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POWERING ENERGY SECURITY: THE ESSENTIAL ROLES OF GREEN FINANCE AND ARTIFICIAL INTELLIGENCE

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Abstract: *A thorough examination of the essential roles of green finance (GF) and artificial intelligence (AI) is crucial for enhancing energy security (ES). By utilising the TVP-VAR-SV framework, the paper reveals the dynamic interactions among the index of GF, AI, and ES, under the influence of the World Uncertainty Index (WUI). Our findings indicate that in the initial phase, GF has a detrimental influence on ES, but this impact reverses to become beneficial in the subsequent second and third stages, highlighting a notable lag in its positive impact. Similarly, AI's influence on ES starts off negatively in the early and second stages before turning positive in the third stage, with an even more pronounced delay in its positive impact. GF consistently demonstrates a positive and promotional effect on AI. Conversely, AI's influence on GF is positive in the first phase but becomes more complex, with alternating positive and negative influences in the subsequent stages. Furthermore, WUI exhibits both positive and negative effects on ES, affirming its validity as a control variable to some extent. Against the backdrop of growing uncertainties in the global energy landscape, this study proposes strategic pathways to enhance the role of GF and AI in strengthening ES.*

Keywords: *energy security, green finance, artificial intelligence, time-dependent*

1. Introduction

This article attempts to study the nexus of green finance, artificial intelligence, and energy security. In this context, ES refers to the assurance of stable, reliable, and unbroken energy supply to meet societal needs while mitigating risks and uncertainties associated with the energy markets (Lee and Fang,2025;

Usman et al., 2025). Energy insecurity arises from a variety of drivers. Political and geopolitical factors include instability in governance, conflicts between energy-exporting nations, and strategic manipulation. Economic influences such as global economic shifts and fluctuations in the business cycle also contribute significantly (Khan, 2025). Moreover, technological advancements and the transition to new energy sources, particularly renewables and energy storage systems, lay a key role (Bashir et al., 2025; Kim et al., 2025). Natural events like disasters, climate change, and pandemics further compound energy insecurity (Shupler et al., 2021). The new and powerful way to move forward with ES is by means of GF, a revolutionary financial concept that includes green development as an integral part of the financial activities. First of all, GF is able to attract investors to finance projects in the energy field by means of issuing relevant bonds and funds, such as the green bonds of the China Development Bank, which had targeted the financing of renewable energy and energy-saving projects, as pointed out by Shi and Zhao (2023). Secondly, a range of financial instruments offered by GF, including green credits and bonds, significantly accelerates progress in energy technology, enabling energy enterprises to secure essential funding for innovation (Iqbal et al., 2025). Thirdly, GF facilitates the green transformation of the energy sector by financing the green development of energy initiatives (Zhang et al., 2025). It encompasses supporting projects related to clean energy, implementing strategies for emission reduction and energy conservation, as well as initiating programs that are aimed at improving energy efficiency (Wang and Xu, 2025; Zhang and Sun, 2025). Accordingly, GF can act as a powerful instrument in advancing ES.

Moreover, AI, including machine learning, deep learning, natural language processing, and computer vision, serves as a powerful tool to enhance ES. The International Energy Agency published a report entitled Digitalization and Energy, which notes that as AI technologies are widely embraced, it is likely to decrease the production cost of oil and gas by 10% to 20%, as cited by Mohammadi and Sohn (2023), Abadi et al. (2025), and Baseer et al. (2025). Furthermore, it is expected to diminish the rates of wind and solar power generation curtailment from 7% to 1.6%. The United States Department of Energy's ARPA-E division has introduced a strategic plan that emphasizes the utilization of smart design principles for enhancing energy efficiency, reducing emissions, and achieving significant technological advancements. In parallel, ExxonMobil, a prominent international oil and gas corporation, leverages AI to enhance the productivity and success rates of its drilling activities. China's Alibaba has taken a leading role in the growing digital energy field, concentrating efforts on site energy management, designing energy solutions tailored for data centers, advancing the development of intelligent photovoltaic systems, and providing power solutions for electric vehicles and modules are among the objectives. To date, Alibaba has delivered digital services to more than 200 power utilities, collaborated with 25 oil and gas companies, and served 20 mining enterprises, while also establishing partnerships with 16 key players in the energy sector. Thus, it's clear that GF and AI are deeply connected to ES, a vital but under-researched subject. Also, the current studies have not sufficiently explored the dynamic interplay between these three elements, which constitutes the main emphasis of our article's investigation and discourse.

