948	3210	738	81.31	7059	2436	1.79	0.62	1.17
Poland	3611	1543	2068	42.73	8685	3804	2.41	1.05	1.35
Czechia	2814	1312	1502	46.62	8876	3411	3.15	1.21	1.94
Türkiye	2726	885	1841	32.47	6460	2927	2.37	1.07	1.30
Saudi Arabia	2562	510	2052	19.91	2222	5616	0.87	2.19	-1.32
Malaysia	2460	1193	1267	48.50	3685	5804	1.50	2.36	-0.86
Hungary	2414	966	1448	40.02	6016	4682	2.49	1.94	0.55
Hong Kong	2387	875	1512	36.66	9403	11501	3.94	4.82	-0.88
South Africa	2048	612	1436	29.88	4899	8569	2.39	4.18	-1.79
Romania	1856	1071	785	57.70	11460	2447	6.17	1.32	4.86
Ukraine	1486	866	620	58.28	4682	1630	3.15	1.10	2.05
Greece	1359	779	580	57.32	7011	2177	5.16	1.60	3.56
Portugal	1158	480	678	41.45	2477	2087	2.14	1.80	0.34
Bulgaria	949	373	576	39.30	2737	2335	2.88	2.46	0.42
Argentina	842	485	357	57.60	2859	1997	3.40	2.37	1.02
Luxembourg	808	524	284	64.85	3061	898	3.79	1.11	2.68
Egypt	668	410	258	61.38	2634	1243	3.94	1.86	2.08
United Arab Emirates	650	339	311	52.15	1073	1136	1.65	1.75	-0.10
Philippines	619	359	260	58.00	2632	1082	4.25	1.75	2.50
Estonia	585	284	301	48.55	1145	1473	1.96	2.52	-0.56
Belarus	533	282	251	52.91	1719	933	3.23	1.75	1.47

Table 6
National AI-Related Policy and AI Innovation

This table reports coefficients of Poisson regressions of the AI innovation inventor-panel on an indicator for national AI-related policies, inventor-by-cohort fixed effects, and year-by-cohort fixed effects. The indicator of panel A is set to 1 if the country has implemented national AI-related policies, while the indicator of panels B and C reflects the implementation of specific categories of AI policies such as governance, guidance & regulation, financial support, and AI enablers & other incentives. The dependent variables are AI patent filings counts, forward citations, backward citations, average forward citations, and average backward citations. The data include inventor-year observations in the 5 years prior and up to 10 years following the implementation of national AI-related policies in each country from 2006 to 2019. For all regressions, robust standard errors are clustered at the country level, and t-statistics are illustrated in parentheses.***,**,* represent the significance level at 1%, 5% and 10% ,respectively.

Panel A

	AI Patent Counts	AI Patent Fcites	Avg AI Fcites	AI Patent Bcites	Avg AI Bcites
	(1)	(2)	(3)	(4)	(5)
DID(AI Policy)	-0.075***	-0.353*	-0.287*	-0.083**	-0.039**
	(-2.59)	(-1.78)	(-1.83)	(-2.34)	(-2.11)
Year × Cohort FE	Yes	Yes	Yes	Yes	Yes
Inventor × Cohort FE	Yes	Yes	Yes	Yes	Yes
Obs.	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518

Panel B

	AI Patent Counts				AI Patent Fcites				Avg AI Fcites			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
DID(Governance)	-0.016				-0.033				-0.082			
	(-0.74)				(-0.46)				(-1.22)			
DID(Financial Support)		-0.082**				-0.376*				-0.306*		
		(-2.43)				(-1.83)				(-1.91)		
DID(Guidance and Regulation)			-0.114***				-0.276***				-0.215***	
			(-3.92)				(-4.02)				(-3.40)	
DID(AI Enablers and Other Incentives)				-0.127***				-0.355				-0.181
				(-3.07)				(-1.58)				(-1.07)
Year × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inventor × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518

Panel C

	AI Patent Bcites				Avg AI Bcites			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DID(Governance)	-0.015				-0.023			
	(-0.49)				(-1.64)			
DID(Financial Support)		-0.100**				-0.035**		
		(-2.46)				(-2.18)		
DID(Guidance and Regulation)			-0.098***				0.012	
			(-2.60)				(1.05)	
DID(AI Enablers and Other Incentives)				-0.116**				-0.034
				(-2.12)				(-1.55)
Year × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inventor × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518

Table 7
National AI-Related Policy and Composition of Cross Country Citations

This table reports coefficients from inventor-panel OLS regressions of inventors' fraction of cross country citations on an indicator for national AI-related policies, inventor-by-cohort fixed effects, and year-by-cohort fixed effects. The AI policy indicator is set to 1 if the country has implemented national AI-related policies, while other indicators reflect the implementation of specific categories of AI policies such as governance, guidance & regulation, financial support, and AI enablers & other incentives. The dependent variables are percentage of cross country forward citations and backward citations. The data include inventor-year observations in the 5 years prior and up to 10 years following the implementation of national AI-related policies in each country from 2006 to 2019. For all regressions, the robust standard errors are clustered at the country level, and t-statistics are illustrated in parentheses.***,**,* represent the significance level at 1%, 5% and 10% ,respectively.

	Cross Country bcites.%					Cross Country fcites.%				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
DID(AI Policy)	4.166**					4.973**				
	(2.60)					(2.18)				
DID(Governance)		1.088					2.570**			
		(1.53)					(2.21)			
DID(Financial Support)			4.264**					5.103**		
			(2.62)					(2.27)		
DID(Guidance and Regulation)				1.237*					3.693***	
				(1.73)					(3.51)	
DID(AI Enablers and Other Incentives)					5.004**					4.977*
					(2.53)					(1.95)
Year × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inventor × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	4,208,397	4,208,397	4,208,397	4,208,397	4,208,397	3,322,203	3,322,203	3,322,203	3,322,203	3,322,203
R^2	0.77	0.77	0.77	0.77	0.77	0.65	0.65	0.65	0.65	0.65

Table 8
National AI-Related Policy and Uniqueness of AI Innovation

This table reports coefficients from inventor-panel Poisson regressions of the number of similar AI patents filed in the same year on an indicator for national AI-related policies, inventor-by-cohort fixed effects, and year-by-cohort fixed effects. The AI policy indicator is set to 1 if the country has implemented national AI-related policies, while other indicators reflect the implementation of specific categories of AI policies such as governance, guidance & regulation, financial support, and AI enablers & other incentives. The dependent variable is the number of similar AI patent filings in the given year. The data include inventor-year observations in the 5 years prior and up to 10 years following the implementation of national AI-related policies in each country from 2006 to 2019. For all regressions, the robust standard errors are clustered at the country level, and t-statistics are illustrated in parentheses.***,**,* represent the significance level at 1%, 5% and 10% ,respectively.

	Similar AI Patent Counts				
	(1)	(2)	(3)	(4)	(5)
DID(AI Policy)	-0.137**				
	(-2.37)				
DID(Governance)		0.009			
		(0.55)			
DID(Financial Support)			-0.136**		
			(-2.39)		
DID(Guidance and Regulation)				-0.104***	
				(-2.97)	
DID(AI Enablers and Other Incentives)					-0.210***
					(-2.76)
Year × Cohort FE	Yes	Yes	Yes	Yes	Yes
Inventor × Cohort FE	Yes	Yes	Yes	Yes	Yes
Obs.	5,431,158	5,431,158	5,431,158	5,431,158	5,431,158

Table 9
National AI-Related Policy and New Co-authorship of AI Innovation

This table reports coefficients from inventor-panel Poisson regressions of the number of similar AI patent filed in the same year on an indicator for national AI-related policies, inventor-by-cohort fixed effects, and year-by-cohort fixed effects. The AI policy indicator is set to 1 if the country has implemented national AI-related policies, while other indicators reflect the implementation of specific categories of AI policies such as governance, guidance & regulation, financial support, and AI enablers & other incentives. The dependent variable is the number of new coauthor of the inventor in the given year. The data include inventor-year observations in the 5 years prior and up to 10 years following the implementation of national AI-related policies in each country from 2006 to 2019. For all regressions, the robust standard errors are clustered at the country level, and t-statistics are illustrated in parentheses.***,**,* represent the significance level at 1%, 5% and 10% ,respectively.

