

The Impact of AI-Innovations and Private AI-Investment on U.S. Economic Growth: An Empirical Analysis

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Abstract

This study aims to empirically analyze the impact of AI-related innovations and private investments in the AI sector on the annual growth of the U.S. Gross Domestic Product (GDP) from 2010 to 2020. Using data from the International Monetary Fund (IMF) and the Center for Security and Emerging Technology (CSET), the dependent variable is the annual percentage change in U.S. GDP, adjusted for inflation. Independent variables include annual private investment in AI and the number of AI-related patent applications and granted patents, across various sectors of U.S. such as Life Sciences, Banking and Finance, and Energy Management. The data were transformed into logarithms to minimize the impact of outliers. Analytical methods included correlation analysis and Random Forest Regression on both current and lagged values. The findings indicate that there is a varying degree of correlation between U.S. GDP growth and AI-related activities. Life Sciences showed the highest immediate correlation with GDP growth. Physical Sciences and Engineering exhibited the most substantial lagged correlation, suggesting their impact may be realized over time. Interestingly, annual private investment in AI had the highest feature importance score in predicting GDP growth, both in current and lagged datasets. This indicates that investments in AI technologies play a crucial role in stimulating economic activity, both immediately and over the long term. The importance of AI-related patents also changes between current and lagged datasets, highlighting the dynamic time-delayed impact of these activities on economic growth. The study underscores the need for policymakers to consider both immediate and time-delayed impacts of AI-related innovations and investments in formulating economic strategies. These insights can be valuable for directing resources to sectors that could most effectively stimulate economic growth.

Keywords: *AI-related innovations, economic growth, empirical analysis, private investment, U.S. Gross Domestic Product*

Introduction

The Fourth Industrial Revolution is characterized by a convergence of digital, biological, and physical innovations that are profoundly affecting various sectors globally (Philippe Aghion et al., 2020b; Kayembe & Nel, 2019; Prisecaru, 2016). Artificial Intelligence (AI) plays a pivotal role in this transformation, offering unprecedented opportunities for enhancing productivity, creating new business models, and driving economic growth (Liao et al., 2018; Petrillo et al., 2018). AI's inherent capability to process massive datasets allows for more effective decision-making, automation of routine tasks, and even the development of intelligent systems capable of learning and improving over time. These advancements are not limited to any particular industry; rather, they have far-reaching implications across healthcare, manufacturing, finance, and many other domains (Davis, 2016; Penprase, 2018).

Efficiency enhancement is one of the most immediate impacts of AI on business operations. Advanced algorithms can optimize supply chain logistics, automate customer service interactions, and even assist in complex problem-solving tasks that

would require a considerable amount of human time and effort. Machine learning models can predict equipment failures in industrial settings, enabling proactive maintenance and minimizing downtime. By increasing operational efficiencies, businesses can reduce costs and become more competitive, contributing to economic growth in a broader sense (Bloem et al., 2014; Maynard, 2015).

The increasing availability of large datasets and computational power has significantly contributed to the rapid advancement of AI technologies. Advanced processors and storage solutions have made it feasible to handle vast amounts of information quickly and efficiently. Open-source platforms and cloud-based services have further democratized access to AI tools, allowing even smaller businesses and startups to leverage advanced analytics and machine learning algorithms. These developments have fueled a surge in AI research and patent applications, indicating a robust ecosystem for continued innovation.

AI patent growth serves as a key indicator of the technology's expanding influence. Between 2010 and 2015, the rate of AI patent applications grew at an average yearly rate of 6% (Szczepanski, 2019), outpacing the growth rate for patents in other technological areas. This reflects the increasing recognition of AI's value across multiple industries and the corresponding investment in R&D activities. Patents in machine learning, natural language processing, and robotics are some of the areas where growth has been particularly strong, underscoring the technology's diverse applications.

