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Working Paper

Green Intelligence: The AI content of green technologies

LEM Working Paper Series, No. 2024/23

Provided in Cooperation with:

Laboratory of Economics and Management (LEM), Sant'Anna School of Advanced Studies

Suggested Citation: Biggi, Gianluca; Iori, Martina; Mazzei, Julia; Mina, Andrea (2024) : Green Intelligence: The AI content of green technologies, LEM Working Paper Series, No. 2024/23, Scuola Superiore Sant'Anna, Laboratory of Economics and Management (LEM), Pisa

This Version is available at:

<https://hdl.handle.net/10419/303267>

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WORKING PAPER SERIES

Green Intelligence: The AI content of green technologies

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2024/23

September 2024

ISSN(ONLINE) 2284-0400

Green Intelligence: The AI content of green technologies

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Abstract

This paper investigates the contribution of Artificial Intelligence (AI) to environmental innovation. Leveraging a novel dataset of USPTO patent applications from 1980 to 2019, it explores the domain of Green Intelligence (GI), defined as the application of AI algorithms to green technologies. Our analyses reveal an expanding landscape where AI is indeed used as a general-purpose technology to address the challenge of sustainability and acts as a catalyst for green innovation. We highlight transportation, energy, and control methods as key applications of GI innovation. We then examine the impact of inventions by using measures and econometric tests suitable to establish 1) how AI and green inventions differ from other technologies and 2) what specifically distinguishes GI technologies in terms of quality and value. Results show that AI and green technologies have a greater impact on follow-on inventions and display greater originality and generality. GI inventions stand out even further in these dimensions. However, when we examine the market response to these inventions, we find positive results only for AI, indicating a mismatch between the technological vis-à-vis market potential of green and GI technologies, arguably due to greater uncertainty in their risk-return profiles.

Keywords: Artificial Intelligence, Environmental innovation, Green Intelligence (GI), Twin transition, Digitalization, Green technologies

JEL Classification: O31, O33, Q55, Q56

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1 Introduction

The urgent need to limit the rise in global temperatures requires a comprehensive transition towards a sustainable and low-carbon future (IPCC, 2018). The importance of achieving a net-zero transition is underscored by the robust evidence now available on the escalating impacts of climate change, from extreme weather events to ecosystem losses (IEA, 2021). As nations around the world consider ambitious climate targets, decoupling economic growth from carbon emissions becomes imperative. Central to this objective is the convergence of environmental protection and technological innovation, with digital technologies emerging as important catalysts of the net-zero transition. Among the relevant digital technologies, Artificial Intelligence (AI) is expected to help mitigate urgent environmental problems in different contexts (Vinuesa et al., 2020; Tomašev et al., 2020; Ardabili et al., 2020). As a general-purpose technology (GPT), AI can be adopted for multiple purposes in a broad range of sectors, and – when used as a research tool – even generate new waves of inventions with the potential to create widespread economic impacts (Trajtenberg, 2018). Researchers and companies are indeed “hoping to leverage AI to address one of the most pressing concerns of the modern era”.¹ In practice, companies are engaging in new projects to leverage AI algorithms for developing and improving green technologies, seeking the so-called “Green Intelligence”. One example is Microsoft’s initiative “AI for Earth”, a huge commitment to finance projects and harness AI to solve global environmental challenges in key focus areas of climate, agriculture, water, and biodiversity conservation.

Through AI algorithms and machine learning, firms could radically transform their products and processes to achieve greater organizational efficiency and flexibility. For example, these techniques can be easily applied in smart grid management to reduce energy production and waste. Furthermore, AI technologies are enablers of change because they can help to incorporate eco-design principles into new product development, optimize heating and cooling systems in production plants, and re-engineer whole processes for efficient waste disposal.

It must also be stressed, however, that despite the potential to improve the efficiency and environmental impact of production and distribution processes, AI technologies could also lead to higher demand for computing power, higher carbon emissions, unanticipated changes in electricity demand patterns, and an accelerated depletion of natural resources (Brevini, 2023). Indeed, ongoing policy and scholarly debates are very concerned as to whether AI will have a positive or negative environmental impact and, as these concerns grow quickly over time, there is a call for new regulations against a backdrop of technological uncertainty (Swiatek, 2024).

This suggests the need to develop better ways to identify, measure, and characterize AI innovations in technologies capable of positive environmental impacts. As a GPT and arguably the most disruptive among all digital technologies (Martinelli, Mina, and Moggi, 2021), AI can, in principle, provide considerable support to green innovations and their diffusion. However, there is a lack of comprehensive evidence on the green inventions that rely on AI technologies –

¹<https://impact.economist.com/perspectives/sustainability/green-intelligence-ai-could-boost-efforts-fight-climate-change> [Last accessed June 27, 2024].

Green Intelligence (GI) inventions hereafter.

The interaction between green and digital technologies has sparked growing research interests in the so-called "twin" (green and digital) transition (Diodato et al., 2023). Existing studies in this area have primarily examined its antecedents (Montresor and Vezzani, 2023), environmental impact (Bianchini, Damioli, and Ghisetti, 2023), and implications for employment (Santoalha, Consoli, and Castellacci, 2021). This literature has described the emergence of a twin transition at the regional level (Damioli, Bianchini, and Ghisetti, 2024; Fazio, Maioli, and Rujimora, 2024) and demonstrated that digital skills foster the development of circular economy technologies in European regions (Fusillo, Quatraro, and Santhià, 2024). The limited research exploring the twin transition at the firm level has predominantly treated green and digital technologies as distinct entities, even when jointly adopted (see, e.g., Cattani, Montresor, and Vezzani, 2023). However, these studies have largely overlooked the identification of "twin" (green-digital) inventions. In this paper, we map the landscape of GI technologies, as the most promising subset of "twin" inventions, and document whether and how AI contributes to the development of green innovations. We start by identifying the main application domains and the most common AI techniques applied to green inventions. We then focus on the most important companies developing GI technologies and examine their geographical distribution compared to other AI and green technologies. Finally, we explore the quality of inventions by designing and implementing econometric tests suitable to establish whether GI inventions are more impactful and valuable than other AI and green technologies.

To provide a precise picture of the GI technology landscape, we leverage a unique patent dataset identifying both green and AI technologies. We focus on AI technologies rather than broadly defined digital technologies on which the literature has focused so far. To this end, we combine the World Intellectual Property Organization (WIPO) classification for Artificial Intelligence (WIPO, 2019) with the OECD Env-Tech classification by Haščič and Migotto (2015) for green patents. Applying this search strategy to patent data retrieved from PATSTAT 2023 (Autumn edition), we select 1,249,798 AI and green patent applications filed with the United States Patent and Trademark Office (USPTO) from 1980 to 2019. Despite well-known limitations, patent data are established indicators of innovation activity (Griliches, 1990) and have been extensively used to study the backbone and evolution of technological knowledge (Hall, Jaffe, and Trajtenberg, 2001). They serve as a valuable data source and a reliable proxy that has already been used to analyze trends in both AI (WIPO, 2019; Cockburn, Henderson, and Stern, 2018; Iori, Martinelli, Mina, et al., 2022) and green technologies (Dechezleprêtre, Martin, and Mohnen, 2013; Popp, 2019; Barbieri, Marzucchi, and Rizzo, 2020; Fusillo, 2023) independently from one another. We then combine these data with the OECD Patent Quality Indicators dataset (Squicciarini, Dernis, and Criscuolo, 2013) and the stock market-based indicators of patent value proposed by Kogan et al. (2017) to obtain a multidimensional perspective on the quality of GI inventions.

Our exploratory analyses show a scenario where AI clearly emerges as a catalyst for green

innovation, highlighting its potential role in achieving environmental sustainability. We identify transportation, energy, and control methods as critical areas of development for GI innovation, with significant efforts observed in the United States, followed by Japan, South Korea, and China. At the sector level, GI inventions are particularly important for automotive and electronics, suggesting a strategic convergence between mobility needs and advanced electronics in the direction of greener technical solutions. Regarding the quality of GI inventions, we find that the convergence of AI and green technologies is associated with a greater impact on further inventions as measured by forward citations. Moreover, green, AI, and GI patents are all more original and general than other patents, thus confirming their GPT features. However, when we inspect the value of patents by using Kogan et al., 2017’s ex-ante market value indicator, we find positive and significant results for AI technologies, negative and significant results for green technologies, and non-significant results for GI technologies. These differences are arguably due to greater perceived uncertainty and lower expected returns for green technologies. A direct comparison of GI technologies with AI and green technologies reveals that GI technologies display higher citation impacts, originality, and generality, but no higher (ex-ante) value, suggesting the existence of a gap between the pace of technological progress and market perceptions.

The remainder of this paper is structured as follows. Section 2 provides an overview of AI in environmental technologies. Section 3 describes data and methods. Sections 4 and 5 report our exploration of the GI patent landscape, and section 6 concludes.

2 The role of AI in environmental innovation

The economic significance of AI lies in its foundational role in spurring technological advancements while also influencing industrial dynamics (Cockburn, Henderson, and Stern, 2018). Considered the latest exemplar of General Purpose Technology (GPT), AI and related methodologies - spanning machine learning, natural language processing, and data analytics - exhibit strong complementarities with other innovations, driving systemic change and altering the entire competitive landscape. A recent WIPO report (WIPO, 2019) reveals an explosive growth in AI inventions, pointing to the technology’s widespread adoption and integration into various domains, including environmental technologies (Vinuesa et al., 2020; Swiatek, 2024). Environmental (or green) technologies, embody a variety of innovations designed to mitigate or adapt to changing environmental conditions, enhance resource efficiency, and adhere to environmental standards (Sun et al., 2023). Previous literature highlights that green technologies have a larger and more pervasive impact on future inventions (Barbieri, Marzucchi, and Rizzo, 2020). Considering the nature of AI as GPT (Martinelli, Mina, and Moggi, 2021), the integration of AI into green technologies is expected to enhance the impact of these technologies further. In addition, since Kogan et al., 2017 show that the market response to the grant of a patent is positively associated with its impact, proxied by the number of future citations, all these technologies should also be associated with higher value. However, it should be considered that emerging

technologies may initially face a less positive short-term market response due to uncertainty and perceived risks associated with new innovations. All in all, we expect the integration of AI in green technologies to ultimately gain a higher positive response from the markets as their combined potential and long-term benefits become more evident. The unique combination of AI capabilities with green technologies can lead to innovations that address not only critical environmental challenges but also drive economic growth through increased efficiency and new market opportunities (Cowls et al., 2023).