	New Coauth. Count				
	(1)	(2)	(3)	(4)	(5)
DID(AI Policy)	-0.039				
	(-0.60)				
DID(Governance)		0.040			
		(0.84)			
DID(Financial Support)			-0.114		
			(-1.52)		
DID(Guidance and Regulation)				-0.218***	
				(-3.37)	
DID(AI Enablers and Other Incentives)					-0.039
					(-0.59)
Year × Cohort FE	Yes	Yes	Yes	Yes	Yes
Inventor × Cohort FE	Yes	Yes	Yes	Yes	Yes
Obs.	5,328,664	5,328,664	5,328,664	5,328,664	5,328,664

Table 10
National AI-Related Policy and Domains of AI Innovation

This table reports coefficients from Poisson regressions of the inventor-panel of the number of AI patent filings/applications domains on an indicator for national AI-related policies, inventor-by-cohort fixed effects, and year-by-cohort fixed effects. The AI policy indicator is set to 1 if the country has implemented national AI-related policies, while other indicators reflect the implementation of specific categories of AI policies such as governance, guidance & regulation, financial support, and AI enablers & other incentives. The dependent variables are inventor's number of AI patent domains and AI patent HHI. The data include inventor-year observations in the 5 years prior and up to 10 years following the implementation of national AI-related policies in each country from 2006 to 2019. For all regressions, robust standard errors are clustered at the country level, and t-statistics are illustrated in parentheses.***,**,* represent the significance level at 1%, 5% and 10% ,respectively.

	Inventor AI Domains					Inventor AI Domains HHI				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
DID(AI Policy)	-0.044**					0.018***				
	(-2.55)					(2.77)				
DID(Governance)		-0.006					0.003			
		(-0.63)					(0.88)			
DID(Financial Support)			-0.047**					0.020**		
			(-2.33)					(2.43)		
DID(Guidance and Regulation)				-0.063***					0.027***	
				(-3.92)					(4.10)	
DID(AI Enablers and Other Incentives)					-0.072***					0.029***
					(-3.01)					(3.07)
Year × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inventor × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518
R^2						0.49	0.49	0.49	0.49	0.49

Table 11
National AI-Related Policy and High-Impact AI Patent

This table reports coefficients from inventor-panel Poisson regressions of the number of High-Impact AI Patent in the filing year on an indicator for national AI-related policies, inventor-by-cohort fixed effects, and year-by-cohort fixed effects. The AI policy indicator is set to 1 if the country has implemented national AI-related policies, while other indicators reflect the implementation of specific categories of AI policies such as governance, guidance & regulation, financial support, and AI enablers & other incentives. The dependent variable is the number of high-impact AI patents in a given year, defined as those ranking in the top 1%. The data include inventor-year observations in the 5 years prior and up to 10 years following the implementation of national AI-related policies in each country from 2006 to 2019. For all regressions, the robust standard errors are clustered at the country level, and t-statistics are illustrated in parentheses.***,**,* represent the significance level at 1%, 5% and 10% ,respectively.

	High-Impact AI Patent Count (Top 1%)				
	(1)	(2)	(3)	(4)	(5)
DID(AI Policy)	-0.182				
	(-0.58)				
DID(Governance)		0.224*			
		(1.65)			
DID(Financial Support)			-0.359		
			(-1.13)		
DID(Guidance and Regulation)				-0.409**	
				(-2.08)	
DID(AI Enablers and Other Incentives)					-0.072
					(-0.27)
Year × Cohort FE	Yes	Yes	Yes	Yes	Yes
Inventor × Cohort FE	Yes	Yes	Yes	Yes	Yes
Obs.	331,951	331,951	331,951	331,951	331,951

Table 12
Patent-level Novelty Analysis

This table presents the patent-level novelty analysis. Panel A reports the correlation between patent novelty, low-impact AI patents (Fcites = 0), AI patent Fcites, and development duration. Panel B and Panel C examine the correlation between patent novelty and the likelihood of being a high-impact (low-impact or Mid-impact) AI patent. The independent variable is AI patent novelty, calculated as 100− the number of similar AI patent filings relative to the focal AI patent in the given year. The dependent variables are high-impact AI patents, mid-impact AI patents, low-impact AI patents, Fcites, and ln(Development Duration). High-impact (Mid-impact or Low-impact) AI patent is a dummy variable equal to 1 if the patent falls within the high (mid or low) threshold for its filing year, and 0 otherwise. Patent development duration is defined as the number of days between the last filing date of backward citations and the filing date of the focal AI patent. All regressions include IPC4 fixed effects, country fixed effects, and year fixed effects. Robust standard errors are clustered at the IPC4 level, and t-statistics are illustrated in parentheses.***, **, * represent the significance level at 1%, 5% and 10% ,respectively. The sample period is from 2006 to 2019.

Panel A

	Low-Impact AI Patent (Fcites = 0)	AI Patent Fcites	ln(Patent Development Duration)
	(1)	(2)	(3)
Patent Novelty	0.007***	-0.005**	0.044***
	(9.59)	(-2.18)	(38.85)
IPC4 FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs.	3,082,859	3,082,772	2,047,860
R^2	0.07		0.10

Panel B

	High-Impact AI Patent (Top 10%)	Low-Impact AI Patent (Bottom 10%)	Mid-Impact AI Patent (10% - 90% Range)
	(1)	(2)	(3)
Patent Novelty	-0.001***	0.007***	-0.006***
	(-6.64)	(9.59)	(-8.39)
IPC4 FE	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs.	3,082,859	3,082,859	3,082,859
R^2	0.04	0.07	0.05

Panel C

	High-Impact AI Patent (Top 0.05%)	High-Impact AI Patent (Top 0.1%)	High-Impact AI Patent (Top 0.5%)	High-Impact AI Patent (Top 1%)
	(1)	(2)	(3)	(4)
Patent Novelty	0.002**	0.004***	0.005*	0.006
	(2.55)	(3.45)	(1.66)	(1.34)
IPC4 FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs.	3,082,859	3,082,859	3,082,859	3,082,859
R^2	0.00	0.01	0.00	0.01

Appendix A. Additional Tables and Figures

Table A1
Examples of National AI Strategies and Policies

This table shows examples of national AI-related strategies and policies with the policy name, country, start year and description.

Policy Name	Country	Start Year	Description
NATIONAL AI R&D STRATEGIC PLAN	United States	2016	The purpose of this Plan is to convey a clear set of R&D priorities that address strategic research goals, focus Federal investments on those areas in which industry is unlikely to invest, and address the need to expand and sustain the pipeline of AI R&D talent.
EXECUTIVE ORDER ON MAINTAINING AMERICAN LEADERSHIP IN AI	United States	2019	This order seeks to spark significant advancements in AI within the federal government, industry, and academia to boost scientific research, economic growth, and national security. It strives to set technical standards, simplify the process for AI testing and deployment, and support the growth of new AI-focused industries and the broader adoption of AI in existing sectors.
AI RESEARCH PROGRAMME	Singapore	2018	AI Research Programme seeds high quality research efforts aimed at developing fundamental AI novel techniques, algorithms and adjacent technologies that will eventually significantly contribute to the other pillars of AI Singapore. The AI Singapore Research Programme will also encourage national research collaborations and nurture local AI talents.
HIGH PERFORMANCE COMPUTING INFRASTRUCTURE PROJECT	Japan	2012	Supercomputer "Fugaku" as a central core, construct high-speed network among universities and public research sectors for various uses to create outstanding results in various fields such as AI, data science, medicine, climate, space, disaster defense.
NATIONAL NEW GENERATION AI PLAN	China	2017	The Plan involves initiatives and goals for R&D, industrialization, talent development, education and skills acquisition, standard setting and regulations, ethical norms, and security. To make China's AI industry "in-line" with competitors by 2020. To reach "world-leading" in some AI fields by 2025. To become the "primary" center for AI innovation by 2030. By 2030, the Chinese government aims to cultivate an AI industry worth RMB 1 trillion (EUR 130 billion), with related industries worth RMB 10 trillion (EUR 1300 billion) . In addition, the Chinese government has also partnered with national tech companies to develop research and industrial leadership in specific fields of AI and will build a USD 2.1 billion (EUR 1.8 billion) technology park for AI research in Beijing.
PAN-CANADIAN AI STRATEGY	Canada	2017	The Government of Canada is providing the Canadian Institute for Advanced Research (CIFAR) with a contribution of $125 million (in Canadian dollars) to launch a Pan-Canadian Artificial Intelligence Strategy to retain and attract top academic talent, and to increase the number of post-graduate trainees and researchers studying AI. Strategy focused on investments in talent, research capacity, commercialization and standardization of (generative) AI.