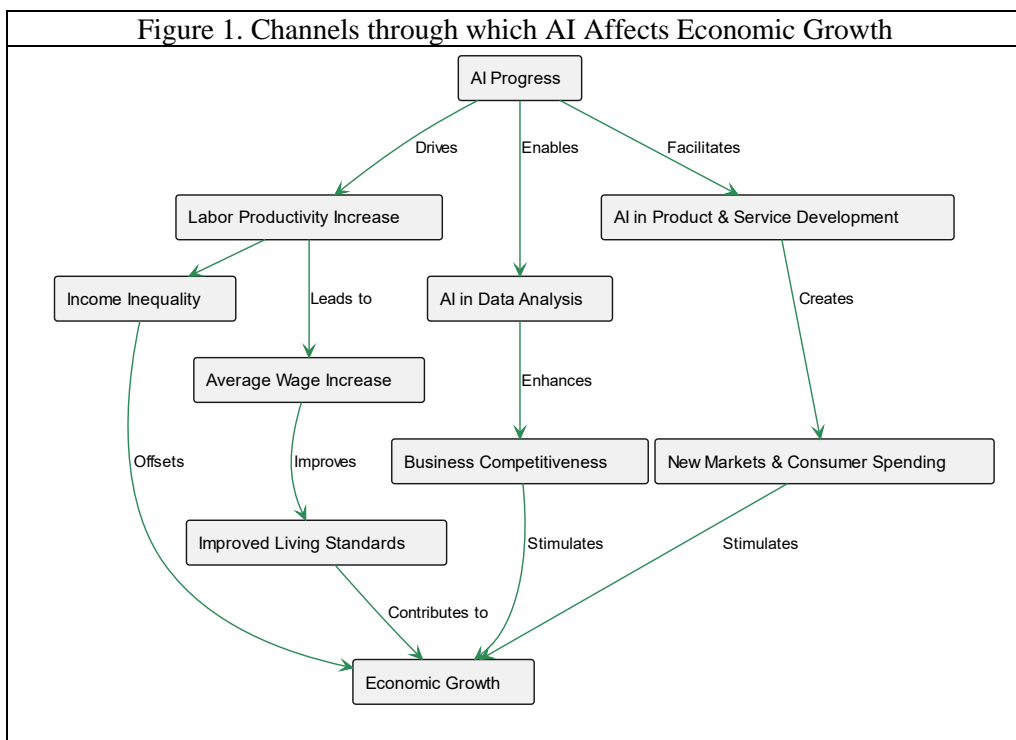
Technological progress serves as a crucial mechanism for the growth of Gross Domestic Product (GDP) per capita. Its importance lies in its ability to enhance productivity, thus allowing for an increase in output that outpaces the contributions of labor and capital. One salient way that technology achieves this is by reducing the labor hours required to generate a unit of output (Ilkka, 2018). For example, automation technologies in manufacturing can significantly reduce the need for human intervention in repetitive tasks, thereby reducing labor costs and time. Similarly, advanced software can automate administrative processes, freeing up human resources for more complex tasks. The implications of these productivity gains are far-reaching, not just for the organization but also for the workforce (Krugman, 1996; Thierer et al., 2017).

Increased labor productivity generally leads to a rise in average wages. As technology takes over repetitive and mundane tasks, human labor can be refocused on specialized and creative tasks, which often come with higher compensation. The benefit of higher average wages is that they give workers the financial flexibility to afford more goods and services, thereby improving their quality of life. Higher wages also allow for the possibility of reduced work hours, giving individuals more leisure time. The effects can lead to an overall improvement in living standards, essentially creating a cycle where technological progress fuels economic growth, which in turn elevates living conditions.

However, this optimistic view does require a note of caution regarding income inequality. Even as technological progress lifts average income and living standards, it doesn't distribute these benefits evenly across society. Skilled workers who can adapt

to new technologies often see the most significant wage increases, while those in jobs that become automated may face unemployment or wage stagnation. This widening gap can offset some of the societal gains made through increases in GDP per capita and can lead to social and economic stratification. Therefore, any discussion of technological progress as a driver for economic growth must also consider measures to address inequality (Russell et al., 2015; Warner & Simon, 1969).

In addition to labor productivity, another significant channel through which technology, particularly Artificial Intelligence (AI), stimulates economic growth is data analysis. AI algorithms have the capability to analyze enormous datasets to provide insights that are actionable and strategically beneficial for businesses. For instance, machine learning algorithms can analyze consumer data to predict market trends, enabling companies to tailor their services or products more effectively. These analytical capabilities help in optimizing various aspects of business, such as supply chain efficiency, customer engagement, and pricing strategies (P. Aghion et al., 2018). Businesses that can effectively implement AI in their operations gain a competitive advantage, which, in a broader sense, stimulates economic growth by fostering a more efficient and responsive market environment. Many sectors have witnessed transformative changes with the introduction of AI-driven tools. Such innovations were either unimaginable or prohibitively expensive in the past. The new products and services not only meet existing consumer needs more effectively but also create entirely new markets. As consumers spend on these new products, economic activity is stimulated, thereby contributing to an increase in GDP. Therefore, the role of technology, especially AI, as a driver for economic growth is multi-dimensional and significant.



A model of automation and economic growth is provided by Zeira (1998) (Zeira, 1998). In this model, firms can choose between two types of technologies for production: labor-intensive technology and capital-intensive (automated) technology. Automation is considered costly in the short term due to initial investment requirements but beneficial in the long term because of reduced labor costs and increased productivity. The model posits that firms that initially invest in automation can gain a competitive advantage over those that do not, leading to market dynamics that further accelerate the adoption of automation technologies.

Additionally, the Zeira model also discusses the implications of automation on income distribution and employment (Philippe Aghion et al., 2020a; He, 2019). The model suggests that while automation may lead to short-term job losses, it can also generate new kinds of employment opportunities, which may or may not require different skill sets compared to the jobs that are automated. Furthermore, automation typically leads to an increase in productivity that can potentially benefit an economy in the long run through higher rates of economic growth.

$$Y = AX_1^{\alpha_1} X_2^{\alpha_2} \dots X_n^{\alpha_n} \quad \text{where} \quad \sum_{i=1}^n \alpha_i = 1$$

and,

$$X_i = \begin{cases} L_i & \text{if not automated} \\ K_i & \text{if automated} \end{cases}$$

Substituting gives,

$$Y_i = AK_i^\alpha L_i^{1-\alpha}$$

The establishment of new artificial intelligence institutes by the U.S. National Science Foundation (NSF) is a significant strategic move aimed at consolidating America's leading position in the evolving global technology ecosystem. The commitment to invest over \$100 million over the course of five years underscores the high priority that the U.S. government places on AI research and its application across various sectors. This initiative by the NSF not only serves as a means to deepen research but also aims to expand the workforce proficient in AI technologies. Moreover, it focuses on resolving issues of national importance that range from healthcare and climate change to national security. This multi-year funding approach ensures that research can be

carried out with a long-term vision, thereby facilitating more robust and impactful outcomes.