Despite the growth of scholarly efforts aimed to identify direct and indirect effects of green innovation across sectors and regions (Crespi, Ghisetti, and Quatraro, 2015; Ghisetti and Quatraro, 2017) and combined effects in association with digital technologies (Bianchini, Damioli, and Ghisetti, 2023), systematic evidence on the specific contributions of AI to environmental technologies is scant. Illustrations of these contributions include innovations in environmental monitoring, renewable energy optimization, and AI-based greenhouse gas reduction applications. For instance, among others, (Robinson, Dilkina, and Moreno-Cruz, 2020) study a simulation model based on AI to predict the impacts of climate-induced migration. Rolnick et al. (2022) identify, instead, machine learning’s potential to impact solutions across energy systems and ecosystem management significantly, a sentiment echoed by the International Energy Agency (IEA, 2021), which highlights AI’s role in enhancing energy efficiency and supporting the shift to renewable energy through smart grids and demand forecasting. An example of this potential impact is a technology developed by Siemens that uses AI-driven solutions to optimize energy distribution and consumption through smart grids. This AI system analyzes vast amounts of data to make real-time decisions on energy distribution, thereby balancing supply and demand, reducing energy waste, and enhancing the grid’s reliability. Similarly, IBM has harnessed AI to promote sustainable agriculture. IBM AI-powered tools assist farmers in making data-driven decisions regarding crop management, using data from weather stations, satellite imagery, and Internet of Things (IoT) sensors. These tools enable precision farming, which reduces waste and environmental impact by optimising the application of water, fertilizers, and pesticides. This application of AI in agriculture not only improves yield but also enhances resource efficiency and helps farmers adapt to changing climatic conditions (for an example of patented technology in this field, see Figure A1).

AI’s transformative impact extends to climate prediction and modelling, where advanced techniques have markedly improved the processing of large datasets, thereby increasing the accuracy of climate projections and deepening our understanding of climate dynamics. Among other techniques, convolutional neural networks have been used to analyze satellite imagery to gain new insights into deforestation, urbanization, and ecosystem changes (Reichstein et al., 2019) (for an example of patented technology in this field, see Figure A2). In agriculture, AI-driven tools optimize resource use, water conservation, and carbon footprint reduction (Kamilaris, Kartakoullis, and Prenafeta-Boldú, 2017). Expanding the scope of AI’s impact, Verendel (2023) perform an extensive analysis of over 6 million US patents to explore AI’s role

in climate-related innovations, identifying significant contributions in transportation, energy, and industrial production. This study highlights AI’s catalytic effect on generating subsequent inventions, with climate patents incorporating AI linked to a considerable increase in technological advancements. In a similar line of research, Li et al. (2023) provides a spatial analysis of climate-related patents in China that reveals the dominance of eastern provinces in innovation and suggests policies to spread clean technology and tailor technical support, highlighting the importance of geographical factors and network dynamics in the diffusion of AI-enhanced climate technologies.

Our study provides a broader assessment of the technologies leveraging AI for green and environmental purposes. The intersection between AI and green technologies is, indeed, a domain largely under-explored in current research. Unlike previous analyses, which use digital innovations as a very broad category of enabling technologies, we take AI apart from other digital technologies and focus sharply on AI and its subcomponents. This approach allows us to uncover specific areas where integrating AI algorithms with green technologies creates innovative solutions to address environmental challenges (Swiatek, 2024). This intersection leverages the capabilities of AI to enhance the efficiency, effectiveness, and scalability of green technologies, thereby fostering sustainable development. In what follows, we will refer to these technologies as Green Intelligence (GI).²

3 Data and methods

3.1 Sample construction

Our empirical analysis is based on a dataset of AI and green patent applications filed at the United States Patent and Trademark Office (USPTO)³ from 1980 to 2019 and retrieved by PATSTAT 2023 (Autumn edition). Due to the recent emergence of GI inventions, we consider patent applications because, contrary to granted patents, they allow us to capture more recent trends in this technology. However, since the USPTO does not consistently report patent applications before 2001, we also perform our analysis on the sub-sample of granted patents.

To identify AI and green patents, we rely on two well-established classifications, namely the WIPO classification for Artificial Intelligence WIPO (2019) and the OECD Env-Tech Classification (Hašič and Migotto, 2015) for technologies with positive environmental outcomes. Both classification schemes use the technology classification codes assigned to each patent – the International Patent Classification (IPC) and Cooperative Patent Classification (CPC) codes – to detect inventions in the sector of interest. The WIPO classification for AI identifies the

²It is worth noticing that the term “Green Intelligence” has been used in other domains with different meanings (see, for instance, Laurent, 2008; Soleimanpouromran and Ahmadimoghadam, 2021; Juo and Wang, 2022). In this paper, we follow the definition provided by the Economist (see Section 1 and Footnote 1).

³We focus on USPTO patents because, in this legislation, it is possible to patent software inventions, contrary to what happens in other patent offices.

use or definition of AI algorithms in inventions by integrating technology codes (e.g., Y10S706 – “Data processing; artificial intelligence” and subcategories of G06N – “Computing arrangements based on specific computational models”) with a keyword-based search to collect patents referring to new AI techniques that may lack specific classification codes (e.g., deep learning). The resulting dataset comprises 794,588 green inventions and 142,032 AI patents, as reported in Table 1. While green patents include climate change mitigation technologies with applications to several sectors (e.g., transportation, energy, and building) and inventions for environmental management, AI technologies refer to the application of AI algorithms (e.g., machine learning and expert systems) to various settings. We then consider the intersection between AI and green patents to identify GI inventions, i.e. the application of AI-based software to green technologies. Only a small fraction of green and AI patents (7,166) belong to both sets and have been classified as GI inventions. They represent about 1% of green patents and 4.8% of AI patents.

For all patents in our dataset, we also retrieved information about patent applicants and identified 483,747 different applicants according to the OECD Harmonised Applicant Name (HAN) database.

Table 1: Dataset composition

Period of analysis	1980-2019
# of patent applications	8,995,626
among which:	
# AI patent applications	141,632
# Green patent applications	792,330
# GI patent applications	7,158
# of granted patents	6,959,125
among which:	
# AI granted patents	105,518
# Green granted patents	602,435
# GI granted patents	5,263
# Patent applicants	483,747

GI patents firmly rely on both AI and green technologies. Assuming that patent backward citations map inventions’ sources of knowledge, patents cited by GI inventions primarily belong to green (26.8%) and AI (22.9%) technologies, signalling a predominant role of these technologies in GI development and confirming the reliability of our classification. 6% of GI’s backward citations refer to other GI patents. The primary reliance of GI on AI and green knowledge is also confirmed when we account for the size of these fields by building a Configuration Null Model (Bollobás, 2001). The models allow us to compare observed backward citations by fields with those expected given the citation-network structure and the occurrence of each field in

the sample of patents across time.⁴ By comparing the expected number of citations with the observed one, we detect a predominant role of AI knowledge, which is cited by GI patents 16.4 times more than expected in the case where citations were random. The same occurs for green technologies since GI cites green inventions 4.4 times more than expected. The reliance on GI patents is even more evident (83.3 times more than expected), suggesting the emergence of a small but coherent technology field. Interestingly, a general AI patent does not cite green inventions (the ratio between observed and expected citations is 0.46), and green patents do not usually rely on AI inventions (the ratio is 0.26). Since the WIPO classification for AI is based on the identification of AI algorithms, we can conclude that GI inventions are a unique combination of AI and green knowledge resulting in AI algorithms applied to green technologies, as illustrated also by the examples of GI patents reported in Figures A1, A2 A3 in Appendix A. Patent US9898688B⁵ protects a system that analyzes and classifies agricultural conditions, such as water-imposed damage, based on data recorded by one or more drones, relying on a neural network technology applied to precision farming. Patent US11555701B⁶ instead covers a system to auto-determine the height and elevation of a building from the terrain. Such information is used to perform a flood risk assessment. In this case, the underlying invention is a clear example of climate change adaptation technology. Finally, Patent US10318821B⁷ refers to a driver assistance apparatus that supports the navigation of a vehicle with a Stop and Go function controlling the engine. This system is conceived to improve fuel efficiency and reduce the vehicle’s carbon dioxide emissions.

To further improve our understanding of GI inventions, our analysis considers subclassifications of AI and green technologies. The WIPO report provides fine-grained patent subclassifications according to the AI technique described or applied in the patent, its functional application, and its application field.⁸ AI techniques refer to the AI algorithms described or applied in the patent. They include logical programming for expert systems, fuzzy logic for machine control, and machine learning. Although early AI patents relied on expert systems, machine learning has been the most popular approach in recent years. Since AI technologies have a variety of application settings, the classification of functional applications categorised the operations that can be realised using AI techniques. They include computer vision, control methods for dynamic systems, knowledge representation and reasoning to solve complex tasks, planning and scheduling activities and assignments, robotics, and speech recognition. Finally, AI application

⁴We compute the expected number of GI’s backward citations to AI, green, and GI patents by defining 10 random networks that preserve the number of links (citations) of each patent and the application year of each cited invention (to account for the emergence of new fields and citation heterogeneity across time) but assign citations randomly. By averaging the number of citations between fields obtained in these random networks, we define the expected number of backward citations from GI to AI, green, and GI.

⁵patents.google.com/patent/US9898688B2.

⁶patents.google.com/patent/US11555701B2.

⁷patents.google.com/patent/US10318821B2.

⁸See www.wipo.int/tech_trends/en/artificial_intelligence/patentscope.html for more details on the subclassification of AI patents [Last accessed June 27, 2024].

fields describe the invention’s sectors of applications.⁹ Since AI subclassifications are based on technology codes and keyword searches, each patent could belong to multiple subclasses or none of them. We consider only classes with at least 150 patents to select out relatively unimportant classes and streamline the analysis.

The OECD Env-Tech Classification divides green technologies into six subclasses. They range from technologies for environmental management (including air and water pollution abatement, waste management, soil remediation, and environmental monitoring) and water-related adaptations to climate change mitigation technologies (CCMT) across various sectors such as energy, transportation, building, and carbon capture and storage.

We complement our dataset with a set of patent-level indicators to proxy various dimensions of invention impact and quality. First, we rely on the OECD Patent Quality Indicators (Squicciarini, Dernis, and Criscuolo, 2013) to retrieve measures widely used in the literature. Second, to proxy the private value of inventions, we use the measure of patent value developed by Kogan et al., 2017.¹⁰ The use of this wide range of measures accounts for the multidimensional nature of patent quality (Higham, Rassenfossé, and Jaffe, 2021).

3.2 Variables

To account for the impact and value of inventions, we consider three well-established variables drawn from the OECD Patent Quality Dataset (Squicciarini, Dernis, and Criscuolo, 2013). Our primary dependent variable is the number of forward citations received by patents over a period of 5 years after the publication date. Forward citations are a standard indicator of technological relevance for follow-on innovation and a well-known proxy for patent impact (Trajtenberg, 1990). It is defined as:

$$\text{fwd cit}_i = \sum_{P_i}^{P_i+5} \sum_{j \in J(t)} C_{j,t}, \quad (1)$$

where i is the focal patent, P_i is the publication year, $J(t)$ is the collection of patent applications filed in year t , and $C_{j,t}$ is a dummy variable indicating whether patent j cites i in year t .