Table A2
Variable Definitions

Table A2 outlines the definitions and sources of all variables used in our study. It includes variables about national AI-related policies and inventors' AI innovation.

Variable Name	Abbrev.	Description
Innovation Variables (Source: Google Patents Public Data and AIPD)		
AI Patent Counts		Number of AI patent in a given year
AI Patent Forward Citations	Fcites	Number of Forward citations of AI patent in a given year with null value replaced by zero in a given year
AI Patent Backward Citations	Bcites	Number of backward citations of AI patent in a given year with null value replaced by zero
Average AI Patent forward citations	Avg Fcites	Number of forward citations of AI patent in a given year divided by Number of AI patent
Average AI Patent Backward Citations	Avg Bcites	Number of backward citations of AI patent in a given year divided by Number of AI patent
Cross Country Fcites(%)		External forward citation is divided by total forward citations in a given year. a forward citation is classified as external if the country of the lead inventor of the citing filing does not match that of the cited filing.
Cross Country bcites(%)		External backward citation is divided by total backward citations in a given year. a backward citation is classified as external if the country of the lead inventor of the citing filing does not match that of the cited filing.
New Coauth. Count		The number of new coauthor for the inventor in a given year with null value replaced by zero
Similar AI Patent Counts		The number of similar AI patents filed in the same year as the AI patent with null value replaced by zero
Inventor AI Domains		The number of distinct AI Patent domain of AI patents in a given year
Inventor AI Domains HHI		Squaring the share of AI patents in each AI domain for an individual inventor, and then summing these squared shares
National AI-related Stratgies & Policies Variables (Source: OECD AI)		
National AI policies i.e."DID(AI Policy)"		The treat-post dummy variable assigning a value of 1 during the periods they are implemented and 0 otherwise.
Governance i.e."DID(Governance)"		The treat-post dummy variable assigning a value of 1 during the periods they are implemented policy focus on governance and 0 otherwise.
Financial Support) i.e."DID(Financial Support))"		The treat-post dummy variable assigning a value of 1 during the periods they are implemented policy focus on financial support and 0 otherwise.
(Guidance and Regulation i.e."DID((Guidance and Regulation)"		The treat-post dummy variable assigning a value of 1 during the periods they are implemented policy focus on guidance and Regulation and 0 otherwise.
AI Enablers and Other Incentives i.e."DID(AI Enablers and Other Incentives)"		The treat-post dummy variable assigning a value of 1 during the periods they are implemented policy focus on AI enablers and other incentives and 0 otherwise.

Table A3
Pretrend Analysis

This table presents the pretrend analysis for our tests. All specifications follow the main table but the treatment is separated by the timing of treatment from $\leq t-3$ to $\geq t+3$.

Panel A

	AI Patent Counts	AI Patent Fcites	Avg AI Fcites	AI Patent Bcites	Avg AI Bcites
	(1)	(2)	(3)	(4)	(5)
t-3	0.005	0.005	0.040	0.008	0.014
	(0.19)	(0.08)	(0.75)	(0.21)	(0.88)
t-2	-0.002	0.040	0.048*	0.019	0.022*
	(-0.24)	(1.39)	(1.82)	(1.03)	(1.84)
t	-0.016	-0.099	-0.105	-0.016	-0.002
	(-1.36)	(-1.26)	(-1.58)	(-0.90)	(-0.14)
t+1	-0.054*	-0.282	-0.227	-0.035	-0.015
	(-1.81)	(-1.50)	(-1.47)	(-1.20)	(-0.79)
t+2	-0.088*	-0.466*	-0.356	-0.067	-0.027
	(-1.76)	(-1.68)	(-1.63)	(-1.18)	(-1.35)
t+3	-0.154***	-0.641**	-0.485**	-0.184**	-0.082**
	(-2.88)	(-2.16)	(-2.17)	(-2.37)	(-2.56)
Year × Cohort FE	Yes	Yes	Yes	Yes	Yes
Inventor × Cohort FE	Yes	Yes	Yes	Yes	Yes
Obs.	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518

Panel B

	Cross Country bcites.%	Cross Country fcites.%	New Coauth. Count	Similar AI Patent Counts	Inventor AI Domains	Inventor AI Domains HHI
	(1)	(2)	(3)	(4)	(5)	(6)
t-3	-1.240**	-1.771**	0.080**	0.042	0.003	-0.001
	(-2.09)	(-2.06)	(2.09)	(0.97)	(0.22)	(-0.24)
t-2	-0.897***	-0.452	0.045*	0.034**	0.003	-0.001
	(-2.71)	(-0.65)	(1.89)	(2.19)	(0.58)	(-0.54)
t	0.950	1.542	0.039	-0.027	-0.009	0.005
	(0.94)	(1.38)	(1.41)	(-0.92)	(-1.15)	(1.56)
t+1	2.421	4.351*	0.003	-0.093	-0.033*	0.013**
	(1.55)	(1.86)	(0.05)	(-1.45)	(-1.93)	(2.09)
t+2	4.653**	5.975*	-0.003	-0.155	-0.050*	0.020*
	(2.27)	(1.96)	(-0.03)	(-1.63)	(-1.72)	(1.80)
t+3	8.143***	8.782***	-0.128	-0.249***	-0.087**	0.035**
	(3.32)	(2.70)	(-1.07)	(-2.62)	(-2.57)	(2.63)
Year × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Inventor × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	4,208,397	3,322,203	5,328,664	5,431,158	5,573,518	5,573,518
R^2	0.77	0.65				0.49

Figure A1
Timeline of USA's Initiatives and Policy Events Related to AI

This figure A1 shows the timeline of the U.S. initiatives and policy events related to AI from 2011 to 2019.