In terms of global competition, the stakes are extraordinarily high. The United States has long enjoyed the fruits of being a pioneer in digital innovation, which has bolstered its economy significantly. The country has been the birthplace of major technology companies that have achieved global reach and impact. However, the international landscape is rapidly changing. Countries such as China and blocks like the European Union are also scaling up their investments and research in AI. They aim to challenge the U.S.'s preeminent role in this critical field, recognizing that AI is poised to be a cornerstone of the future global economy. Initiatives like the NSF's Artificial Intelligence Institutes are, therefore, not just a domestic investment but also a competitive maneuver in a broader international context.

The escalation in commercial investment in machine learning and artificial intelligence (AI) technologies over the past decade is a notable trend that underscores the growing recognition of these technologies' potential for value generation. In 2016, a report by McKinsey indicated that the global commercial investment in AI, spearheaded by technology giants such as Google and Baidu, ranged between \$20 and \$30 billion. A significant portion of these investments, approximately 90%, was allocated to research and development (R&D) and the deployment of AI technologies, while the remaining 10% was used for corporate acquisitions. This heavy investment in R&D suggests a focus on innovation and the development of new technologies or the refinement of existing ones, emphasizing the integral role AI plays in the strategic operations of these corporations.

Venture capital (VC) and private equity (PE) firms also constitute a considerable part of the investment landscape, although they operate on a smaller scale compared to tech giants. According to the McKinsey report (*Artificial intelligence the next digital frontier*, 2020), VC and PE investment in AI was estimated to be between \$6 and \$9 billion in 2016. Dana Olsen, writing for PitchBook, reported an even more dramatic surge in VC investment in AI and machine learning, amounting to more than \$10.8 billion in 2017 (Allen & Chan, 2017). This figure represents nearly a two-fold increase from approximately \$5.7 billion in 2016 (Allen & Chan, 2017).

The growth in investment is not just limited to a few years but represents a significant leap when compared to the investment climate a decade ago. In 2010, the estimated investment in AI and machine learning was less than \$500 million. The stark contrast between the investment figures from 2010 and those from more recent years indicates not just an increasing interest but also a substantial commitment from both large corporations and venture capital firms to advance AI and machine learning technologies. This surge in funding resources is likely a reaction to the transformative capabilities these technologies offer in data analytics, automation, and other critical business operations.

The trend in private equity investment in AI is indicative of the technology's promise and potential economic impact. After experiencing steady growth for five years, the sector saw an increase from 2016 to 2017, with the amount of private equity invested doubling in that period. By mid-2018, it was estimated that AI start-ups had attracted more than USD 50 billion in investment (Oecd, 2018). This upsurge in private funding is not random; it reflects a growing realization among investors that AI technologies are likely to be at the forefront of the next wave of economic transformation. This aligns well with public investment strategies and highlights the symbiotic relationship that can exist between government-led and private sector-driven initiatives in technology development.

Methods

This study used time series data spanning from 2010 to 2020. The dependent variable, Annual Growth of US GDP, was sourced from the IMF database. Data for other variables were obtained from the Center for Security and Emerging Technology (CSET).

Variable Type	Variable Name	Data Source	Definition
Dependent	Annual Growth of US GDP	IMF	Yearly rate of change in the U.S. Gross Domestic Product, adjusted for inflation, along with near-term projections.
Independent	Annual Private Investment in US in AI	CSET	Yearly sum of private-market investments in AI companies within the U.S., excluding publicly traded firms. Values are inflation-adjusted and may include estimates.
Independent	Annual US Patent Applications Related to AI	CSET	Total number of AI-related patent applications submitted in the U.S. during a specific year.
Independent	Annual US Granted Patents Related to AI, by Industry	CSET	Yearly total of U.S. granted patents in AI, categorized by various industries such as Banking, Manufacturing, and Energy, among others.

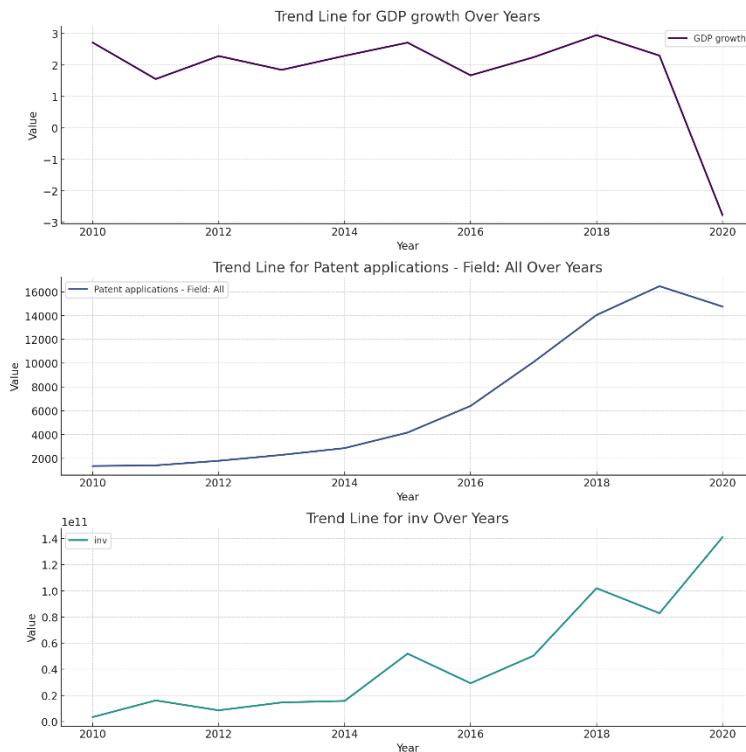
CSET, and IMF stand for *Center for Security and Emerging Technology*, and *The International Monetary Fund*, respectively