This paper shows three key innovations. Firstly, existing research has mainly focused on isolated relations among GF, energy, AI, and combinations of these factors, neglecting a holistic, global perspective that encompasses all three simultaneously. Accordingly, this research offers a pioneering examination of the complex relationships among GF, AI and ES. Secondly, much of the current research on ES primarily relies on theoretical evaluations and focuses on energy costs and consumption, yet lacks comprehensive empirical data. Thereupon, our study introduces a novel methodology by employing Google Trends data as a precise indicator to gauge the prevalent state of ES. Furthermore, we make a significant contribution by introducing the S& P Green Bond U.S. Dollar Select and the S&P Kensho New Economy RAIC indices as measurements to evaluate developments in GF and AI. Thirdly, the intricate interplay between them is evolves, which has been overlooked in previous studies. This study addresses a significant gap in the literature by employing parameter estimation combined with MCMC to assess the viability of constructing a TVP-VAR-SV model. The application of this methodology enables a more profound understanding of the intricate relationships among GF, AI and ES, thus adding considerable value to the field.

2. Literature Review

2.1. The relation between GF and energy

The existing research has delved into the relation between GF and energy. Madaleno et al. (2022) present the three faces of GF: financing environmental conservation, supporting green technologies, and fostering the development of renewable energy in order to pursue ES. On the other hand, Nepal et al. (2024) go on to offer that GF is able to effectively enhance China's energy resilience, with particular importance for eastern and western regions in helping industrial transformation so as to develop other economic and social dimensions of ES. Liu et al. (2023) give an indication of the vital role that GF plays in furthering sustainable energy growth, particularly in wind and solar energy. Shi and Zhao (2023) even show some striking results of a dynamic relationship between

GF development and energy security; with one unit rise in GF, there is an initial negative response of ES, followed by a turn for the positive. Variance decomposition results indicate that the trend for the initial shock of GF on ES keeps on increasing with time. According to Bhattacharyya (2023), in the transition from a carbon-intensive, fossil fuel-based system to a sustainable, low-carbon system, much financial supply is needed. The classification framework of GF may act as guiding principles for investors. Finally, this work shows that energy insecurity is an issue which underlines its interaction with GF and ES dynamics, manifestation of the associated uncertainties and risks in supply and demand for energy. According to Lee and Fang (2025), GF exerts a significantly positive effect on the ES of the recipient countries. It especially exerts its impact on the reinforcement of ES more in low-income countries, while in high-income countries, it is not significant. Liu et al. (2025) have cited that GF is a game-changing step toward ES, in those countries or regions where energy transition and economic growth are more profound. Meanwhile, Wang and Xu (2025) emphasize that GF offers robust support for enhancing ES in China.

2.2. The relation between AI and energy

Scholars have increasingly concentrated their investigations on examining the connections between AI and energy systems. Ghenai et al. (2022) underscore the growing integration of digitalization and interconnectedness in the global energy sector, fueled by advancements in digital technologies like AI. This digitization allows for the implementation of advanced technologies and strategies, significantly enhancing ES. Yu et al. (2022) emphasize the transformative impact of energy digital twin technology on the process and energy industries, leading to improvements in energy management, service and maintenance, energy-efficient designs, and infrastructure upgrades, while also facilitating seamless integration with local and regional renewable energy resources. Arowoiya et al. (2024) find that various algorithms, including AI and ANNs, are utilized to forecast energy consumption in buildings. According to Huang and Lin (2023), digitalization can markedly lower the carbon intensity of power generation, primarily through energy mix optimization, with this effect strengthening as renewable energy capacity grows. Lu and Li (2024) emphasize that the degree of AI innovation is positively associated with the enhancement of overall energy efficiency, where larger-scale innovations yield more substantial benefits. Additionally, AI innovation strengthens ES by reinforcing environmental accountability and upgrading internal governance systems. Qin et al. (2024) reveal that AI exerts dual effects on renewable energy: while its positive impacts promote renewable adoption, they are unsustainable long-term due to the cost advantage of non-renewables. Meanwhile, Choi et al. (2024) highlight four key factors influencing AI-driven energy use: energy mix, network infrastructure, trading markets, and industrial structure shifts. Zhao et al. (2025) emphasise that enhancements in ES facilitated by AI are mainly due to improvements in the efficiency of coal and electricity usage. Zhai et al. (2025) find that AI can successfully address inefficient investments in energy enterprises, leading to improved ES.