We also consider other dimensions of quality (Higham, Rassenfossé, and Jaffe, 2021) by using the originality and generality of a patent as alternative dependent variables. Originality measures the diversity of technological fields on which a patent relies. Following Hall, Jaffe, and

⁹Among others, we identify agriculture, business (including customer service, e-commerce, and enterprise computing), energy management, physical sciences and engineering, industry and manufacturing, life and medical sciences (including bioinformatics, biological engineering, nutrition/food science, drug discovery, and neuroscience), personal devices/computing/HCI, networks (including Internet of Things, smart cities, and social networks), security (including anomaly detection, authentication, cryptography, cybersecurity, and privacy), telecommunications (including computer networks and internet, radio/television broadcasting, telephony, and videoconferencing), and transportation (including aerospace, aviation, autonomous vehicles, vehicle recognition, transportation, and traffic engineering).

¹⁰The data are available here: <https://github.com/KPSS2017>.

Trajtenberg (2001), we define originality as:

$$\text{originality}_i = 1 - \sum_j^{n_i} s_{ij}^2, \quad (2)$$

where s_{ij} is the share of citations made by patent i to technology class j , considering the set n_i of International Patent Classification (IPC) 4-digit codes assigned to patent cited by i .

Similarly, generality measures the range of technological fields relying on the knowledge codified in the focal patent, reflecting its capacity to enable advancements across multiple technological areas. We can consider generality as an alternative indicator of patent impact since it accounts both for the number of citations and their spread across fields. Generality is defined as:

$$\text{generality}_i = 1 - \sum_k^{n_i} r_{ik}^2, \quad (3)$$

where r_{ik} is the percentile of citations received by patent i from the technology class j belonging to the set n_i of International Patent Classification (IPC) 4-digit codes assigned to patent citing i .

We complement this analysis by including the indicator of stock market patent value as defined by Kogan et al. (2017). This indicator captures the stock market response to news about granted patents. By construction, it is available for patents granted by listed companies only. Contrary to previous indicators capturing the technological dimension of inventions' quality, this index adds the market dimension to our technology impact analysis. In this way, our analysis allows us to test both the degree of technological impact and the response and expectations of the market to these emerging technologies.

In the patent quality analysis of AI and green inventions, we also control for the number of backward citations and the number of citations to the non-patent literature (NPL) contained in a patent, patent family size (i.e., the number of patents regarding the same inventions, possibly filed in different jurisdictions), the number of inventors, and the number of claims.¹¹

3.3 Methods

To test whether GI inventions have a higher quality and are more valuable than other AI and Green inventions, we rely on an OLS regression to estimate the impact of GI inventions on the different proxies of impact and value we use as outcome variables. Specifically, we estimate the following model:

$$Y_{i,f,t} = \beta_0 \text{Green}_i + \beta_1 \text{AI}_i + \beta_2 \text{Green}_i \times \text{AI}_i + \chi_i + \gamma_f + \delta_t + \epsilon_{i,t,y}, \quad (4)$$

¹¹As the number of claims is available only for granted patents, the analyses including this control variable are performed only on the subset of granted patents.

where Y_{ift} is a proxy for patent impact or value, while $Green_i$ and $\beta_1 AI_i$ are dummy variables signalling green and AI patents, respectively. We also include a set of controls at the patent level (χ_i), such as the number of backward citations and the patent family size. The analysis incorporates time- and technology-fixed effects (γ_f and δ_t , respectively) to account for time- and field-specific variations. Y_{ift} includes the variables defined in the previous section, namely the number of forward citations (Equation 1), originality (Equation 2), generality (Equation 3), and patent value as defined by Kogan et al., 2017. The regression model is specified as follows: first, we include dummy variables for patents classified as Green or AI to observe their individual effects. Then, we examine the interaction between these two variables to assess any combined impact on the outcome variables. We also consider other model specifications to refine our analysis by including the relevant control variables.

Given the potential presence of confounding factors that could undermine the validity of our findings, we estimate the Average Treatment Effect (ATE) of being classified as GI patents, considering the outcome variables previously introduced, via IPWRA (Inverse Probability Weighting Regression Adjustment) methods (Wooldridge, 2007; Słoczyński and Wooldridge, 2018). IPWRA addresses selection bias by re-weighting the observations, allocating more weight to observations that are underrepresented and less weight to those overrepresented in the treatment group based on their covariates. The IPWRA estimates use weighted regression coefficients to compute averages of treatment-level predicted outcomes, with the weights being the inverse of the probabilities of receiving treatment (propensity scores). These scores are derived from a preliminary linear probability model that takes the GI dummy as the dependent variable and patent characteristics as covariates. The ATE is then calculated by contrasting the averages of predicted outcomes across treated and untreated units:

$$ATE = E(Y^m|T = m) - E(Y^l|T = m), \quad (5)$$

where m denotes the treatment level, l represents the comparison group (the treatment level to which m is compared, termed matched controls by Czarnitzki, Ebersberger, and Fier, 2007), and Y^m and Y^l denote outcomes in states m and l respectively. While Inverse Probability Weighting (IPW) may be sensitive to the correct specification of the propensity scores, and Regression Adjustment (RA) heavily relies on the assumption that the relationship between the outcome and propensity scores is correctly specified, IPWRA is doubly robust and allows for explicit checking of overlap assumptions. This property makes IPWRA less sensitive to model misspecification as compared, for instance, to propensity score matching (PSM), which relies solely on the propensity score model (Waernbaum, 2012). We also define multiple control groups to better account for the double nature of GI inventions. First, we compare GI and AI patents, matched by both AI techniques and AI functional applications. Second, we consider GI vs. green inventions, controlling for green subclassifications.

4 Exploring Green Intelligence

In this section, we explore the role of AI in green innovations and examine the quantity, trends, and evolution of GI inventions. We analyze the sectors where AI spurs green technologies, the most impactful AI technologies and applications, and applicants’ profiles and geographical distribution.

Figure 1a shows the differences in the number of patents across AI, green, and GI technologies and the 5-year growth rates for GI inventions¹². We observe a significant increase in green technology patents over time, with a sharp rise beginning in the early 2000s. Even if they are fewer than green patents, AI patents also display an upward trend, indicating growing innovation investments in this area, especially after 2010. The data show a general increase in the growth rate of GI inventions from around 2010 onwards, reflecting a more and more pronounced convergence between green and AI technologies in patent filings. This convergence suggests that innovators progressively integrate AI capabilities with green technology developments, indicating the growth of a more systemic approach to environmental challenges through AI solutions. This preliminary finding is confirmed by Figure 1b, which reports the trends of GI inventions compared to AI and green patents, respectively. Although the proportion of GI patents relative to AI patents is higher, it is noteworthy to observe a significant increase in the GI patents share within green patents after 2010. This suggests that GI inventions are becoming an important component of green innovations, highlighting a potential shift in the innovation landscape where AI is increasingly applied to environmental challenges.

4.1 Key application domains

In exploring the GI patent landscape, we are also interested in detecting specific features of these technologies. Therefore, we analyze the distribution of GI inventions across AI and green domains and compare them with more general trends observed in other AI and green inventions.

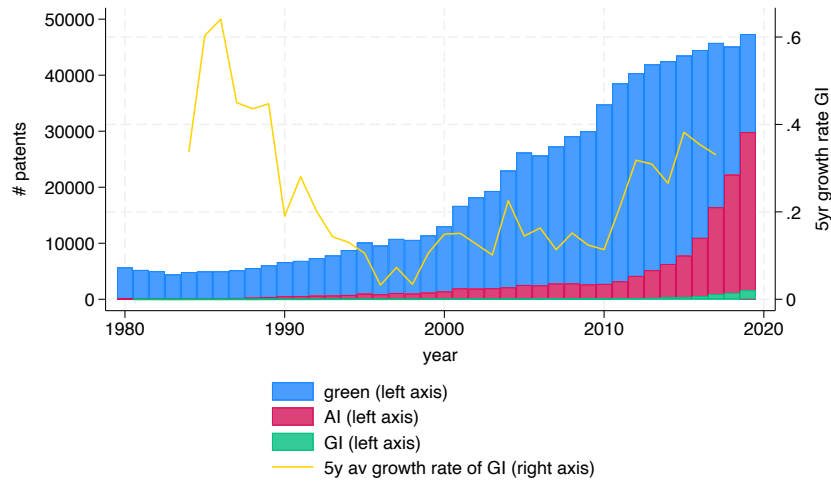
Table 2 reports the number of GI inventions considering all possible subclassifications of AI and green technologies.¹³ To complement this information with trends in AI and green technologies, we also include information on the share of GI inventions over the number of AI or green patents in the same class. While machine learning is the most common AI technique used in GI inventions in absolute terms, GI patents represent less than 4% of machine learning patents. The prevalence of GI inventions in expert systems and fuzzy logic is, instead, close to 10% of all AI patents in these subclasses. This comparison suggests an extensive use of AI in green technologies for control systems, automated processes, and planning. The intuition is confirmed by the distribution of patents among functional applications. The most prevalent class, in both absolute and relative terms, is control methods, followed by knowledge representation and reasoning and computer vision, indicating the demand for understanding and interpreting

¹²For greater details on the number of green, AI and GI patent applications over time, see the Table A1.

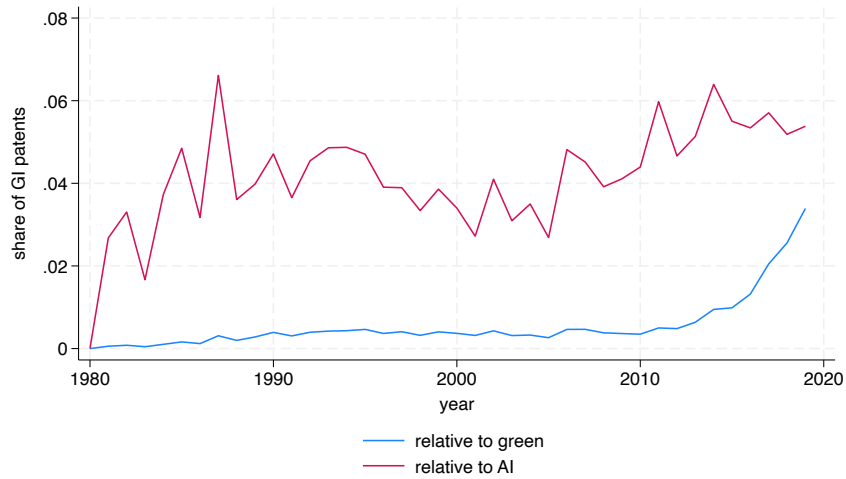
¹³Patents may belong to zero, one or multiple subclasses for each categorization.