The trend line for GDP growth over the observed years exhibits fluctuations, including a notable dip into negative values. This decline happened during the period of the COVID-19 pandemic, reflecting the substantial economic disruption caused by health-related lockdowns, reduced consumer spending, and overall uncertainty. The negative value serves as an anomaly in the otherwise fluctuating trend, highlighting the severe economic repercussions of the pandemic on GDP growth.

On the other hand, the trend lines for the number of AI related patent applications across all fields and investment levels both demonstrate a generally upward trajectory. This suggests that despite economic ups and downs, there has been consistent growth in innovation and investment activities. The rising trend in patent applications could indicate an increase in research and development efforts, while the growing investment

levels may signify positive market sentiment in sectors other than those directly measured by GDP. These upward trends in patent applications and investment stand in contrast to the fluctuating and at times negative growth observed in the GDP data.

Figure 2. Trend lines for GDP growth AI related patents and private investment in AI during the sample period.



Variables

Dependent Variable:

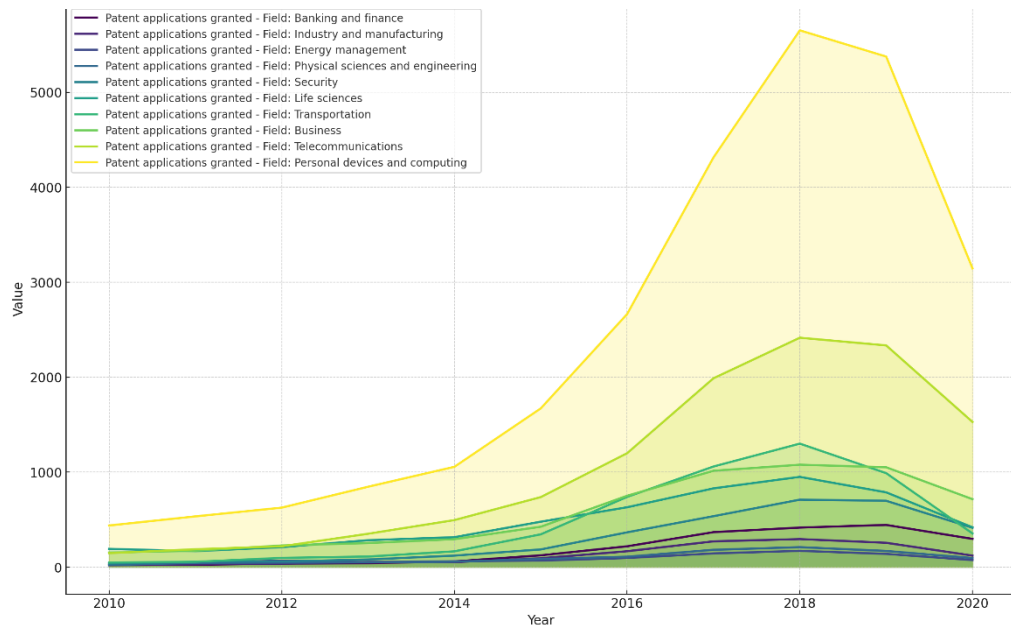
The dependent variable is the annual growth rate of the United States Gross Domestic Product (GDP), expressed as a percentage change from the previous year. This rate is calculated with adjustments made for inflation to reflect the real value of the economy's output.

Independent Variables:

1) Annual Private Investment in the US in Artificial Intelligence:

This variable refers to the yearly total sum of investments made in artificial intelligence companies within the United States, specifically from private markets like venture capital funds. The data excludes any investments made in publicly traded corporations, including major technology firms often referred to as "Big Tech." The values are expressed in U.S. dollars and are adjusted for inflation. When exact amounts of investments are not publicly available, estimates are made. These estimates are determined by taking the median value of similar types of investments, as reported in databases such as Crunchbase.

Figure 3. AI related patent applications by in the United States different industries during the sample period (2010-2020)



2) Annual US Patent Applications Related to Artificial Intelligence:

This variable refers to the aggregate number of patent applications filed within a given year that pertain to artificial intelligence technologies. These applications are submitted to the appropriate patent office in the United States.

4) Annual US Granted Patents Related to Artificial Intelligence, by Industry:

This variable pertains to the total number of patents related to artificial intelligence that have been officially granted within a year in the United States. Additionally, the data is further categorized by different sectors to provide a detailed view of the distribution of artificial intelligence innovation across various industries. The industries covered in the data include: Banking and Finance, Industry and Manufacturing, Energy Management, Physical Sciences and Engineering, Security, Life Sciences, Transportation, Business, Telecommunications, and Personal Devices and Computing.