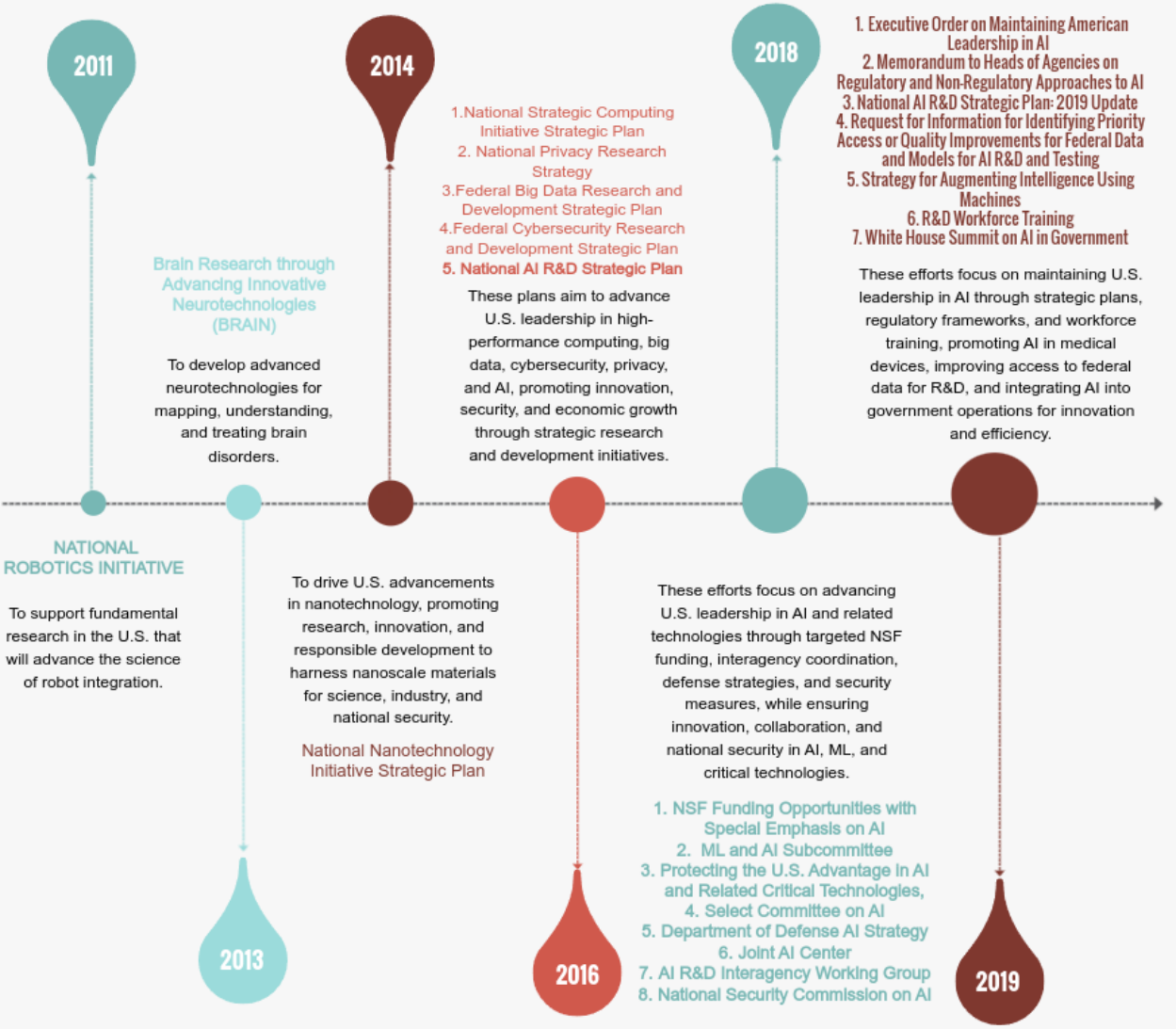


Table A4
National AI-Related Policy's ln(1+Budget) and AI Innovation

This table reports coefficients from inventor-panel Poisson regressions of inventors' AI innovation on budgets for national AI-related policies, inventor-by-cohort fixed effects, and year-by-cohort fixed effects. Panel A's total budget is ln(1+ Total Budgets) for the policy of the country, while Panel B and C's budget reflects ln(1+budget) of specific categories of AI policies such as governance, guidance & regulation, financial support, and AI enablers & other incentives. The dependent variables are AI patent filings counts, forward citations, backward citations, average forward citations and average backward citations. The data include inventor-year observations in the 5 years prior and up to 10 years following the implementation of national AI-related policies in each country from 2006 to 2019. For all regressions, the robust standard errors are clustered at the country level, and t-statistics are illustrated in parentheses.***,**,* represent the significance level at 1%, 5% and 10% ,respectively.

Panel A

	AI Patent Counts	AI Patent Fcites	Avg AI Fcites	AI Patent Bcites	Avg AI Bcites
	(1)	(2)	(3)	(4)	(5)
ln(1+Total Budget)	-0.010**	-0.053	-0.047*	-0.009*	-0.006*
	(-2.46)	(-1.61)	(-1.86)	(-1.72)	(-1.72)
Year × Cohort FE	Yes	Yes	Yes	Yes	Yes
Inventor × Cohort FE	Yes	Yes	Yes	Yes	Yes
Obs.	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518

Panel B

	AI Patent Counts				AI Patent Fcites				Avg AI Fcites			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ln(1+Governance)	0.001				0.008				-0.009			
	(0.14)				(0.59)				(-0.84)			
ln(1+Financial Support)		-0.023***				-0.101*				-0.082*		
		(-2.66)				(-1.85)				(-1.94)		
ln(1+Guidance and Regulation)			-0.026***				-0.071***				-0.066***	
			(-3.63)				(-3.18)				(-3.09)	
ln(1+AI Enbalers and Other Incentives)				-0.033***				-0.089				-0.046
				(-3.40)				(-1.63)				(-1.09)
Year × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inventor × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518

Panel C

	AI Patent Bcites				Avg AI Bcites			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(1+Governance)	0.003				-0.002			
	(0.47)				(-0.73)			
ln(1+Financial Support)		-0.026**				-0.009**		
		(-2.51)				(-2.20)		
ln(1+Guidance and Regulation)			-0.020**				0.001	
			(-2.47)				(0.26)	
ln(1+AI Enbalers and Other Incentives)				-0.032**				-0.009*
				(-2.39)				(-1.75)
Year × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inventor × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518

Table A5
National AI-Related Policy Indicator and AI Innovation (OLS)

This table reports coefficients from inventor-panel OLS regressions of inventor's AI innovation on an indicator for national AI-related policies, inventor-by-cohort fixed effects, and year-by-cohort fixed effects. Panel A's indicator is set to 1 if the country has implemented national AI-related policies, while Panel B and C's indicator reflects the implementation of specific categories of AI policies such as governance, guidance & regulation, financial support, and AI enablers & other incentives. The dependent variables are ln(AI patent filings counts), ln(forward citations), ln(backward citations), ln(average forward citations) and ln(average backward citations). The data include inventor-year observations in the 5 years prior and up to 10 years following the implementation of national AI-related policies in each country from 2006 to 2019. For all regressions, the robust standard errors are clustered at the country level, and t-statistics are illustrated in parentheses.***,**,* represent the significance level at 1%, 5% and 10% ,respectively.

Panel A

	ln(AI Patent Counts)	ln(AI Patent Fcites)	ln(Avg AI Fcites)	ln(AI Patent Bcites)	ln(Avg AI Patent Bcites)
	(1)	(2)	(3)	(4)	(5)
DID(AI Policy)	-0.056***	-0.372**	-0.311**	-0.145***	-0.084***
	(-3.04)	(-2.20)	(-2.21)	(-3.81)	(-4.33)
Year × Cohort FE	Yes	Yes	Yes	Yes	Yes
Inventor × Cohort FE	Yes	Yes	Yes	Yes	Yes
Obs.	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518
R^2	0.54	0.57	0.56	0.63	0.63

Panel B

	ln(AI Patent Counts)				ln(AI Patent Fcites)				ln(Avg AI Fcites)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
DID(Governance)	-0.018				-0.121*				-0.116**			
	(-1.04)				(-1.97)				(-2.36)			
DID(Financial Support)		-0.061**				-0.351**				-0.285**		
		(-2.64)				(-2.09)				(-2.06)		
DID(Guidance and Regulation)			-0.090***				-0.228***				-0.157**	
			(-4.09)				(-3.42)				(-2.45)	
DID(AI Enablers and Other Incentives)				-0.092***				-0.285				-0.188
				(-3.31)				(-1.51)				(-1.25)
Year × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inventor × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518
R^2	0.54	0.54	0.54	0.54	0.57	0.57	0.57	0.57	0.56	0.56	0.56	0.56