Figure 1: Patenting trends over time

(a) Number of green, AI and GI patent applications and growth rate of GI



(b) Number of GI patent applications relative to green and AI patents



(a) AI subclasses

	# GI inventions	% GI inventions in same-class AI patents
<i>Techniques</i>		
Machine Learning	2,744	3.98%
Logic Programming	645	9.14%
Fuzzy Logic	190	8.85%
<i>Functional applications</i>		
Control Methods	2,784	10.00%
Knowledge Representation & Reasoning	963	4.92%
Computer Vision	9,46	2.79%
Robotics	600	9.58%
Speech Processing	506	1.82%
Planning & Scheduling	153	8.17%
<i>Application Fields</i>		
Transportation	4,316	6.01%
Life & Medical Sciences	1,434	7.38%
Telecommunications	1,427	5.05%
Industry & Manufacturing	967	16.42%
Energy Management	810	57.82%
Physical Sciences & Engineering	726	21.28%
Security	714	6.24%
Business	524	5.92%
Agriculture	318	17.74%
Personal Devices, Computing & HCI	181	3.30%
Networks	175	12.88%

(b) Green subclasses

	# GI inventions	% GI inventions in same-class green patents
CCMT Transportation	2,473	1.75%
Environmental Management	791	0.37%
CCMT Energy	750	0.31%
CCMT Buildings	494	0.73%
Water Related Adaptation	72	0.35%
CCMT Carbon Capture & Storage	4	0.05%

Table 2: Subclassification of AI and Green technologies

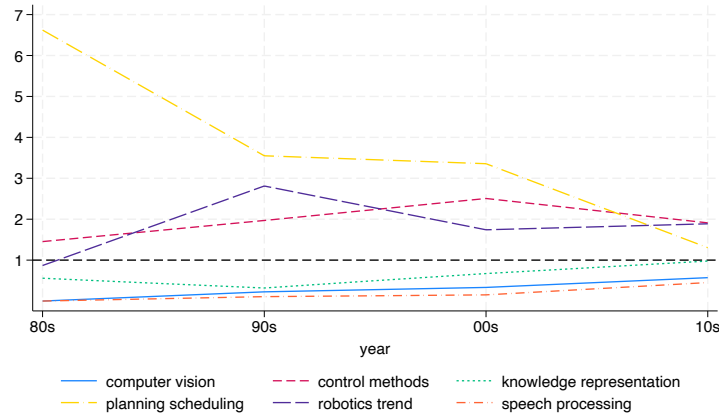
complex data in environmental applications. Along the same line, robotics and planning and scheduling show a high prevalence of GI inventions in their category. Concerning application fields, transportation is the prevalent application of GI inventions, counting 4,316 patents, followed by life and medical sciences patents and telecommunications. Interestingly, nearly 58% of the energy management patents based on AI are GI inventions. High shares of GI inventions are also present in AI patents with applications in physical science and engineering, agriculture, and industry and manufacturing.

The importance of transportation needs in GI inventions is confirmed in the green subclassification, where a high share of GI patents belongs to climate change mitigation technologies for transportation. A not negligible fraction of the GI inventions also describe AI applications to environmental management, CCMT energy, and CCMT buildings. Water-related adaptation and CCMT carbon capture and storage technologies represent only a minority of GI patents. Therefore, we will discard these categories in the following empirical analysis.

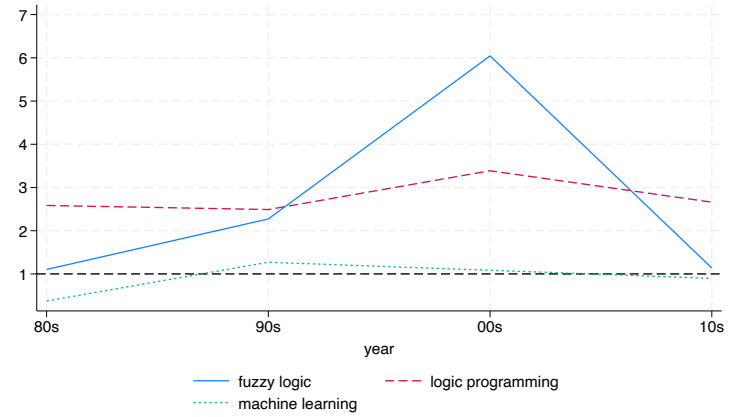
To uncover more fine-grained developmental patterns of GI technologies, we chart the evolution of GI patents across different application domains and periods (decades) compared to the trends observed for other AI and green technologies. Specifically, we test whether the share of GI patents in one domain exceeds, over time, the share of AI and green patents in the same application sector. By applying this normalization, we disentangle patterns specific to GI technologies from more general trends in AI and green inventions. Figure 2 shows those patterns in the different GI classifications. To discern domains in which GI is more present than expected, we add a straight line corresponding to ordinate 1: all values above this line indicate a high prevalence of GI in the corresponding domain compared to AI and green technologies in general; the opposite occurs for values below the straight line.

Figure 2a reports the trends of GI patents within AI functional applications by decade. Throughout all decades, planning and scheduling, robotics, and control methods have been relevant among GI technologies. While planning and scheduling applications show a constant decrease in importance, we observed a growth in patents related to robotics and control methods in the last few years. This shift suggests a growing interest and investment in physical automation and control systems, likely driven by their potential to enhance efficiency and reduce environmental impact in various applications. Conversely, areas such as speech processing, computer vision, and knowledge representation, despite being foundational components of AI research, remain relatively less prominent within the context of GI patents.

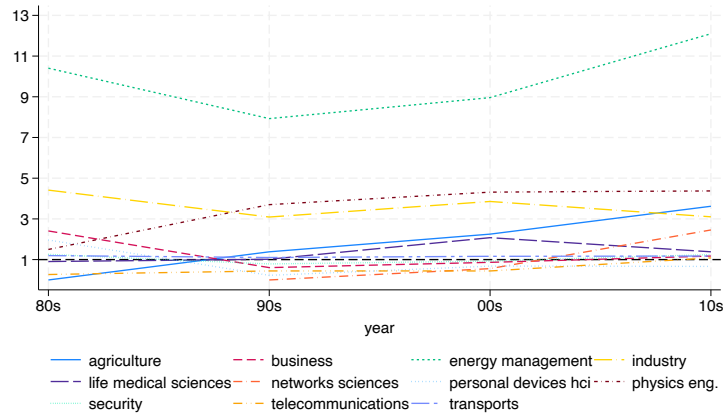
Figure 2b shows the evolution of GI patents across AI techniques. Although machine learning is the predominant AI technique in GI patents in absolute terms (see Table 2a), its evolution mirrors the trend observed in all AI patents since the relevance of machine learning is the same in AI and GI inventions. We observe less than expected GI patents using machine learning only in the 1980s, signalling a possible delay in the application of this emerging methodology to green technologies. The most relevant AI techniques in relative terms are, on the contrary, logic programming and fuzzy logic. The latter is significantly relevant in the 1990s and 2000s, being



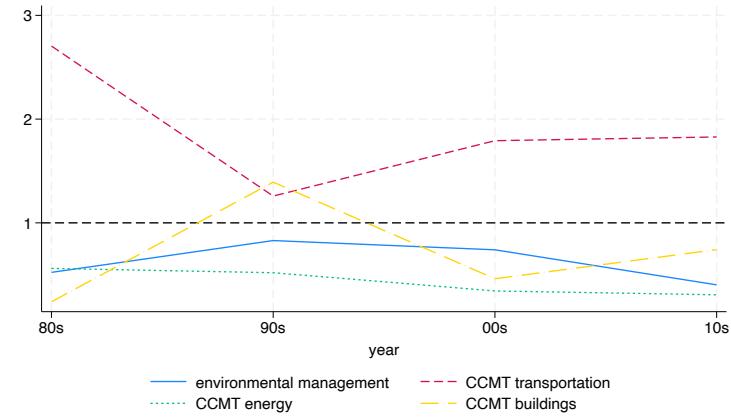
(a) AI functional applications



(b) AI techniques



(c) AI application fields



(d) Green classes

Figure 2: Relative trends by AI and Green patent classifications

Note: We drop those sub-classifications for which we register less than 150 patent applications over the entire period (see Table 2a).

even six times more present in GI inventions than in all AI patents. This picture confirms the extensive use of AI in green technologies for rule-based applications, such as control methods, planning and scheduling.

For what concerns AI application fields reported in Figure 2c, green technologies are, by far, the most relevant applications of AI-based energy management. Its prevalence in GI, around ten times higher than in AI inventions, increased in the last decade after a stagnating period. We also observe a prevalence of industrial, engineering, and physical AI applications in green technologies. Finally, it is interesting to note that the importance of green technologies is systematically increasing in AI applications for agriculture and network systems.

Finally, Figure 2d makes explicit that the first field of application of AI in green technologies is transportation. The prevalence of this field has been constant over time, except for the 1990s, in which we detected a significant number of AI applications to CCMT for buildings. Despite the initial spike, AI applications for green buildings have had low relevance in recent years. At the same time, AI applications are still marginal in environmental management and CCMT for energy systems.

4.2 Top corporate applicants and patenting by country

Table 3 reports the list of the top applicants for AI, green, and GI patents. Large high-tech American companies such as IBM, Microsoft, Google, and Amazon dominate the AI patent landscape, showcasing the capacity for digital and cognitive technological advancements. Japanese companies such as Toyota, Panasonic, and Honda show a strong presence in green technologies. German companies (e.g. BOSCH and Siemens) account for significant contributions across both AI and green patent categories, reflecting their focus on engineering and technology that intersects with green innovation. When examining GI patents, it becomes apparent that the top applicants are divided between automotive and electronics, suggesting these sectors' strategic convergence toward greener technology pathways. This pattern is interesting because it indicates a broader systemic approach to innovation, where the integration of AI in environmental technologies is becoming a highly relevant aspect of new product development.