From 2010 to 2020, there has been a significant growth in AI-related patent applications granted in the U.S across various fields. In the domain of Banking and Finance, the number of granted patents started at 22 in 2010 and saw a surge, reaching a peak of 445 in 2019 before dropping to 298 in 2020. For Industry and Manufacturing, the initial count was 24, peaking at 296 in 2019 and then decreasing to 122 in 2020. Energy Management experienced a rise from 38 patents in 2010 to 172 in 2019, concluding the decade with 75 patents in 2020. The Physical Sciences and Engineering field showed a modest increase, with 23 patents in 2010, reaching 211 by 2019, and finishing with 96 in 2020.

Security-related AI patents displayed impressive growth. The decade began with 37 patents in 2010 and reached its zenith with 699 in 2019, ending with 415 in 2020. In the Life Sciences sector, the numbers grew from 193 in 2010 to a substantial 788 in 2019, and concluded the decade with 420 granted patents in 2020. Transportation, an essential field for AI applications, started with 49 patents in 2010, achieved its peak with 990 in 2019, and decreased to 355 in 2020. The Business sector had 154 patents at the start of the decade, escalating to 1052 in 2019 and finishing with 716 in 2020.

Telecommunications began with 148 patents in 2010, saw a notable rise to 2416 in 2019, and ended with 1529 in 2020. However, the field of Personal Devices and Computing displayed the most significant increase amongst all. With 439 patents in 2010, the number dramatically escalated to 5376 in 2019, before reducing to 3146 in the final year of the decade. This data underscores the rapid advancement and integration of AI technologies across multiple sectors, emphasizing its growing importance and influence in various industries in the U.S. over the past decade.

Method

Random Forest Regression algorithm constructs multiple decision trees during the training phase and outputs the mean prediction of individual trees for regression problems. The individual trees are built in a randomized manner, relying on a bootstrapped sample of the data and a random subset of features for each split in the decision tree. This bootstrapping and feature randomization contribute to the model's ability to generalize well, reducing the risk of overfitting that is commonly associated with single decision trees.

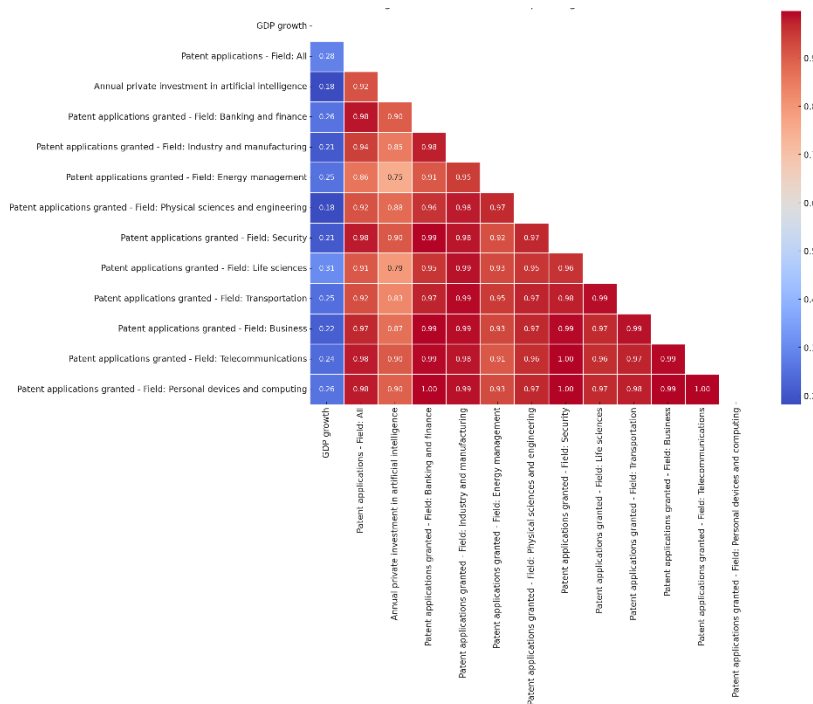
Hyperparameters such as the number of trees in the forest, the maximum depth of the trees, and the minimum samples required to split an internal node can significantly influence the performance of a Random Forest Regression model. Optimizing these hyperparameters is often achieved through techniques like grid search or random search coupled with cross-validation. Furthermore, Random Forest offers an intrinsic way to evaluate feature importance, which is calculated based on the average decrease in impurity caused by splits on each feature across all trees.

Results

Figure 4. represents the correlation matrix that highlights the relationship between different economic indicators and patent application activities across various fields.

Correlation coefficients range between -1 and 1, where 1 indicates a perfect positive correlation, -1 a perfect negative correlation, and 0 no correlation. GDP growth shows a low to moderate correlation with patent applications in various fields. The highest correlation is with the field of Life Sciences at 0.31, while the lowest is with Annual private investment in artificial intelligence and Physical sciences and engineering, both at 0.18. These values suggest that while GDP growth has some relationship with the innovation activities in these areas, other factors could be at play. Patent applications across all fields show a high correlation with patents granted in specific domains. Notably, it shares a remarkably high correlation with patents granted in Banking and Finance (0.98) and in Industry and Manufacturing (0.94).