Panel C

	ln(AI Patent Bcites)				ln(Avg AI Patent Bcites)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DID(Governance)	-0.052				-0.040			
	(-1.00)				(-1.03)			
DID(Financial Support)		-0.141***				-0.076***		
		(-3.37)				(-3.96)		
DID(Guidance and Regulation)			-0.060				0.018	
			(-1.32)				(0.56)	
DID(AI Enablers and Other Incentives)				-0.195***				-0.100***
				(-3.71)				(-3.47)
Year × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inventor × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518
R^2	0.63	0.63	0.63	0.63	0.63	0.63	0.63	0.63

Table A6
National AI-Related Policy Budget and AI Innovation (Poisson Regressions Controlling GDP)

This table reports coefficients from inventor-panel Poisson regressions of inventors' AI innovation on an indicator for national AI-related policies, inventor-by-cohort fixed effects, and year-by-cohort fixed effects. The indicator of AI policy is set to 1 if the country has implemented national AI-related policies. The dependent variables are AI patent filings counts, forward citations, backward citations, average forward citations and average backward citations. The data include inventor-year observations in the 5 years prior and up to 10 years following the implementation of national AI-related policies in each country from 2006 to 2019. For all regressions, we include control variables ln(GDP per Capita) and GDP Growth. The robust standard errors are clustered at the country level, and t-statistics are illustrated in parentheses.***,**,* represent the significance level at 1%, 5% and 10% ,respectively.

	AI Patent Counts	AI Patent Fcites	Avg AI Fcites	AI Patent Bcites	Avg AI Bcites
	(1)	(2)	(3)	(4)	(5)
DID(AI Policy)	-0.049**	-0.156*	-0.157**	-0.058**	-0.040**
	(-2.29)	(-1.88)	(-2.22)	(-2.04)	(-2.06)
ln(GDP per capita)	0.967***	4.008***	2.986***	1.372**	-0.037
	(4.53)	(6.30)	(4.68)	(2.47)	(-0.23)
Year × Cohort FE	Yes	Yes	Yes	Yes	Yes
Inventor × Cohort FE	Yes	Yes	Yes	Yes	Yes
Obs.	5,573,518	5,573,518	5,573,518	5,573,518	5,573,518

Table A7
National AI-Related Policy Indicator and AI Innovation (Country Level)

This table reports the impact of AI policy on AI innovation at country level and pretrend analysis. The Panel A reports coefficients from country-panel Poisson regressions of countries' AI innovation on an indicator for national AI-related policies, inventor-by-cohort fixed effects, and year-by-cohort fixed effects. The dependent variables are AI patent filings counts, forward citations, and backward citations. The data include country-year observations in the 5 years prior and up to 10 years following the implementation of national AI-related policies in each country from 2006 to 2019. The Panel B presents the pretrend analysis for our tests. All specifications follow the main table but the treatment is separated by the timing of treatment from $\leq t-3$ to $\geq t+3$. The robust standard errors are clustered at the country level, and t-statistics are illustrated in parentheses.***,**,* represent the significance level at 1%, 5% and 10% ,respectively.

Panel A — Impact of AI Policy on AI Innovation

	AI Patent Counts	AI Patent Fcites	AI Patent Bcites
	(1)	(2)	(3)
DID(AI Policy)	-0.244**	-0.366*	-0.405***
	(-2.26)	(-1.79)	(-3.91)
Year × Cohort FE	Yes	Yes	Yes
Country × Cohort FE	Yes	Yes	Yes
Obs.	3,213	3,213	3,213

Panel B — Pretrend Analysis

	AI Patent Counts	AI Patent Fcites	AI Patent Bcites
	(1)	(2)	(3)
t-3	0.084*	0.046	0.062
	(1.69)	(0.51)	(1.03)
t-2	0.069***	0.051	0.066**
	(3.07)	(1.15)	(2.22)
t	-0.056	-0.103	-0.165***
	(-1.11)	(-1.14)	(-2.95)
t+1	-0.165*	-0.311*	-0.294***
	(-1.65)	(-1.92)	(-2.97)
t+2	-0.283*	-0.438*	-0.376***
	(-1.95)	(-1.85)	(-2.88)
t+3	-0.337**	-0.510*	-0.621***
	(-2.30)	(-1.90)	(-4.10)
Year × Cohort FE	Yes	Yes	Yes
country × Cohort FE	Yes	Yes	Yes
Obs.	3,213	3,213	3,213

Table A8
F-test based on Similar Patent Filings

This table presents the variance of forward citations among groups of AI patent filings, classified by the number of similar patent filings relative to a focal AI patent filing in the same year from Panel A. The Panel B reports F-tests to compare the differences between these groups.

Panel A	Variance (Fcites)	Sample Size
Similar Patent Filing Count = 0 (Group 1)	2145.70	1,044,067
Similar Patent Filing Count = 1 (Group 2)	1142.16	1,262,280
Similar Patent Filing Count = 2 (Group 3)	701.01	1,048,379
Similar Patent Filing Count = 3 (Group 4)	601.45	735,471
Similar Patent Filing Count > 3 (Group 5)	501.10	1,254,127

Panel B	F-statistic	P-value	Larger Variance Group
F-test (Group 1 vs Group 2)	1.88	0.00	Group 1
F-test (Group 1 vs Group 3)	3.06	0.00	Group 1
F-test (Group 1 vs Group 4)	3.57	0.00	Group 1
F-test (Group 1 vs Non-Group 1)	2.84	0.00	Group 1

Table A9
National AI-Related Policy and High Productivity Inventors' AI Innovation

This table reports coefficients from inventor-panel Poisson regressions of inventors' AI innovation on an interaction terms of high productivity inventor indicator and national AI-related policies indicator, inventor-by-cohort fixed effects, and year-by-cohort fixed effects. Inventors are classified annually as high-productivity based on their AI patent filings (Panel A) and forward citations (Panel B) over the previous five years. The high productivity inventor indicator is set to 1 if the inventors rank in the top 10% within their countries. The national AI-related policies indicator is set to 1 if the country has implemented national AI-related policies, while other policy indicators reflect the implementation of specific categories of AI policies such as governance, guidance & regulation, financial support, and AI enablers & other incentives. The dependent variables are AI patent filing counts, forward citations, backward citations, average forward citations, and average backward citations. The data include inventor-year observations in the 5 years prior and up to 10 years following the implementation of national AI-related policies in each country from 2006 to 2019. For all regressions, robust standard errors are clustered at the country level, and t-statistics are illustrated in parentheses.***,**,* represent the significance level at 1%, 5% and 10% ,respectively.