2.3. The relation between GF and AI

In investigating the relation between GF and AI, Liu et al. (2023) confirm that GF functions as a promoter for developments in green technology innovations, which in turn indirectly promotes AI. Xiong and Dai (2023) show that green finance (GF) promotes environmental improvement by advancing AI, where non-state-owned enterprises act as key intermediaries. Zhang et al. (2022) note that lagging technological innovation can restrict the financial sector's ability to offer diverse energy-saving products, thereby hindering GF development. Nonetheless, as AI advancements reach a more advanced stage, both consumers and businesses would have access to diverse energy-consuming products and innovative machine utilization pathways, which can subsequently stimulate the expansion of GF. Zeng et al. (2024) determine that the beneficial effects of GF on AI are particularly pronounced in eastern and central urban areas, in cities that do not depend on natural resources, in cities with populations under 5 million, and in cities that have relatively modest levels of AI development. Research by Zhou et al. (2025) shows that the issuance of green bonds enhances intelligent manufacturing by an average margin of 1.22%, with green innovation serving as the mechanism through which this impact is achieved. Kuang et al. (2024) indicate that industrial AI promotes the growth of GF in particular segments of the data distribution across various economies. A study by Nepal et al. (2025) reveals that innovations in AI technology propel the development of advancements in GF.

3. Methodology

The TVP-VAR-SV model, as described by Dong et al. (2024), integrates features of Time-Varying Parameters, Vector Autoregression, and Stochastic Volatility. A key characteristic of this framework is its time-varying parameters, which enhance its flexibility in reflecting dynamic changes within economic systems. Due to the nature of dynamic relations among economic variables including green finance, artificial intelligence, energy security, and world uncertainty index, this model would be able to capture their time variation with more accuracy by virtue of the time-varying attribute; such was also asserted by

Zhong et al. (2023). VAR accounts for interrelations between different economic variables. Variables in an economic system are usually interdependent; changes in one variable may lead to changes in the other. The VAR aspect allows for the consideration of all the interactions within the variables in a wide scope, hence arriving at more realistic predictions and analyses, according to Qin et al. (2023). Thirdly, the SV component incorporates the random fluctuations that variables generally take in economics. The variability in most economic systems has to take stochastic variations in light of stochastic influences of many stochastic factors. In that perspective, Sevillano et al. (2024) argued that the salient features of the TVP-VAR-SV model will be able to represent those random fluctuations. In a word, TVP-VAR-SV considers both dynamic changes in all aspects of the economic system and inner uncertainty simultaneously; it has excellent practical value in economic analysis and forecast.

The TVP-VAR-SV model is formulated as follows:

$$Z_t = Y_t^{'}\beta_t + A_t^{-1}\sum{}_t\varepsilon_t \qquad t = w+1,\ldots,W \tag{1}$$

In this context, drawing upon Primiceri's (2005) framework, the TVP-VAR-SV is formulated in such a manner that specific components, β_t, A_t and Σ_t denoted by specific symbols, exhibit time-varying property. The dynamic parameters in the TVP-VAR-SV model could be written as:

$$\begin{array}{l} \beta_t = \beta_{t-1} + u_t \\ a_t = a_{t-1} + \mu_t \\ h_t = h_{t-1} + \nu_t \end{array} \quad \begin{pmatrix} \varepsilon_t \\ u_t \\ \mu_t \\ \nu_t \end{pmatrix} \sim N\left(0, \begin{pmatrix} I & 0 & 0 & 0 \\ 0 & \sum_\beta & 0 & 0 \\ 0 & 0 & \sum_a & 0 \\ 0 & 0 & 0 & \sum_h \end{pmatrix}\right) \tag{2}$$

where $\beta_{w+1} \sim N(u_0, \sum_{\beta_0})$, $a_{w+1} \sim N(\mu_0, \sum_{a_0})$ and $h_{w+1} \sim N(\nu_0, \sum_{h_0})$. Z_t in the Equation (2) would be further rewritten as $Z_t = (\mathrm{GF}_t, \mathrm{AI}_t, \mathrm{ES}_t, \mathrm{WUI}_t)'$.
Moreover, the study implements the Markov Chain Monte Carlo (MCMC) method within a Bayesian statistical paradigm to perform quantitative assessments, which enables the extraction of conclusions that are both more resilient and precise, as detailed by Zhu et al. (2024). This methodological approach is employed to mitigate errors stemming from the instability of initial values, as advocated by Ha et al. (2024).