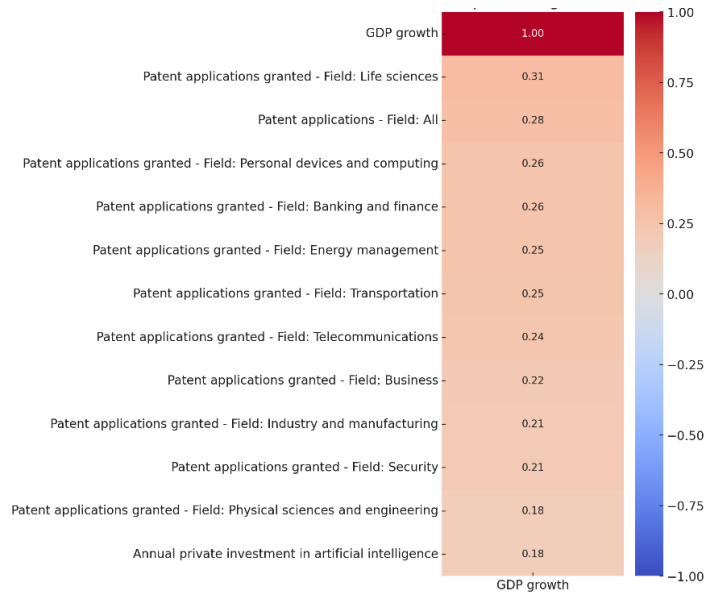
Figure 4. correlation heatmap among the variables



This suggests that when there's a surge in patent applications across the board, these specific fields see a significant increase in patents granted. Annual private investment in artificial intelligence has a strong correlation with patent applications across all fields at 0.92. This implies that higher investments in AI are associated with a broader increase in innovation across various domains. When examining patents granted across specific fields, there are very strong correlations between them. For instance, patents granted in Banking and Finance have almost a perfect correlation with patents in Industry and Manufacturing, Security, and Personal devices and computing, all scoring around 0.99. High levels of correlation in innovation spikes across different fields suggest that advancements in one area are often accompanied by similar progress in other domains. The phenomenon may be attributed to various factors such as technological convergence, where the tools or findings from one field enable progress in another. For

instance, breakthroughs in computational capabilities can facilitate advancements in fields like biotechnology, material science, and even social sciences by providing more powerful analytical tools or simulation capabilities. Another contributing factor could be the interdisciplinary nature of modern research, where expertise from different domains is integrated to solve complex problems. In this scenario, an innovation in one field could directly contribute to progress in others, as research efforts often draw from multiple areas of expertise.

Figure 5. Correlation Heatmap of GDP growth with Other Series

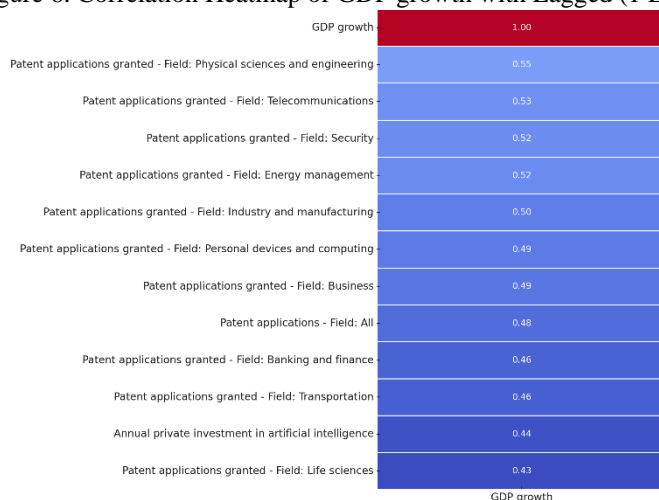


Funding dynamics also play a significant role in this correlated growth. Financial investment in research and development often follows trends, pouring money into sectors that are currently showing promise or have potential for significant advancements. When a breakthrough occurs in one field, it attracts more investment not just into that area, but also into related fields where similar breakthroughs might be possible. This increased funding can lead to accelerated research activities and consequently, more rapid innovation. Additionally, a successful innovation can inspire researchers in other fields, providing them with new approaches or validating the effectiveness of similar methods, thereby creating a cycle of correlated innovative activity.

GDP growth demonstrates various levels of correlation with different sectors in terms of patent applications and private investments. The highest correlation observed is with patent applications granted in the field of Life sciences, showing a coefficient of 0.305500886. This is closely followed by patent applications in all fields with a correlation of 0.283941882. Other notable sectors with substantial correlation include Personal devices and computing (0.25673042), Banking and finance (0.255055809), and Energy management (0.251913945).

The most pronounced correlation is with the lagged patent applications granted in the field of Physical sciences and engineering, recording a correlation coefficient of 0.545543501. This is followed by the lagged values in Telecommunications with a correlation of 0.525494189 and Security with 0.521088746. Moreover, the lagged values for sectors such as Industry and manufacturing (0.500532854), Personal devices and computing (0.494944288), and Business (0.490619741) also indicate substantial correlations. On the other hand, fields with marginally reduced correlations in their lagged values include Banking and finance (0.463602757), Transportation (0.459214525), and Life sciences (0.433976361). Interestingly, the Annual private investment in artificial intelligence, when lagged by one period, records a correlation of 0.441429522. This pattern insinuates that certain sectors might experience a time lag effect wherein the influence of GDP growth on patent applications manifests with a slight delay.