Figure 3 reports time trends for the top countries of origin of applicants filing AI, green, and GI patents. The US dominates all three technological domains. However, it is noteworthy that despite their absence from the list of top applicants, Chinese companies have recently experienced a significant increase in the number of patents across all three categories, particularly in GI patents. Concerning green patents only (Figure 3a), we observe a significant increase in green inventions, especially in the US, around 2005. For top applicants' countries – including the US, Japan, South Korea, and Germany, – this period of growth has been replaced by a steady state in the last decade. Different patterns are present in AI patents (Figure 3b). Contrary to green technologies, this field has been growing consistently since 2015 in all countries. Specifically, we have observed an exponential increase in AI patents in the US in the last decade. While they are still behind the US, Japan, South Korea, and China have followed a similar trend in recent

Table 3: Top applicants by number of patents in the entire period

AI patents				Green patents				GI patents			
Country	Company	#	Share	Country	Company	#	Share	Country	Company	#	Share
US	IBM	8,739	6.15%	JP	TOYOTA	17,005	2.14%	JP	TOYOTA	196	2.74%
US	MICROSOFT	3,597	2.53%	KR	SAMSUNG	15,392	1.94%	US	FORD	152	2.12%
US	GOOGLE	3,097	2.18%	US	GE	13,286	1.67%	US	IBM	134	1.87%
KR	SAMSUNG	2,858	2.01%	DE	BOSCH	8,480	1.07%	US	INTEL	126	1.76%
US	AMAZON	2,017	1.42%	US	FORD	7,757	0.98%	KR	LG	108	1.51%
JP	TOYOTA	1,978	1.39%	JP	HONDA	7,300	0.92%	KR	SAMSUNG	105	1.47%
JP	SONY	1,728	1.22%	JP	PANASONIC	7,263	0.91%	US	BOEING	97	1.35%
KR	LG	1,540	1.08%	DE	SIEMENS	6,903	0.87%	US	DEXCOM	93	1.30%
US	INTEL	1,495	1.05%	US	UTC	5,615	0.71%	US	GE	89	1.24%
DE	SIEMENS	1,324	0.93%	KR	HYUNDAI	5,283	0.66%	US	GOOGLE	88	1.23%
JP	HONDA	1,252	0.88%	US	U. CAL	5,190	0.65%	DE	SIEMENS	86	1.20%
US	FORD	1,243	0.88%	US	IBM	5,140	0.65%	US	IROBOT	84	1.17%
JP	NEC	1,067	0.75%	US	GM	4,912	0.62%	KR	HYUNDAI	73	1.02%
US	GM	915	0.64%	JP	HITACHI	4,764	0.60%	JP	HONDA	70	0.98%
US	NUANCE	897	0.63%	US	INTEL	4,706	0.59%	US	MICROSOFT	68	0.95%
DE	BOSCH	889	0.63%	KR	LG	4,671	0.59%	JP	HITACHI	64	0.89%
US	BOEING	852	0.60%	JP	DENSO	4,471	0.56%	US	GM	60	0.84%
JP	FUJITSU	808	0.57%	JP	NISSAN	4,455	0.56%	US	WALMART	53	0.74%
IS	APPLE	796	0.56%	JP	TOSHIBA	4,178	0.53%	KR	KIA	51	0.71%
JP	TOSHIBA	790	0.56%	JP	SONY	3,569	0.45%	DE	BOSCH	51	0.71%

Harmonised names from PATSTAT are used. An additional manual cleaning is applied to the harmonised names. Patent assertion entities are excluded from the list.

years. Despite being at a lower order of magnitude, similar patterns are observed in GI patents (Figure 3c), as already noted in Figure 1b. Differently from what happens in AI, the growth of Japanese GI patents appears to have stopped in the last few years, while countries such as the US, China, and South Korea still show strong growth in this area.

5 The impact of Green Intelligence

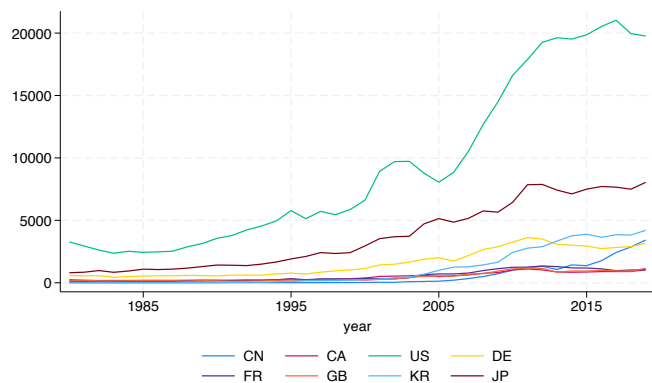
This section studies the impact of Green Intelligence inventions compared to other USPTO patents, especially those belonging only to the AI and green domains. Specifically, we report how AI, green and GI technologies correlate with various dimensions of patent quality and value. Table 4 displays the OLS estimates of the model presented in Equation 4. Our dependent variable is the number of forward citations a patent receives within five years. All models include fixed effects for the application year and technology field. The first and second columns include dummy variables representing whether a patent is classified as green or AI, respectively. The third column reveals, instead, the coefficient of interaction between these two dummies. The fourth and fifth columns also account for the number of backward citations and the patent family size as additional control variables. Finally, the last columns include the number of citations to the NPL, the number of inventors, and the number of claims. Across all model specifications, we observe that green and AI technologies positively correlate with patent quality, measured as the number of forward citations. Notably, the interaction coefficient’s magnitude is particularly high, suggesting that the nature of GI inventions increases the likelihood of forward citations¹⁴. GI is, indeed, a more novel and promising sector that combines two highly cited technological domains. In the following analyses, we will not observe this inflation in the magnitude of GI coefficients, which suggests that technological exploration in GI is still ongoing and its potential is arguably yet to be realised.

By using the complete regression specification (Table 4, column 8), we also test whether results hold with alternative measures that capture different dimensions of invention quality and value. More specifically, in columns 1 and 2 of Table 5 we evaluate the originality and generality of inventions. Our findings indicate a positive association of AI, Green, and GI patents with both indicators of patent quality. This result is not unexpected, and a plausible explanation is related to the recent emergence of these fields and their wide range of possible applications. It also suggests the capacity of these fields to build on a diversified set of pre-existing technologies and confirms that AI can be seen as a very promising GPT in the green sector.

Finally, in the last column, we test whether the positive associations persist when we use an ex-ante measure of value as computed by Kogan et al., 2017. Contrary to the previous quality indicators, this measure captures the market perceptions of a new invention, going beyond the

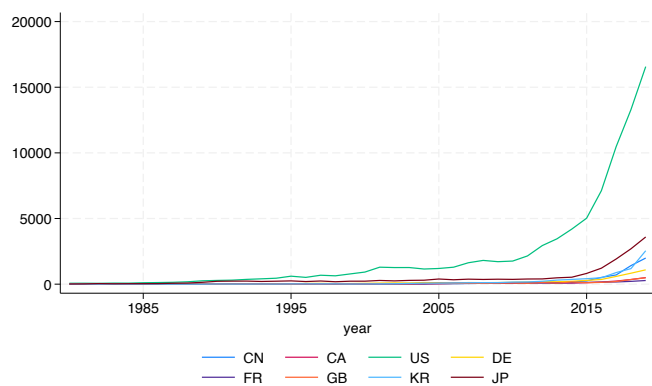
¹⁴Note that by adding the number of claims as a control variable (column 8) the number of observations drops because this information is missing for non-granted patents in the dataset. Therefore, by including this control, our main regression specification focuses on granted patents only, significantly reducing the number of AI and GI patents in the sample (see Table 1).

Figure 3: Trends by applicants' country of residence



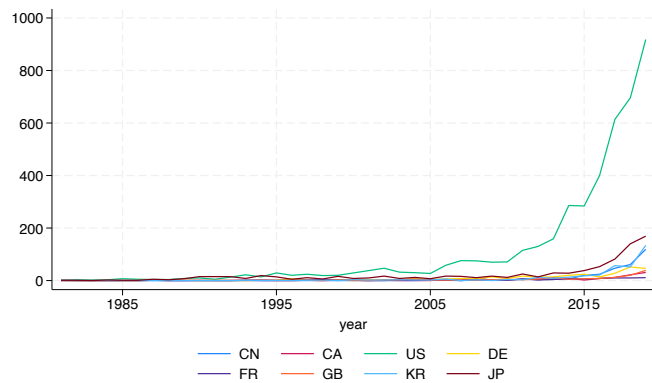
(a) Green patents

Note: We use the variable person_etry_code in PATSTAT to detect the applicants' country of origin.



(b) AI patents

Note: We use the variable person_etry_code in PATSTAT to detect the applicants' country of origin.



(c) GI patents

Note: We use the variable person_etry_code in PATSTAT to detect the applicants' country of origin.

Table 4: The impact of green, AI and GI patents

DV: forward citations 5yrs								
	1	2	3	4	5	6	7	8
Green = 1	4.602*** (0.074)	4.622*** (0.074)	4.053*** (0.068)	3.853*** (0.066)	3.006*** (0.065)	2.909*** (0.065)	2.757*** (0.064)	2.835*** (0.076)
AI =1		8.739*** (0.255)	5.993*** (0.227)	5.831*** (0.223)	5.867*** (0.222)	5.609*** (0.222)	5.349*** (0.222)	5.967*** (0.269)
Green = 1 × AI =1			53.46*** (2.541)	50.13*** (2.493)	49.22*** (2.460)	49.17*** (2.456)	49.18*** (2.459)	38.07*** (2.295)
bwd cites				0.124*** (0.001)	0.120*** (0.001)	0.105*** (0.001)	0.104*** (0.001)	0.102*** (0.001)
family size					1.404*** (0.008)	1.340*** (0.008)	1.281*** (0.008)	1.132*** (0.008)
NPL cites						0.136*** (0.005)	0.135*** (0.004)	0.139*** (0.005)
nr inventors							0.956*** (0.012)	0.933*** (0.015)
nr claims								0.181*** (0.002)
Observations	8,995,626	8,995,626	8,995,626	8,995,626	8,995,626	8,995,626	8,995,510	6,959,125
R-squared	0.022	0.023	0.024	0.078	0.092	0.096	0.097	0.116
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Tech. Field	YES	YES	YES	YES	YES	YES	YES	YES

OLS estimates. Robust standard errors in parentheses. Time period: 1980-2019.

Legend: *** p<0.01, ** p<0.05, * p<0.1.

pure technological content of the patent. The results show a positive association between AI technologies and the ex-ante value of technologies as captured by the stock market response to patent grants. When using this outcome variable, the coefficient turns negative for green technologies. No significant relation is found between GI patents and ex-ante value.¹⁵ These results are in line with the idea that AI technologies are expected to generate strong returns for investors and shareholders, whereas there is much more uncertainty over the future profitability of green technologies, which are generally associated with lower stock market valuations. As an emerging and relatively new field, GI is still perceived as a higher risk, arguably because of the complexity and costs of environmental challenges.

To further examine this relation and ensure the most appropriate comparisons between patents, Table 6 reports the estimated ATEs of being classified as GI inventions against AI and green inventions, respectively (see Equation 5).¹⁶ This approach allows us to validate our findings by reweighting observations to mimic a randomised control trial, thus reducing biases associated with nonrandom assignment. This aspect makes IPWRA a robust method to validate and strengthen causal inferences drawn from OLS estimates. Appendix B provides IPWRA treatment model estimations and diagnostics. As shown in Table B1, control methods and robotics are highly represented as GI functional applications, while the predominant techniques are fuzzy logic and logic programming. Conversely, machine learning and computer vision are underrepresented in the GI domain. Within green subclasses, instead, GI stands out in transportation. In all the dimensions of quality and value we consider, results on GI patents presented in Table 6 are consistent with those reported in tables 4 and 5. Compared to green or AI technologies, GI innovations have greater technological impact, as well as higher originality and generality. The same does not hold in terms of stock market response, for which GI technologies are not seen as more valuable than green and AI inventions.