Furthermore, Gibbs sampling from an MCMC framework has been utilized during this study for the purpose of accurate estimation. We calculate the dynamic impulse responses to GF, AI, ES, and WUI. In doing so, it adopts two methods: the local projection approach proposed by Canova and Gambetti in 2009, and another approach called generalized impulse response function technique developed by Nakajima et al. (2011). Since most literature compares the impact magnitude by applying the generalized impulse response function method, which is supposed to mitigate estimation biases, such as Qiao et al. (2023), Maghyereh et al. (2024), Rodriguez et al. (2024), and Choi and Hadad (2025), this paper follows suit and applies it to derive the time-varying impulse responses of GF, AI, ES, and WUI.

4. Data

In this paper, monthly data from January 2015 to December 2024 is employed in considering the changing relationships among GF, AI, and ES. Research of Global Energy Security starts in 2015 because in this year, the Global Energy Sector faced unprecedented and profound changes. On one hand, the rapid evolution of emerging energy technologies, including renewable energy and shale gas, is progressively altering the conventional energy mix and presenting novel avenues for energy supply. On the other hand, shifts in the international political and economic landscape, particularly the escalation of geopolitical tensions, pose challenges to the stability of energy supply. Concurrently, the escalating issue of global climate change, coupled with heightened environmental awareness, has prompted heightened focus on the safe, clean, and sustainable utilization of energy. Consequently, since 2015, the investigation of global energy security has assumed paramount importance, aimed at delving into the challenges and opportunities associated with energy security and providing a scientific rationale for formulating effective energy policies and strategies. In this study, we select Google Trends as the primary data source, with its reference value being manifested in the global search volume for the keyword “energy security”. A higher ES score indicates a greater risk to energy security, while a lower score means better security.

Amid the current wave of technological transformation, GF and AI have become central drivers in advancing ES. In this study, the Global Green Bond Index, sourced from S&P Global, serves as a core measure of GF development. Launched on June 17, 2019, this index employs a market capitalization-weighted methodology and comprises 502 USD-denominated constituent securities. Data prior to the launch date are based on back-tested calculations that replicate the index’s construction approach, though potential biases may exist due to historical influences on constituent selection. Nevertheless, these estimates provide a reasonable approximation of GF performance. Higher index values reflect more substantial progress in GF, while lower values suggest slower growth. To evaluate AI advancement, we use the S&P Kensho New Economy RACI, also obtained from S&P Global. This paper therefore investigates the interrelationships among GF, AI, and ES, with their temporal trends visualized in Figure 1.

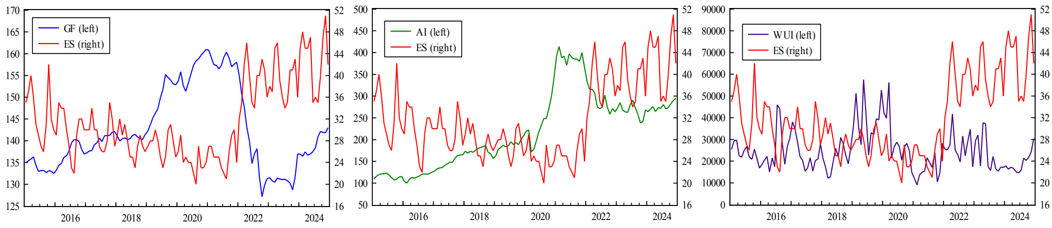

Figure 1. The trends of GF, AI, WUI, and ES

Figure 1 reveals that the dynamics of the interactions between GF, AI, ES, and WUI possess complexities that may be difficult for standard analytical techniques to fully comprehend. Consequently, conventional approaches like SVAR and VAR are inadequate for capturing such dynamically evolving relationships, making the TVP-VAR-SV model better suited for quantitative analysis. Moreover, the strong correlation between WUI and factors like GF, AI, and ES means that any fluctuations in WUI significantly affect their interconnectedness. Therefore, we have incorporated WUI data as a control variable in our analysis. By scrutinizing the evolving impulse responses of GF, AI, and ES, while accounting for the influence of WUI, we can gain deeper insights into the time-varying relationships among GF, AI, and ES.