Panel A — High Productivity Inventor Based on AI Patent Filing Counts

	AI Patent Counts					AI Patent Fcites					Avg AI Fcites					AI Patent Bcites					Avg AI Bcites				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)
DID(AI Policy)	0.025					-0.359					-0.313					-0.002					-0.059				
	(1.09)					(-1.59)					(-1.61)					(-0.07)					(-2.68)				
High Productivity Inventors (Prior 5-Year AI Count)	0.541***	0.536***	0.545***	0.530***	0.528***	0.482***	0.492***	0.512***	0.510***	0.511***	0.027	0.035	0.031	0.032	0.030	0.439	***0.441	***0.479	***0.451	***0.420	***0.029	***0.034	***0.031	***0.037	***0.039	***
	(14.50)	(14.15)	(13.68)	(13.08)	(13.02)	(9.79)	(8.64)	(8.12)	(7.78)	(9.00)	(0.82)	(0.85)	(0.89)	(0.85)	(0.92)	(1.49)	(9.11)	(9.24)	(8.25)	(6.42)	(3.84)	(5.40)	(3.61)	(5.39)	(5.88)	
DID(AI Policy)× High Productivity Inventors	-0.110***					0.080*					-0.035					-0.120	***				0.023	***				
	(-4.50)					(1.78)					(-1.17)					(-3.21)					(3.63)					
DID(Governance)		0.058**					-0.045					-0.020					0.051	*				-0.034	**			
		(2.30)					(-0.54)					(-0.21)					(1.92)					(-2.19)				
DID(Governance) ×High Productivity Inventors		-0.126***					0.181***					-0.021					-0.118	***				0.023	***			
		(-2.89)					(5.71)					(-0.54)					(-2.61)					(3.63)				
DID(Financial Support)			0.011					-0.348*					-0.345*					0.000					-0.052	***		
			(1.45)					(-1.71)					(-1.75)					(0.01)					(-2.71)			
DID(Financial Support)×High Productivity Inventors			-0.186***					-0.038					-0.047					-0.191	***				0.024	***		
			(-5.20)					(-0.55)					(-1.01)					(-5.05)					(3.06)			
DID(Guidance and Regulation)				-0.014					-0.309***					-0.235***					0.002					0.011		
				(-0.40)					(-3.31)					(-2.76)					(0.07)					(0.64)		
DID(Guidance and Regulation)×High Productivity Inventors				-0.231***					0.064					-0.008					-0.207	***				0.018	***	
				(-5.97)					(0.93)					(-0.20)					(-5.12)					(3.63)		
DID(AI Enablers and Other Incentives)					0.003					-0.309					-0.240					-0.020					-0.025	
					(0.09)					(-1.35)					(-1.10)					(-0.38)					(-0.94)	
DID(AI Enablers and Other Incentives)×High Productivity Inventors					-0.224***					-0.088***					-0.069	***				-0.151	**				0.026	**
					(-3.97)					(-2.91)					(-3.06)					(-2.28)					(2.17)	
Year × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Inventor × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Obs.	6,236,255	6,236,255	6,236,255	6,236,255	6,236,255	5,551,851	5,551,851	5,551,851	5,551,851	5,551,851	5,551,851	5,551,851	5,551,851	5,551,851	5,551,851	5,969,233	5,969,233	5,969,233	5,969,233	5,969,233	5,969,233	5,969,233	5,969,233	5,969,233	5,969,233

Panel B — High Productivity Inventor Based on AI Patent Filing Fcites

	AI Patent Counts					AI Patent Fcites					Avg AI Fcites					AI Patent Bcites					Avg AI Bcites				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)
DID(AI Policy)	-0.007					-0.141					-0.135					-0.030					-0.046	**			
	(-0.46)					(-0.80)					(-0.95)					(-1.05)					(-2.09)				
High Productivity Inventors (Prior 5-Year AI CITES)	0.321***	0.311***	0.317**	0.299***	0.299***	0.873***	0.846***	0.866**	0.835**	0.828***	0.607***	0.589***	0.578***	0.561***	0.559	***0.225	***0.304	***0.339	***0.309	***0.286	***0.097	***0.098	***0.095	**0.097	***0.091	***
	(5.15)	(5.01)	(5.71)	(5.22)	(5.14)	(5.39)	(4.80)	(5.52)	(4.98)	(4.88)	(5.58)	(5.02)	(6.13)	(5.58)	(5.56)	(7.41)	(6.55)	(6.32)	(6.01)	(4.92)	(7.90)	(8.56)	(7.80)	(8.66)	(15.09)	
DID(AI Policy)×High Productivity Inventors	-0.135***					-0.289***					-0.309**					-0.107	***				-0.016	*				
	(-6.82)					(-4.71)					(-2.47)					(-5.17)					(-1.88)					
DID(Governance)		0.028					0.188*					0.143					0.022					-0.020				
		(1.06)					(1.90)					(1.26)					(0.71)					(-1.28)				
DID(Governance)×High Productivity Inventors		-0.136***					-0.243***					-0.370***					-0.090	***				-0.024	**			
		(-8.21)					(-6.14)					(-3.74)					(-4.16)					(-2.00)				
DID(Financial Support)			-0.008					-0.157					-0.218					-0.033					-0.040	**		
			(-0.37)					(-0.94)					(-1.26)					(-1.35)					(-2.08)			
DID(Financial Support)×High Productivity Inventors			-0.198**					-0.358***					-0.247**					-0.158	***				-0.013			
			(-4.13)					(-2.60)					(-2.43)					(-3.44)					(-1.44)			
DID(Guidance and Regulation)				-0.056					-0.089					-0.098					-0.039					0.024		
				(-1.64)					(-0.79)					(-1.02)					(-1.19)					(1.48)		
DID(Guidance and Regulation)×High Productivity Inventors				-0.207***					-0.346***					-0.297***					-0.143	***				-0.026	***	
				(-4.84)					(-2.80)					(-3.54)					(-3.76)					(-2.58)		
DID(AI Enablers and Other Incentives)					-0.051**					-0.103					-0.057					-0.060					-0.013	
					(-2.08)					(-0.51)					(-0.29)					(-1.39)					(-0.55)	
DID(AI Enablers and Other Incentives)×High Productivity Inventors					-0.208***					-0.386***					-0.380	***				-0.096	*				-0.010	
					(-4.66)					(-3.97)					(-7.09)					(-1.87)					(-0.78)	
Year × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Inventor × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Obs.	6,236,255	6,236,255	6,236,255	6,236,255	6,236,255	5,551,851	5,551,851	5,551,851	5,551,851	5,551,851	5,551,851	5,551,851	5,551,851	5,551,851	5,551,851	5,969,233	5,969,233	5,969,233	5,969,233	5,969,233	5,969,233	5,969,233	5,969,233	5,969,233	5,969,233

Table A10
National AI-Related Policy and High Productivity Inventors' Cross Country Citations

This table reports coefficients from inventor-panel OLS regressions of inventors' percentage of cross country citations on an interaction terms of high productivity inventor indicator and national AI-related policies indicator, inventor-by-cohort fixed effects, and year-by-cohort fixed effects. Inventors are classified annually as high-productivity based on their AI patent filings/applications (Panel A) and forward citations (Panel B) over the previous five years. The high productivity inventor indicator is set to 1 if the inventors ranked in the top 10% within their countries. The national AI-related policies indicator is set to 1 if the country has implemented national AI-related policies, while other policy indicators reflect the implementation of specific categories of AI policies such as governance, guidance & regulation, financial support, and AI enablers & other incentives. The dependent variables are percentage of cross country backward citations and percentage of cross country forward citations. The data include inventor-year observations in the 5 years prior and up to 10 years following the implementation of national AI-related policies in each country from 2006 to 2019. For all regressions, the robust standard errors are clustered at the country level, and t-statistics are illustrated in parentheses.***,**,* represent the significance level at 1%, 5% and 10% ,respectively.

Panel A — High Productivity Inventor Based on AI Patent Filing Counts

	Cross Country bcites.%					Cross Country fcites.%				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
DID(AI Policy)	3.926**					5.181**				
	(2.34)					(2.33)				
High Productivity Inventors (Prior 5-Year AI Count)	0.528	0.326	0.499	0.365	0.453	0.647	0.474	0.391	0.306	0.509
	(1.30)	(0.96)	(1.37)	(1.08)	(1.23)	(1.24)	(0.81)	(0.66)	(0.51)	(0.93)
DID(AI Policy)×High Productivity Inventors	0.056					-0.452				
	(0.29)					(-0.84)				
DID(Governance)		0.735					2.967**			
		(1.17)					(2.29)			
DID(Governance)×High Productivity Inventors		0.288*					-0.642			
		(1.85)					(-1.49)			
DID(Financial Support)			4.089**					5.149**		
			(2.50)					(2.48)		
DID(Financial Support)×High Productivity Inventors			0.001					0.278		
			(0.00)					(0.44)		
DID(Guidance and Regulation)				1.016					3.788***	
				(1.35)					(3.29)	
DID(Guidance and Regulation)×High Productivity Inventors				0.228					0.301	
				(1.48)					(0.63)	
DID(AI Enablers and Other Incentives)					4.400**					5.428**
					(2.25)					(2.22)
DID(AI Enablers and Other Incentives)×High Productivity Inventors					0.254					-1.125***
					(0.85)					(-3.59)
Year × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inventor × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	4,623,847	4,623,847	4,623,847	4,623,847	4,623,847	3,474,636	3,474,636	3,474,636	3,474,636	3,474,636
R^2	0.77	0.77	0.77	0.77	0.77	0.65	0.65	0.65	0.65	0.65