5.1 Heterogeneity across countries of applicants

Our main analysis focuses on patents filed at the USPTO since not all other jurisdictions allow the patenting of software technologies. Still, some heterogeneity may emerge across the countries of origin of the patent applicants. In Table 7, we test this source of heterogeneity by showing the results of a split sample by applicants' countries of origin considering only main countries as detected in Figure 3. In this additional analysis, we test whether the impact of green, AI, and GI technologies, captured by forward citations, varies across countries. Our findings indicate that green technologies are always of greater impact than other patents, except for patents filed by Korean and UK assignees. The same holds for AI patents, with the exception of Canadian applicants (where the coefficient is positive but not significant). The main differences across

¹⁵The measure of patent value developed by Kogan et al., 2017 is available for patents granted by listed companies only, causing a considerable drop in the number of observations (Table 5, column 3).

¹⁶Treatment model in the case of GI vs AI patents is computed considering AI technologies as well as AI functional applications as reported in Table 6.

Table 5: Originality, generality and KPSS value of green, AI and GI patents

	originality	generality	KPSS value
Green = 1	0.0298*** (0.000)	0.0412*** (0.000)	-1.083*** (0.075)
AI =1	0.0405*** (0.001)	0.161*** (0.001)	1.310*** (0.194)
Green = 1 × AI =1	0.0325*** (0.002)	0.0222*** (0.003)	-0.486 (0.683)
bwd cites	7.86e-05*** (0.000)	1.47e-05*** (0.000)	0.00493*** (0.000)
family size	0.00220*** (0.000)	0.00332*** (0.000)	0.205*** (0.009)
NPL cites	0.000275*** (0.000)	0.000298*** (0.000)	0.0256*** (0.001)
nr inventors	0.00244*** (0.000)	0.00348*** (0.000)	0.274*** (0.013)
nr claims	0.00100*** (0.000)	0.00144*** (0.000)	0.120*** (0.002)
Observations	6,902,236	5,822,795	2,343,535
R-squared	0.120	0.097	0.067
Year FE	YES	YES	YES
Tech. Field	YES	YES	YES

OLS estimates. Robust standard errors in parentheses.
Time period: 1980-2019. Legend: *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Average treatment effects of GI on the quality and value of patents

GI vs AI					
		fwd cites 5y	originality	generality	KPSS value
GI vs AI (Techniques)	ATE	0.03820*** (0.00004)	0.01332*** (0.00438)	0.08528*** (0.00302)	-0.00006 (0.00002)
GI vs AI (Functional appl.)	ATE	0.02340*** (0.00002)	0.05387*** (0.00401)	0.06612*** (0.00325)	-0.00003 (0.00002)
GI vs Green					
GI vs Green	ATE	0.04621*** (0.00133)	0.05310*** (0.00342)	0.05136*** (0.00321)	0.00032 (0.00001)

IPWRA model. Robust standard errors in parentheses. Time period: 1980-2019.
Legend: *** p<0.01, ** p<0.05, * p<0.1.

Table 7: The value of GI - split sample by main countries of the applicants

	US	JP	CN	DE	KR	FR	GB	CA
Green = 1	4.809*** (0.138)	0.621*** (0.090)	2.653*** (0.316)	1.114*** (0.098)	-0.249 (0.156)	1.474*** (0.183)	0.317 (0.291)	1.783*** (0.428)
AI =1	7.860*** (0.408)	0.689*** (0.136)	2.265*** (0.440)	1.503*** (0.285)	0.922*** (0.309)	3.006*** (0.879)	7.511*** (2.170)	0.982 (1.010)
Green = 1 × AI =1	57.88*** (3.484)	0.505 (0.567)	-0.560 (2.725)	2.502 (1.641)	3.816*** (1.222)	-2.412 (1.583)	1.841 (4.625)	27.48** (13.144)
bwd cites	0.102*** (0.001)	0.273*** (0.010)	0.201*** (0.040)	0.0757*** (0.012)	0.187*** (0.017)	0.102*** (0.007)	0.202*** (0.022)	0.110*** (0.008)
family size	1.485*** (0.013)	0.889*** (0.024)	0.656*** (0.079)	0.394*** (0.018)	1.465*** (0.040)	0.314*** (0.013)	0.841*** (0.041)	1.372*** (0.062)
NPL cites	0.161*** (0.005)	0.00878 (0.014)	0.194*** (0.034)	0.297*** (0.029)	0.243*** (0.031)	0.115*** (0.014)	0.0422* (0.022)	0.163*** (0.018)
nr inventors	1.056*** (0.025)	0.705*** (0.021)	0.149*** (0.027)	0.376*** (0.029)	0.361*** (0.025)	0.587*** (0.048)	1.475*** (0.090)	1.293*** (0.080)
nr claims	0.149*** (0.003)	0.122*** (0.005)	0.148*** (0.016)	0.147*** (0.010)	0.0605*** (0.007)	0.0922*** (0.006)	0.100*** (0.012)	0.0775*** (0.010)
Observations	3,667,544	1,328,159	151,776	433,502	294,076	170,053	140,943	139,962
R-squared	0.124	0.084	0.123	0.140	0.125	0.096	0.136	0.119
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Tech. Field	YES	YES	YES	YES	YES	YES	YES	YES

OLS estimates. Robust standard errors in parentheses. Time period: 1980-2019.

Legend: *** p<0.01, ** p<0.05, * p<0.1.

countries occur for GI inventions. GI patents are, indeed, characterised by greater impact only in the case of US, Korean, and Canadian applicants, while for the rest of the countries, the coefficient displayed is not significant. This result might be partially driven by the distribution of GI patents across countries, as shown in Figure 3, and by connections between US and Canadian markets. However, it might also suggest the presence of competitive advantages among US companies in this relatively new and expanding field.

5.2 Robustness

In this section, we discuss the results of some additional exercises to test the robustness of our findings (see Appendix C for detailed results). First, we use alternative dependent variables to measure the quality of patents (Squicciarini, Dernis, and Criscuolo, 2013). Specifically, we use the breakthrough indicator, which identifies patents appearing in the top 1% of cited patents as breakthrough inventions (Ahuja and Morris Lampert, 2001), as an alternative measure of impact. We consider, instead, patent scope, defined as the number of distinct 4-digit International Patent Classification subclasses assigned to a patent (Lerner, 1994), as an alternative measure of diversification across technological domains. Given its definition, this measure should produce results in line with those we obtain with the use of the originality and generality measures. As shown in Table C1 (columns 1 and 2), our findings are indeed robust if we use these alternative dependent variables in our analysis. In addition, as the number of forward citations may be subject to different strategies across technological domains, in the third and fourth columns of Table C1 we test the robustness of our results by including the interaction between the two fixed effects of year and technological field (column 4) and by normalising the number of forward citations by the average number of citation in the field-year.¹⁷

Second, as shown in Table C2, very similar results are found if we restrict the period of analysis to the last decade (2010-2019). As shown in Table 1a, the emergence of AI and GI patents is a recent trend that has picked up in the last decade. However, the quality and value of these technologies does not change over that period.

Finally, as our main dependent variable in the regression analysis (forward citations) is a count variable, as a third robustness check we use a Poisson model in our estimations, and all our results are confirmed (see Table C3).

6 Conclusion

Through a comprehensive analysis of patent data, this paper explores the intersection between AI and green technologies, shedding new light on how progress in AI can contribute to sustainability. Our results unveil a landscape where the role of AI algorithms is expanding and is harnessed to spur green innovation. This kind of innovation spans various domains, showcas-

¹⁷Note that the use of the normalised number of citations changes the interpretation of the coefficient magnitude.

ing AI's versatility of application and impact in relation to several environmental challenges. The study pinpoints transportation, energy, and control methods as key areas where GI inventions are most prevalent. We also observe a high concentration of GI activities in the United States, with growing innovative efforts from Japan, South Korea, and China. From a technological viewpoint, GI inventions are characterised by strong technological impact (as proxied by forward citations), alongside greater originality and generality. However, indicators of market perceptions suggest some misalignment relative to these advancements. The observed discrepancy between the high technological impact of Green Intelligence inventions and their expected market value is a likely indication of stronger uncertainty and the presence of barriers that might require policy intervention. Further research could focus on the specific need for and potential of financial incentives for companies pioneering GI inventions, public-private partnerships to foster GI innovation ecosystems, schemes fostering growth in the supply of GI skills, and educational campaigns to raise awareness about the benefits of GI technologies. The balance between efficiency gains generated by the application of GI and the energy needs of these technologies should arguably be an integral part of this assessment.

The lack of positive stock market reactions to green intelligence patents compared to AI patents suggests that the barriers reside on the 'green side'. However, some barriers to innovation might be specific to Green Intelligence technologies relative to the broader pool of green inventions. In their careful assessment of eco-innovation barriers, De Jesus and Mendonça (2018) note that these barriers concern different dimensions of the green transition, and vary across fields. Moreover, these barriers differ from one another in terms of strength. They argue that there are high-order institutional, legal, social, and cultural barriers, but the 'hardest' barriers to overcome seem to be technical and financial. Both technical bottlenecks and financial constraints are arguably slowing down innovation in green products, processes and services. For the sectors and subsectors where this occurs, useful policy interventions could take the form of direct support to business R&D through innovation grants, which can target the specific aims and objectives of the green transition (Howell, 2017; Santoleri et al., 2022). Where the slow adoption of eco-innovation can be attributed to weak demand (hence a weaker, absent or even negative stock market reaction to green inventions), useful policy measures can include both information diffusion and demand-building interventions. A detailed assessment of sector-specific barriers to innovation is beyond the scope of this contribution, but more granular analyses could identify which actions constitute the most effective mix among the options available to policy-makers (Steinmueller, 2010; Bloom, Van Reenen, and Williams, 2019). This mix could accelerate the market's recognition and adoption of GI innovations, ensuring that technological advancements translate into tangible environmental and economic benefits.

The study is of course not without limitations. Primarily, our reliance on patent data as the sole indicator of innovation in Green Intelligence may not fully capture the complexities of GI technology development, let alone the dynamics of GI adoption. Consequently, more could be done to explore, on the one hand, how organizations or sectors are financing, researching

and commercialising these technologies, and, on the other, how the demand for GI solutions is shaped by market and non-market forces. Moreover, our focus on the United States Patent and Trademark Office (USPTO), as the sole legislation where software inventions can be patented, may not give the full picture of global investments in GI inventions. This geographical limitation underscores the need for a more expansive view that should include multiple regions to capture the global landscape of GI technological advancement, its global value chains, and global market outcomes.

Future research could also address how companies integrate GI inventions into their operations and the impact on their economic performance, as well as the market performance of GI innovators applying different corporate strategies to heterogeneous market conditions and regulatory environments.

As the world struggles with the urgent need for effective solutions to environmental challenges, the role of AI in advancing green innovations could become increasingly important. Further explorations of GI technologies and GI markets could also inform collaborative efforts among researchers, policymakers, and industry players and help to design new ways to harness the potential of AI for sustainability.