Figure 6. Correlation Heatmap of GDP growth with Lagged (1 Lag) Other Series



The feature with the highest importance score for the GDP growth rate is Annual private investment in artificial intelligence, which has a score of approximately 0.2011. This indicates that investments in the field of artificial intelligence have a more significant impact compared to other variables in the model. This could be due to the high potential of AI technologies to transform various sectors of the economy and contribute to productivity gains.

The importance of patent applications in various fields also stands out in the model. For instance, patents granted in the field of Industry and manufacturing and Energy management have the second and third highest importance scores of approximately 0.1361 and 0.1291, respectively. This suggests that innovation captured by patents in these domains plays a substantial role in the model's predictive power. On the lower end of the importance scale are patents in the fields of Personal devices and computing and Transportation, with scores of approximately 0.0330 and 0.0400, respectively, indicating lesser contributions to the dependent variable in comparison to other features.

The feature importance plot was derived from the Random Forest Regression model trained on the lagged dataset. Notably, the variable Annual private investment in artificial intelligence (Lag 1) emerged as the most important feature, indicating its significant role in the model's predictions. This suggests that previous year's investments in artificial intelligence could have a considerable impact on GDP growth, a finding that could be of interest to policymakers and economists.

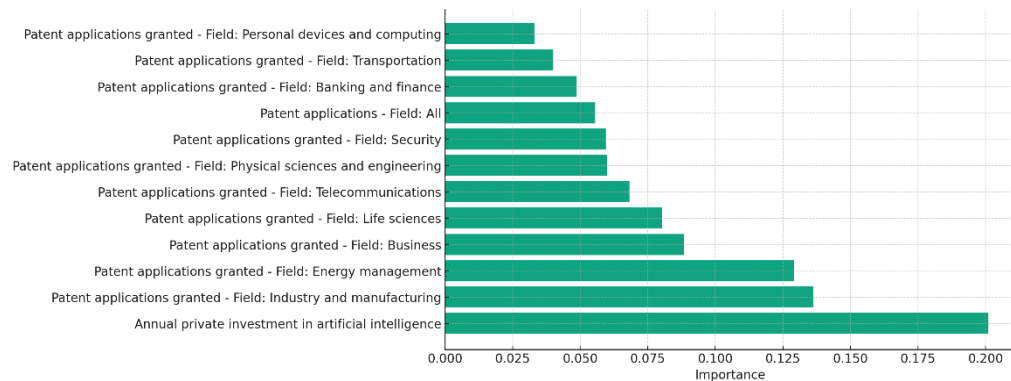
Other variables related to patent applications in various fields also showed varying degrees of importance. For instance, patents in "Banking and Finance (Lag 1)" and "Industry and Manufacturing (Lag 1)" were among the top features, highlighting the potential influence of technological advancements in these sectors on economic growth.

with the current date datasets, annual private investment in artificial intelligence shows the highest feature importance of 0.201, while its lagged value drops to 0.153. Similarly, patent applications in the field of industry and manufacturing are ranked second in the current data set with an importance of 0.136, but they are demoted to a lower ranking in the lagged dataset with an importance of 0.098. Energy management moves up the list in the lagged dataset with an importance of 0.144 compared to its current value of 0.129, indicating a delayed impact on the dependent variable.

On the other hand, some categories appear to be more stable over time, maintaining similar levels of importance in both current and lagged datasets. For instance, AI patent applications in the field of physical sciences and engineering have a feature importance of 0.060 in the lagged dataset compared to 0.060 in the current data. This stability suggests that certain variables may have a persistent influence over the dependent variable, GDP growth, regardless of the time frame considered. Also, it is shown that some fields emerge only in the lagged dataset, such as banking and finance with an importance of 0.066, indicating that their impact on the GDP growth may not be immediately observable but become significant over time.

Conversely, sectors with relatively lower correlations with GDP growth include Physical sciences and engineering (0.184588547) and Annual private investment in artificial intelligence (0.18142678). Although these areas still show a positive relationship with GDP growth, they are not as strongly linked as the previously mentioned sectors. It can be inferred that while these sectors contribute to economic growth, their impact might not be as significant as sectors like Life sciences or Banking and finance in terms of patent applications.

Figure 6. Feature importance



The findings that Life Sciences innovations have the highest correlation with GDP growth in the United States have significant implications for policy formulation. Policymakers can use this information to prioritize sectors that contribute more efficiently to GDP growth. Investment in research and development, tax incentives, and subsidies could be more heavily tilted toward the Life Sciences sector. The potential for spillover effects in other sectors linked to Life Sciences—such as pharmaceuticals, healthcare, and even agriculture—could also mean that investments in this sector may yield multi-sectoral benefits. Therefore, a targeted policy focusing on Life Sciences could serve as a catalyst for more broad-based economic growth.

Moreover, the data suggesting strong correlations in sectors like Personal Devices and Computing, Banking and Finance, and Energy Management further expand the scope for policy action. Tailored policies can be developed to stimulate innovation in these areas, possibly accelerating GDP growth. Regulatory frameworks could be adapted to encourage private investments in these sectors, and public-private partnerships could be more vigorously pursued. This could also help in creating a more favorable environment for startups and established businesses alike to innovate and thrive, thereby creating jobs and contributing to economic expansion.