Panel B — High Productivity Inventor Based on AI Patent Filing Fcites

	Cross Country bcites.%					Cross Country fcites.%				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
DID(AI Policy)	3.724**					5.082**				
	(2.39)					(2.39)				
High Productivity Inventors (Prior 5-Year AI CITES)	-0.721**	-0.807**	-0.699***	-0.712***	-0.616***	-0.077	-0.367	-0.215	-0.402	-0.170
	(-2.51)	(-2.47)	(-2.92)	(-2.81)	(-2.81)	(-0.11)	(-0.50)	(-0.33)	(-0.61)	(-0.27)
DID(AI Policy)×High Productivity Inventors	0.529*					-0.339				
	(1.73)					(-0.55)				
DID(Governance)		0.627					2.662**			
		(0.96)					(2.02)			
DID(Governance)×High Productivity Inventors		0.644					0.266			
		(1.54)					(0.35)			
DID(Financial Support)			3.882**					5.196**		
			(2.55)					(2.50)		
DID(Financial Support)×High Productivity Inventors			0.581**					-0.093		
			(2.25)					(-0.15)		
DID(Guidance and Regulation)				0.918					3.539***	
				(1.33)					(3.03)	
DID(Guidance and Regulation)×High Productivity Inventors				0.519					1.025	
				(1.37)					(1.29)	
DID(AI Enablers and Other Incentives)					4.302**					5.328**
					(2.32)					(2.19)
DID(AI Enablers and Other Incentives)×High Productivity Inventors					0.326					-1.062**
					(1.40)					(-2.30)
Year × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inventor × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	4,623,847	4,623,847	4,623,847	4,623,847	4,623,847	3,474,636	3,474,636	3,474,636	3,474,636	3,474,636
R^2	0.77	0.77	0.77	0.77	0.77	0.65	0.65	0.65	0.65	0.65

Table A11
National AI-Related Policy and the uniqueness of High Productivity Inventors' AI Innovation

This table reports coefficients from inventor-panel Poisson regressions of the number of similar AI patents filed in the same year on an interaction terms of high productivity inventor indicator and national AI-related policies indicator, inventor-by-cohort fixed effects, and year-by-cohort fixed effects. Inventors are classified annually as high-productivity based on their AI patent filings (Panel A) and forward citations (Panel B) over the previous five years. The high productivity inventor indicator is set to 1 if the inventors ranked in the top 10% within their countries. The national AI-related policies indicator is set to 1 if the country has implemented national AI-related policies, while other policy indicators reflect the implementation of specific categories of AI policies such as governance, guidance & regulation, financial support, and AI enablers & other incentives. The dependent variable is the number of similar AI patent filings in the given year. The data include inventor-year observations in the 5 years prior and up to 10 years following the implementation of national AI-related policies in each country from 2006 to 2019. For all regressions, the robust standard errors are clustered at the country level, and t-statistics are illustrated in parentheses.***,**,* represent the significance level at 1%, 5% and 10% ,respectively.

Panel A — High Productivity Inventor Based on AI Patent Filing Counts

	Similar AI Patent Counts				
	(1)	(2)	(3)	(4)	(5)
DID(AI Policy)	-0.023				
	(-0.43)				
High Productivity Inventors (Prior 5-Year AI Count)	0.618***	0.616***	0.624***	0.613***	0.613***
	(15.77)	(15.41)	(14.58)	(14.40)	(15.74)
DID(AI Policy)×High Productivity Inventors	-0.085**				
	(-2.21)				
DID(Governance)		0.088***			
		(4.26)			
DID(Governance)×High Productivity Inventors		-0.093*			
		(-1.81)			
DID(Financial Support)			-0.007		
			(-0.18)		
DID(Financial Support)×High Productivity Inventors			-0.171***		
			(-6.12)		
DID(Guidance and Regulation)				0.015	
				(0.42)	
DID(Guidance and Regulation)×High Productivity Inventors				-0.222***	
				(-6.34)	
DID(AI Enablers and Other Incentives)					-0.050
					(-0.89)
DID(AI Enablers and Other Incentives)×High Productivity Inventors					-0.208***
					(-4.82)
Year × Cohort FE	Yes	Yes	Yes	Yes	Yes
Inventor × Cohort FE	Yes	Yes	Yes	Yes	Yes
Obs.	6,085,710	6,085,710	6,085,710	6,085,710	6,085,710

Panel B — High Productivity Inventor Based on AI Patent Filing Fcites

	Similar AI Patent Counts				
	(1)	(2)	(3)	(4)	(5)
DID(AI Policy)	-0.050				
	(-1.25)				
High Productive Inventors (Prior 5-Year AI CITES)	0.380***	0.371***	0.379***	0.360***	0.361***
	(5.44)	(5.24)	(5.89)	(5.46)	(5.60)
DID(AI Policy)×High Productive Inventors	-0.134***				
	(-4.67)				
DID(Governance)		0.062***			
		(3.00)			
DID(Governance)×High Productive Inventors		-0.126***			
		(-5.50)			
DID(Financial Support)			-0.037		
			(-1.10)		
DID(Financial Support)×High Productive Inventors			-0.228***		
			(-4.84)		
DID(Guidance and Regulation)				-0.023	
				(-0.64)	
DID(Guidance and Regulation)×High Productive Inventors				-0.234***	
				(-4.67)	
DID(AI Enablers and Other Incentives)					-0.103**
					(-2.14)
DID(AI Enablers and Other Incentives)×High Productive Inventors					-0.216***
					(-4.72)
Year × Cohort FE	Yes	Yes	Yes	Yes	Yes
Inventor × Cohort FE	Yes	Yes	Yes	Yes	Yes
Obs.	6,085,710	6,085,710	6,085,710	6,085,710	6,085,710

Table A12
National AI-Related Policy and High Productivity Inventors' New Co-authorship of AI Innovation

This table reports coefficients from inventor-panel Poisson regressions of the number of AI patent filings' domains on an interaction terms of high productivity inventor indicator and national AI-related policies indicator, inventor-by-cohort fixed effects, and year-by-cohort fixed effects. Inventors are classified annually as high-productivity based on their AI patent filings (Panel A) and forward citations (Panel B) over the previous five years. The high productivity inventor indicator is set to 1 if the inventors ranked in the top 10% within their countries. The national AI-related policies indicator is set to 1 if the country has implemented national AI-related policies, while other policy indicators reflect the implementation of specific categories of AI policies such as governance, guidance & regulation, financial support, and AI enablers & other incentives. The dependent variables are inventor's number of AI patent domains, average AI patent domains and AI patent HHI. The data include inventor-year observations in the 5 years prior and up to 10 years following the implementation of national AI-related policies in each country from 2006 to 2019. For all regressions, the robust standard errors are clustered at the country level, and t-statistics are illustrated in parentheses.***,**,* represent the significance level at 1%, 5% and 10% ,respectively.