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Appendix A Additional figures and tables

Figure A1: Patent US9898688B2

<p>(12) United States Patent Bleiweiss</p> <p>(54) VISION ENHANCED DRONES FOR PRECISION FARMING</p> <p>(71) Applicant: Intel Corporation, Santa Clara, CA (US)</p> <p>(72) Inventor: Amit Bleiweiss, Yad Binyamin (IL)</p> <p>(73) Assignee: Intel Corporation, Santa Clara, CA (US)</p> <p>(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 0 days.</p> <p>(21) Appl. No.: 15/169,972</p> <p>(22) Filed: Jun. 1, 2016</p> <p>(65) Prior Publication Data US 2017/0351933 A1 Dec. 7, 2017</p> <p>(51) Int. Cl. G06K 9/00 (2006.01) G06K 9/62 (2006.01) G06T 7/40 (2017.01) G06T 17/05 (2011.01) B64C 39/02 (2006.01)</p> <p>(52) U.S. Cl. CPC G06K 9/627 (2013.01); B64C 39/024 (2013.01); G06K 9/00201 (2013.01); G06T 7/408 (2013.01); G06T 17/05 (2013.01); B64C 2201/123 (2013.01); B64C 2201/141 (2013.01); B64C 2201/146 (2013.01); G06T 2207/10024 (2013.01); G06T 2207/10028 (2013.01); G06T 2207/10032 (2013.01); G06T 2207/20081 (2013.01); G06T 2207/20084 (2013.01); G06T 2207/30188 (2013.01); G06T 2207/30244 (2013.01)</p>	<p>(10) Patent No.: US 9,898,688 B2</p> <p>(45) Date of Patent: Feb. 20, 2018</p> <p>(58) Field of Classification Search CPC B64C 39/024; B64C 2201/123; B64C 2201/141; B64C 2201/146; G06K 9/6267; G06K 2209/17; A01B 79/005 USPC 382/156-159 See application file for complete search history.</p> <p>(56) References Cited U.S. PATENT DOCUMENTS 2016/0106038 A1* 4/2016 Boyd A01D 41/141 56/10.4 2016/0148104 A1* 5/2016 Itzhaky G06N 5/04 706/12 2016/0196688 A1* 7/2016 Bergman G06T 17/05 345/420 2017/0032258 A1* 2/2017 Miresmailli A01G 7/00</p> <p>OTHER PUBLICATIONS Vineview, "Scientific Aerial Imaging", vineview.com, retrieved Apr. 13, 2016, 1 page.</p> <p>* cited by examiner</p> <p><i>Primary Examiner</i> — Daniel Mariam (74) <i>Attorney, Agent, or Firm</i> — Jordan IP Law, LLC</p> <p>(57) ABSTRACT Methods, apparatuses and systems may provide for a neural network that analyzes and classifies agricultural conditions based on depth data and color data recorded by one or more drones, and generates an annotated three dimensional (3D) map with the agricultural conditions. Additionally, an object recognition model may be trained for use by a drone controller to trigger drones to conduct a collection of depth data at an increased proximity to crop-related objects based on agricultural conditions.</p> <p>21 Claims, 8 Drawing Sheets</p>
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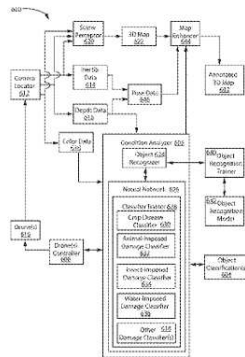


Figure A2: Patent US11555701B2

(12) **United States Patent**
Du et al.

(10) **Patent No.:** **US 11,555,701 B2**
(45) **Date of Patent:** **Jan. 17, 2023**

(54) **USE OF A CONVOLUTIONAL NEURAL NETWORK TO AUTO-DETERMINE A FLOOR HEIGHT AND FLOOR HEIGHT ELEVATION OF A BUILDING**

(71) Applicant: **CORELOGIC SOLUTIONS, LLC**, Irvine, CA (US)

(72) Inventors: **Wei Du**, Springfield, VA (US); **David Frederick Smith**, Oakland, CA (US); **Taylor Bryant Brown**, Euless, TX (US)

(73) Assignee: **CORELOGIC SOLUTIONS, LLC**, Irvine, CA (US)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 312 days.

(21) Appl. No.: **16/864,342**

(22) Filed: **May 1, 2020**

(65) **Prior Publication Data**
US 2020/0348132 A1 Nov. 5, 2020

Related U.S. Application Data

(60) Provisional application No. 62/842,023, filed on May 2, 2019.

(51) **Int. Cl.**
G01C 15/00 (2006.01)
G01C 5/00 (2006.01)
G06N 3/04 (2006.01)
G06V 20/20 (2022.01)

(52) **U.S. Cl.**
CPC **G01C 15/002** (2013.01); **G01C 5/00** (2013.01); **G06N 3/04** (2013.01); **G06V 20/20** (2022.01)

(58) **Field of Classification Search**
CPC . G01C 15/00; G01C 5/00; G06N 3/04; G06N 3/0454; G06N 3/08; G06V 20/20; G06V 10/82; G06V 20/10; G06V 20/176

USPC 382/106
See application file for complete search history.

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H. Nakahara, T. Fujii and S. Sato, "A fully connected layer elimination for a binarized convolutional neural network on an FPGA," 2017 27th International Conference on Field Programmable Logic and Applications (FPL), 2017, pp. 1-4, doi: 10.23919/FPL.2017.8056771. (Year: 2017).*

Primary Examiner — Marnie A Matt
(74) *Attorney, Agent, or Firm* — Xsensus LLP

(57) **ABSTRACT**

A system, apparatus, computer program product, and method use a convolutional neural network to auto-determine a first floor height (FFH) and a FFH elevation (FFE) of a building. The FFH, and FFE of the building are determined with respect to the terrain or surface of the parcel of land on which the building is located. In turn, by knowing the FFH and/or FFE of the building on the parcel, it is possible to use that information while performing a flood risk assessment to a property without requiring a personal inspection of the parcel by a human.

20 Claims, 59 Drawing Sheets
(39 of 59 Drawing Sheet(s) Filed in Color)

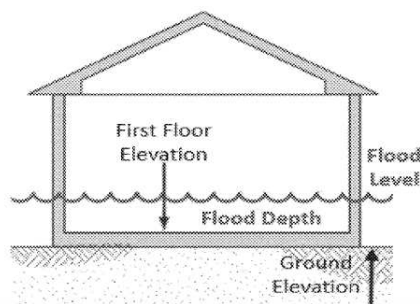


Figure A3: Patent US10318821B2

(12) **United States Patent**
Kim et al.

(10) **Patent No.:** **US 10,318,821 B2**
(45) **Date of Patent:** **Jun. 11, 2019**

(54) **DRIVER ASSISTANCE FOR A VEHICLE**

(71) Applicant: **LG ELECTRONICS INC.**, Seoul (KR)

(72) Inventors: **Jeongsu Kim**, Seoul (KR); **Hyeonju Bae**, Seoul (KR)

(73) Assignee: **LG Electronics Inc.**, Seoul (KR)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 0 days.

(21) Appl. No.: **15/081,342**

(22) Filed: **Mar. 25, 2016**

(65) **Prior Publication Data**
US 2016/0318523 A1 Nov. 3, 2016

(30) **Foreign Application Priority Data**
Apr. 30, 2015 (KR) 10-2015-0061846

(51) **Int. Cl.**
B60W 30/18 (2012.01)
B60W 50/00 (2006.01)
(Continued)

(52) **U.S. Cl.**
CPC **G06K 9/00791** (2013.01); **B60R 1/00** (2013.01); **B60W 30/18018** (2013.01); **B60W 30/18154** (2013.01); **F02N 11/0837** (2013.01); **B60K 37/02** (2013.01); **B60K 2350/1072** (2013.01); **B60K 2350/1096** (2013.01); **B60K 2350/905** (2013.01); **B60R 2300/105** (2013.01); **B60R 2300/205** (2013.01); **B60R 2300/307** (2013.01); **B60W 2050/0095** (2013.01); **B60W 2420/42** (2013.01); **B60W 2550/22** (2013.01); **B60W 2550/402** (2013.01); **B62D 15/0285** (2013.01);
(Continued)

(58) **Field of Classification Search**
None
See application file for complete search history.

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(Continued)
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(Continued)
OTHER PUBLICATIONS
Machine translation of JP 2014-195195.*
(Continued)
Primary Examiner — Navid Ziaianmehdizadeh
(74) Attorney, Agent, or Firm — Fish & Richardson PC.

(57) **ABSTRACT**
Disclosed are systems and techniques for automated driver assistance in a vehicle having an Idle Stop and Go (ISG) function that controls an engine of the vehicle. A driver assistance apparatus includes at least one object detection sensor configured to acquire an image of a view ahead of the vehicle or a view around the vehicle, and a processor configured to detect information from the acquired image. The processor determines navigation information related to the vehicle, and provides a control signal to enable or disable the ISG function based on at least one of the information detected from the acquired image or the navigation information.

32 Claims, 58 Drawing Sheets

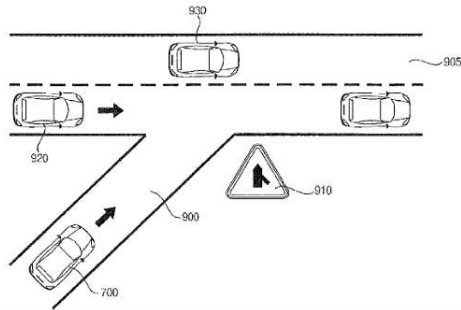


Table A1: Number of green, AI and GI patent applications by 5-year sub-periods

period	# green	# AI	# GI
1980-1984	25,239	579	14
1985-1989	26,752	1,328	58
1990-1994	37,446	3,224	147
1995-1999	52,473	5,235	206
2000-2004	90,194	9,377	315
2005-2009	138,188	13,339	535
2010-2014	198,064	21,651	1,178
2015-2019	226,232	87,299	4,713

Appendix B IPWRA: Treatment models and diagnostics

Table B1 presents the estimates of the treatment models, which are utilised as IPWRA weights for GI patents across AI functional applications, AI technologies, and Green subclassifications. The findings indicate a more significant representation of certain AI technologies, such as control methods and logic programming, in GI innovations. Conversely, machine learning and computer vision are comparatively underrepresented in the GI context. Moreover, within the green subclasses, the substantial and positive coefficient for transportation suggests it is a domain where GI has a pronounced influence.

We also report standard diagnostics supporting the reliability of the IPWRA estimates. Figures B1, B2 and B3 show the kernel density estimates of the p-scores of inclusion in either the treated or control group, respectively for GI patents vs AI functional applications, GI vs AI technologies and GI vs Green technologies. They reveal that the overlap assumption is not violated. We also observe no concentration around 0 or 1, thus essentially ruling out bias and excessive variance that may drive the estimates due to extreme p-scores.