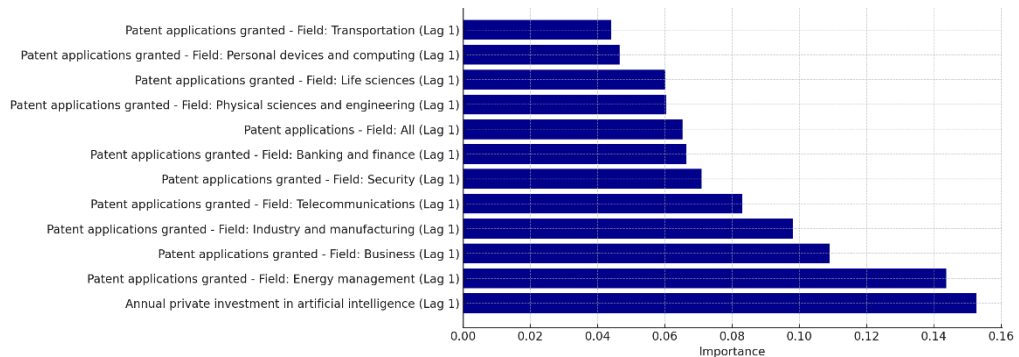
When considering the lagged values, Physical Sciences and Engineering show a delayed but significant influence on GDP growth. This brings into focus the need for a long-term outlook in policy planning. Investments in these sectors may not show immediate economic returns but could be essential for sustainable growth in the long term. Infrastructure projects and educational programs targeting these fields could be beneficial, even if they require a longer time horizon to yield noticeable economic benefits. Policymakers should therefore balance short-term gains with long-term investments when allocating resources.

Similarly, sectors like Telecommunications and Security also show significant correlations when lagged values are considered. This could imply that policies targeting these sectors should be designed with an understanding that the economic benefits may take time to materialize. Strategic planning should account for this latency and provide sustained support over a more extended period. This could involve multi-year funding

commitments and consistent regulatory support to foster long-term innovation and development in these sectors.

One limitation in implementing these policies is the risk of over-specialization. Focusing too heavily on sectors that currently show high correlation with GDP growth could make the economy vulnerable to shocks in those specific industries. Diversification is generally considered a safeguard against economic volatility, and policymakers should be cautious not to undermine this. Another challenge is the allocation of resources, as sectors that currently show lower correlations with GDP growth may argue that with more support, they too could become more influential in affecting the economy. This creates a complex decision-making environment for policymakers, requiring them to weigh short-term benefits against long-term gains carefully.

Figure 7. Feature importance for lagged variables



Conclusion

Artificial intelligence (AI) has become a point of discussion in business operations and the economy in the United States. The technology has witnessed significant advancements, including cutting-edge algorithms and applications that are pushing the boundaries of what is technically feasible. From machine learning techniques that can analyze massive data sets to identify market trends, to natural language processing algorithms that handle customer service interactions, AI is progressively becoming an integral part of how businesses function.

The findings indicate that the United States economy's GDP growth related to varying extents with AI-related patent applications and private investments in different sectors. Notably, innovations in Life Sciences demonstrate the highest level of correlation with GDP growth, suggesting that innovation in this sector might have a significant impact on the economy. Innovations in other sectors such as Personal Devices and Computing, Banking and Finance, and Energy Management also show strong correlations. The relationship between AI-related patent activity in these sectors and GDP growth can provide indicator for policymakers in identifying sectors with higher economic impact.

By channeling resources and focus toward these high-correlation sectors, there may be an opportunity for stimulating overall economic growth.

When examining lagged values, Physical Sciences and Engineering emerge with the most high correlation. This implies that the economic influence of innovations in this sector may manifest over time, rather than immediately. Similarly, sectors like Telecommunications and Security also show substantial correlations when lagged, indicating that they may have a delayed but impactful effect on GDP growth. Policymakers may therefore need to consider both immediate and delayed impacts of technological innovations when planning economic strategies, as different sectors appear to affect the economy in different time frames.

The feature with the highest importance score for GDP growth is Annual Private Investment in Artificial Intelligence, denoting the critical role of funding in stimulating economic activity. Investments in AI technologies have the potential to drive productivity gains across various sectors, thereby having a more pronounced impact on GDP growth. This finding can serve as an impetus for government agencies and private institutions to foster investment landscapes that are conducive to AI development, especially since AI has broad applications that can catalyze growth in multiple sectors.

Another point of significance is the variable importance in predicting GDP growth, as derived from the Random Forest Regression model trained on the lagged dataset. Here, the lagged value of annual private investment in AI emerged as the most important feature, indicating its long-term impact on GDP growth. Also, the importance of AI-related patents in sectors like Banking and Finance and Industry and Manufacturing in the lagged dataset suggests that innovations in these sectors may have a time-delayed yet significant effect on economic growth. Understanding the time-lagged influences of these variables could be instrumental in shaping long-term economic policy.

The feature-importance scores for AI-related patent applications in various fields also change between current and lagged datasets, revealing the dynamic nature of their impact on GDP growth. While some sectors like Industry and Manufacturing may show immediate impact, others like Energy Management might have their economic significance realized over time. Additionally, some variables maintain consistent levels of importance, indicating a steady impact on GDP growth regardless of the timeframe considered. This finding recommends the necessity for a method in policy development that considers both the immediate and long-term impacts of activities related to artificial intelligence across various sectors on economic growth in the United States.

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