Panel A — High Productivity Inventor Based on AI Patent Filing Counts

	New Coauth. Count				
	(1)	(2)	(3)	(4)	(5)
DID(AI Policy)	0.006				
	(0.11)				
High Productivity Inventors (Prior 5-Year AI Count)	0.257***	0.252***	0.274***	0.262***	0.267***
	(5.12)	(4.72)	(5.14)	(4.57)	(4.97)
DID(AI Policy)×High Productivity Inventors	-0.006				
	(-0.21)				
DID(Governance)		0.055			
		(1.25)			
DID(Governance)×High Productivity Inventors		0.017			
		(0.61)			
DID(Financial Support)			-0.044		
			(-0.71)		
DID(Financial Support)×High Productivity Inventors			-0.131***		
			(-2.65)		
DID(Guidance and Regulation)				-0.177**	
				(-2.06)	
DID(Guidance and Regulation)×High Productivity Inventors				-0.095	
				(-1.56)	
DID(AI Enablers and Other Incentives)					0.005
					(0.06)
DID(AI Enablers and Other Incentives)×High Productivity Inventors					-0.166***
					(-4.96)
Year × Cohort FE	Yes	Yes	Yes	Yes	Yes
Inventor × Cohort FE	Yes	Yes	Yes	Yes	Yes
Obs.	5,981,364	5,981,364	5,981,364	5,981,364	5,981,364

Panel B — High Productivity Inventor Based on AI Patent Filing Fcites

	New Coauth. Count				
	(1)	(2)	(3)	(4)	(5)
DID(AI Policy)	0.020				
	(0.39)				
High Productivity Inventors (Prior 5-Year AI CITES)	0.225***	0.215***	0.221***	0.209***	0.208***
	(3.18)	(2.93)	(3.79)	(3.34)	(3.29)
DID(AI Policy)×High Productivity Inventors	-0.085***				
	(-2.98)				
DID(Governance)		0.071			
		(1.48)			
DID(Governance)×High Productivity Inventors		-0.065**			
		(-2.16)			
DID(Financial Support)			-0.046		
			(-0.79)		
DID(Financial Support)×High Productivity Inventors			-0.170***		
			(-3.81)		
DID(Guidance and Regulation)				-0.168**	
				(-1.99)	
DID(Guidance and Regulation)×High Productivity Inventors				-0.158***	
				(-3.39)	
DID(AI Enablers and Other Incentives)					-0.016
					(-0.23)
DID(AI Enablers and Other Incentives)×High Productivity Inventors					-0.137***
					(-2.89)
Year × Cohort FE	Yes	Yes	Yes	Yes	Yes
Inventor × Cohort FE	Yes	Yes	Yes	Yes	Yes
Obs.	5,981,364	5,981,364	5,981,364	5,981,364	5,981,364

Table A13
National AI-Related Policy and Domains of High Productivity Inventors' AI Innovation

This table reports coefficients from inventor-panel Poisson regressions of the domains of AI patent filings on an interaction terms of high productivity inventor indicator and national AI-related policies indicator, inventor-by-cohort fixed effects, and year-by-cohort fixed effects. Inventors are classified annually as high-productivity based on their AI patent filings (Panel A) and forward citations (Panel B) over the previous five years. The high productivity inventor indicator is set to 1 if the inventors ranked in the top 10% within their countries. The national AI-related policies indicator is set to 1 if the country has implemented national AI-related policies, while other policy indicators reflect the implementation of specific categories of AI policies such as governance, guidance & regulation, financial support, and AI enablers & other incentives. The dependent variables are inventor's number of AI patent domains, average AI patent domains and AI patent HHI. The data include inventor-year observations in the 5 years prior and up to 10 years following the implementation of national AI-related policies in each country from 2006 to 2019. For all regressions, the robust standard errors are clustered at the country level, and t-statistics are illustrated in parentheses.***,**,* represent the significance level at 1%, 5% and 10% ,respectively.

Panel A — High Productivity Inventor Based on AI Patent Filing counts

	Inventor AI Domains					Inventor AI Domains HHI				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
DID(AI Policy)	-0.004					0.004				
	(-0.40)					(1.11)				
High Productivity Inventors (Prior 5-Year AI Count)	0.280***	0.278***	0.286***	0.279***	0.278***	-0.121***	-0.120***	-0.124***	-0.121***	-0.121***
	(8.28)	(8.34)	(7.92)	(7.84)	(7.95)	(-6.74)	(-6.82)	(-6.34)	(-6.34)	(-6.45)
DID(AI Policy)×High Productivity Inventors	-0.045***					0.020***				
	(-3.48)					(3.17)				
DID(Governance)		0.017					-0.003			
		(1.64)					(-0.73)			
DID(Governance)×High Productivity Inventors		-0.049**					0.020*			
		(-2.17)					(1.88)			
DID(Financial Support)			-0.001					0.004		
			(-0.09)					(0.97)		
DID(Financial Support)×High Productivity Inventors			-0.098***					0.046**		
			(-3.20)					(2.67)		
DID(Guidance and Regulation)				-0.026					0.016*	
				(-1.32)					(1.98)	
DID(Guidance and Regulation)×High Productivity Inventors				-0.119***					0.054***	
				(-3.74)					(3.01)	
DID(AI Enablers and Other Incentives)					-0.018					0.012**
					(-1.22)					(2.07)
DID(AI Enablers and Other Incentives)×High Productivity Inventors					-0.126***					0.059***
					(-3.35)					(3.29)
Year × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inventor × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	6,236,255	6,236,255	6,236,255	6,236,255	6,236,255	6,236,255	6,236,255	6,236,255	6,236,255	6,236,255
R^2						0.49	0.49	0.49	0.49	0.49

Panel B — High Productivity Inventor Based on AI Patent Filing Fcites

	Inventor AI Domains					Inventor AI Domains HHI				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
DID(AI Policy)	-0.012*					0.007**				
	(-1.68)					(2.12)				
High Productivity Inventors (Prior 5-Year AI CITES)	0.177***	0.171***	0.175***	0.164***	0.165***	-0.075***	-0.071***	-0.074***	-0.069***	-0.069***
	(3.76)	(3.67)	(4.14)	(3.86)	(3.87)	(-3.16)	(-3.08)	(-3.38)	(-3.16)	(-3.17)
DID(AI Policy)×High Productivity Inventors	-0.077***					0.038***				
	(-4.73)					(4.53)				
DID(Governance)		0.012					-0.003			
		(0.98)					(-0.51)			
DID(Governance)×High Productivity Inventors		-0.072***					0.035***			
		(-6.73)					(6.47)			
DID(Financial Support)			-0.013					0.008*		
			(-1.26)					(1.69)		
DID(Financial Support)×High Productivity Inventors			-0.114***					0.054***		
			(-3.26)					(2.97)		
DID(Guidance and Regulation)				-0.038**					0.019**	
				(-2.04)					(2.40)	
DID(Guidance and Regulation)×High Productivity Inventors				-0.117***					0.054***	
				(-3.32)					(2.98)	
DID(AI Enablers and Other Incentives)					-0.038***					0.018***
					(-2.96)					(3.29)
DID(AI Enablers and Other Incentives)×High Productivity Inventors					-0.124***					0.038***
					(-3.92)					(3.52)
Year × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inventor × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	6,236,255	6,236,255	6,236,255	6,236,255	6,236,255	6,236,255	6,236,255	6,236,255	6,236,255	6,236,255
R^2						0.48	0.48	0.48	0.48	0.48

Table A14
National AI-related Policy and AI Innovation's Forward Citation by Methodology from Callaway and Sant'Anna (2021)

This Table A14 shows the average treatment effect of the national AI- related policies on AI patents' forward citation follow Methodology from Callaway and Sant'Anna (2021).

	AI Patent Fcites			
	ATT on Treated	ATT by Before & After treatment	ATT by Calendar Period	ATT by Group
	(1)	(2)	(3)	(4)
Simple ATT	-0.298**			
	(-2.15)			
Pre Avg		0.122*		
		(1.93)		
Post Avg		-0.447***		
		(-3.43)		
CAverage			-0.379**	
			(-2.47)	
GAverage				-0.178***
				(-2.63)
Obs.	1,026,365	1,026,365	1,026,365	1,026,365

Figure A2
Pretrend Analysis by Methodology from Callaway and Sant'Anna (2021)

This figure A2 presents the pretrend analysis for our tests. The specification follow the methodology from Callaway and Sant'Anna (2021) and the treatment is separated by the timing of treatment from $\leq t - 8$ to $\geq t + 8$.