Figure B1: Propensity scores plot - GI technologies vs AI functional applications

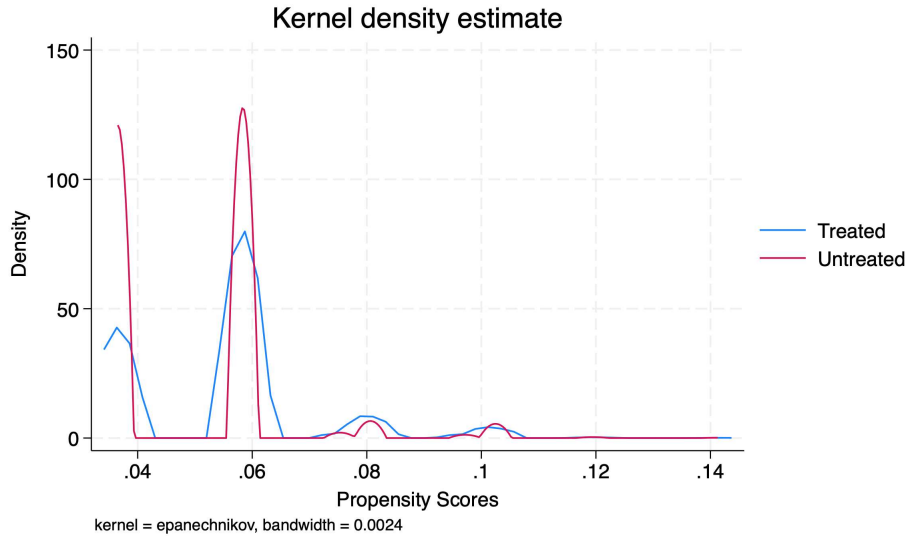


Table B1: GI technologies and AI and green subclasses - treatment model

		GI vs. AI	GI vs. AI	Gi vs. Green
Functional applications	Control methods		0.0487*** (0.00209)	
	Computer vision		-0.0310*** (0.00130)	
	Knowledge representation		-0.000377 (0.00183)	
	Robotics		0.0221*** (0.00383)	
	Speech processing		-0.0335*** (0.00129)	
	Planning scheduling		0.00713 (0.00649)	
Techniques	Fuzzy logic	0.0388*** (0.00620)		
	Logic programming	0.0441*** (0.00350)		
	Machine learning	-0.0218*** (0.00115)		
Green subclasses	Environmental management			-0.0121*** (0.000251)
	CCMT energy			-0.0116*** (0.000234)
	CCMT transportation			0.00811*** (0.000363)
	CCMT buildings			-0.00526*** (0.000373)
	Constant	0.0584*** (0.000895)	0.0539*** (0.00109)	0.0148*** (0.000223)
	Observations	141,632	141,632	792,330
	R-squared	0.005	0.019	0.006

Linear probability model. Robust standard errors in parentheses. Time period: 1980-2019.
 Legend: *** p<0.01, ** p<0.05, * p<0.1

Figure B2: Propensity scores plot - GI vs AI techniques

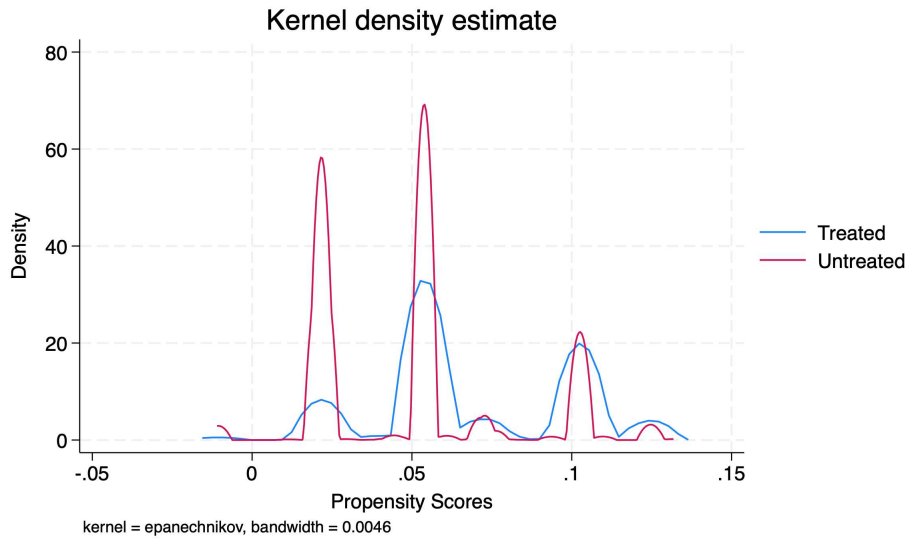
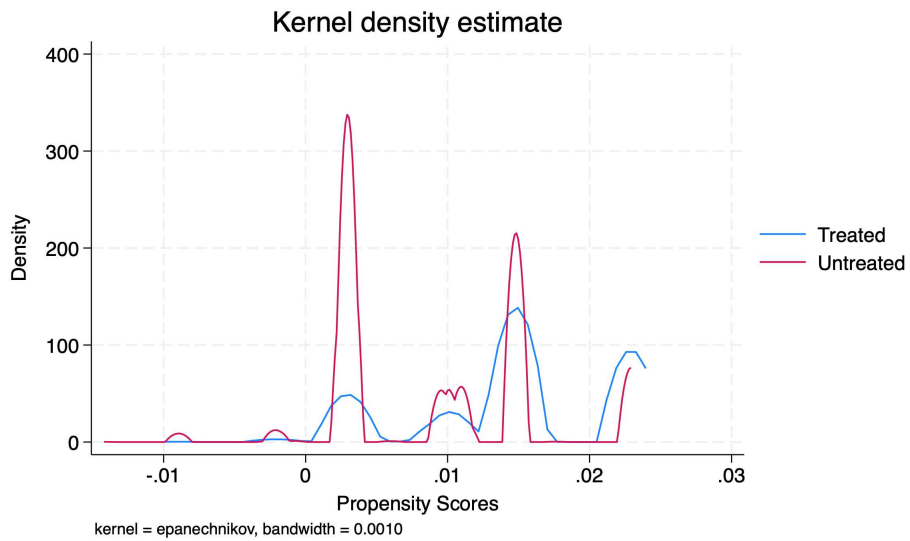


Figure B3: Propensity scores plot - GI vs green subclasses



Appendix C Robustness checks

Table C1: Breakthrough, patent scope and normalised forward citations of green, AI and GI patents

	breakthrough	patent scope	fwd cites 5yrs	fwd cites 5yrs normalised
Green = 1	0.00531*** (0.000)	0.378*** (0.002)	2.962*** (0.076)	0.284*** (0.006)
AI =1	0.00619*** (0.000)	0.783*** (0.005)	6.614*** (0.276)	0.512*** (0.022)
Green = 1 × AI =1	0.0637*** (0.004)	0.946*** (0.043)	37.66*** (2.295)	2.720*** (0.161)
bwd cites	7.07e-05*** (0.000)	8.85e-05*** (0.000)	0.101*** (0.001)	0.00469*** (0.000)
family size	0.00208*** (0.000)	0.0446*** (0.000)	1.143*** (0.008)	0.0984*** (0.001)
NPL cites	0.000256*** (0.000)	0.000819*** (0.000)	0.139*** (0.005)	0.0150*** (0.000)
nr inventors	0.00145*** (0.000)	0.0159*** (0.000)	0.939*** (0.015)	0.0862*** (0.001)
nr claims	0.000349*** (0.000)	0.00217*** (0.000)	0.178*** (0.002)	0.0187*** (0.000)
Observations	6,959,125	6,959,125	6,959,125	6,959,125
R-squared	0.028	0.125	0.119	0.075
Year FE	YES	YES	YES	YES
Tech. Field	YES	YES	YES	YES
Year FE × Tech. Field	NO	NO	YES	NO

OLS estimates. Robust standard errors in parentheses. Time period: 1980-2019.
Legend: *** p<0.01, ** p<0.05, * p<0.1.

Table C2: The quality and value of green, AI and GI patents - split sample last decade

	fwd cites 5yrs	originality	generality	KPSS value
Green = 1	3.737*** (0.135)	0.0274*** (0.000)	0.0382*** (0.001)	-1.871*** (0.096)
AI =1	6.989*** (0.339)	0.0468*** (0.001)	0.169*** (0.001)	2.498*** (0.250)
Green = 1 × AI =1	40.48*** (2.759)	0.0266*** (0.002)	0.00952*** (0.004)	0.611 (0.875)
bwd cites	0.0977*** (0.001)	4.33e-05*** (0.000)	9.70e-07 (0.000)	0.00483*** (0.000)
family size	2.071*** (0.021)	0.00183*** (0.000)	0.00310*** (0.000)	0.155*** (0.015)
NPL cites	0.110*** (0.005)	0.000229*** (0.000)	0.000268*** (0.000)	0.0186*** (0.001)
nr inventors	0.890*** (0.025)	0.00160*** (0.000)	0.00182*** (0.000)	0.479*** (0.020)
nr claims	0.314*** (0.007)	0.00125*** (0.000)	0.00202*** (0.000)	0.255*** (0.005)
Observations	2,803,102	2,791,931	2,227,999	836,299
R-squared	0.123	0.103	0.089	0.087
Year FE	YES	YES	YES	YES
Tech. Field	YES	YES	YES	YES

OLS estimates. Robust standard errors in parentheses. Time period: 2010-2019.
Legend: *** p<0.01, ** p<0.05, * p<0.1.

Table C3: Impact of green, AI and GI patents - Poisson model

DV: forward citations 5 yrs								
	1	2	3	4	5	6	7	8
Green=1	0.447*** (0.006)	0.449*** (0.006)	0.404*** (0.006)	0.394*** (0.006)	0.308*** (0.006)	0.305*** (0.006)	0.298*** (0.007)	0.295*** (0.007)
AI=1		0.518*** (0.012)	0.393*** (0.012)	0.404*** (0.012)	0.409*** (0.012)	0.366*** (0.013)	0.359*** (0.013)	0.349*** (0.016)
Green=1 × AI=1			1.16*** (0.035)	1.15*** (0.035)	1.03*** (0.031)	1.05*** (0.034)	1.06*** (0.034)	0.867*** (0.039)
bwd cites				0.0006*** (0.000004)	0.0006*** (0.000004)	0.0005*** (0.000004)	0.0005*** (0.000004)	0.0005*** (0.000004)
family size					0.086*** (0.0003)	0.085*** (0.0003)	0.081*** (0.0003)	0.075*** (0.0004)
NPL cites						0.002*** (0.00004)	0.002*** (0.00004)	0.002*** (0.00004)
nr inventors							0.039*** (0.003)	0.035*** (0.004)
nr claims								0.008*** (0.0004)
Observations	8,995,626	8,995,626	8,995,626	8,995,626	8,995,626	8,995,626	8,995,510	6,959,125
Pseudo R ²	0.116	0.118	0.119	0.143	0.204	0.212	0.217	0.240
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Tech.field	YES	YES	YES	YES	YES	YES	YES	YES

Poisson estimates. Time period: 1980-2019.
 Robust standard errors in parentheses.
 Legend: *** p<0.01, ** p<0.05, * p<0.1.