Table 1. Descriptive statistics for GF, AI, WUI, and ES

	GF	AI	WUI	ES
Observations	120	120	120	120
Mean	142.565	219.586	24947.01	31.775
Median	140.362	196.063	22394.10	30.000
Maximum	160.954	413.990	57518.00	51.000
Minimum	127.130	100.011	9050.300	20.000
Standard Deviation	9.401	85.696	9540.084	7.119
Skewness	0.567	0.480	1.190	0.667
Kurtosis	2.078	2.266	4.469	2.579
Jarque-Bera	10.667 ***	7.298 **	39.109 ***	9.797 ***
Probability	0.005	0.026	0.000	0.007

Table 1 presents the descriptive statistics of the variables, with mean values of 142.565, 219.586, 24947.01, and 31.775, indicating that the observations are generally clustered around these central tendencies. Nevertheless, the considerable spread between the maximum and minimum values reflects substantial fluctuations over time. The Jarque-Bera test results reject the normality assumption for GF, WUI, and ES at the 1% significance level, and for AI at the 5% level. To facilitate computation and reduce the influence of outliers, a natural logarithm transformation is applied. Furthermore, first-order differencing is employed for all variables to prevent spurious regression in the TVP-VAR-SV model.

5. Quantitative Discussions

To ascertain whether GF, AI, ES, and WUI possess unit roots, we utilize three distinct tests: the ADF test, the PP test, and the KPSS test. Upon reviewing the results presented in the subsequent table, we can confidently prove that these variables do not exhibit unit roots.

Table 2. Results of unit root tests

	ADF	PP	KPSS
GF	-4.559 (2) ***	-7.243 [5] ***	0.135 [6]
AI	-7.284 (1) ***	-8.672 [8] ***	0.137 [1]
WUI	-11.031 (1) ***	-15.395 [8] ***	0.051 [9]
ES	-9.428 (2) ***	-11.493 [4] ***	0.202 [10]

Employing the SIC, a lag length of 2 was determined to be optimal for the TVP-VAR-SV model incorporating GF, AI, ES, and WUI. As shown in Table 3, the mean values of the estimates fall within the 95% confidence intervals. To verify estimation reliability, we ensured that the coefficients align closely with their posterior distributions. Moreover, inefficiency factors below 100 indicate that the system generates adequately independent samples. We therefore conclude that the parameter estimates are statistically credible.

Table 3. The parameter estimated results in the TVP-VAR-SV process

Parameters	Mean	Standard Deviation	95% Confidence Interval	Geweke	Inefficiency Factors
$(\Sigma_\beta)_1$	0.023	0.003	[0.018, 0.029]	0.239	5.44
$(\Sigma_\beta)_2$	0.022	0.002	[0.018, 0.027]	0.522	6.59
$(\Sigma_a)_1$	0.093	0.054	[0.043, 0.218]	0.327	82.98

$(\Sigma_a)_2$	0.083	0.036	[0.042, 0.177]	0.411	71.89
$(\Sigma_h)_1$	0.484	0.097	[0.345, 0.722]	0.868	47.63
$(\Sigma_h)_2$	0.387	0.075	[0.265, 0.559]	0.757	53.77

Figure 2 offers further support for the use of the TVP-VAR-SV model that includes GF, AI, ES, and WUI. The upper section displays the sample autocorrelation function, where the red line approaches zero, indicating negligible autocorrelation across the sample period. These results confirm that the TVP-VAR-SV framework, integrating GF, AI, ES, and WUI, is both feasible and effective in representing the evolving interactions among these variables. This suitability also highlights the limitations of conventional approaches, such as VAR and SVAR models, which lack the flexibility to account for the time-varying complexity inherent in the relationships between GF, AI, ES, and WUI.

Figure 2. The sample auto-correlations, paths and posterior densities of MCMC estimated results

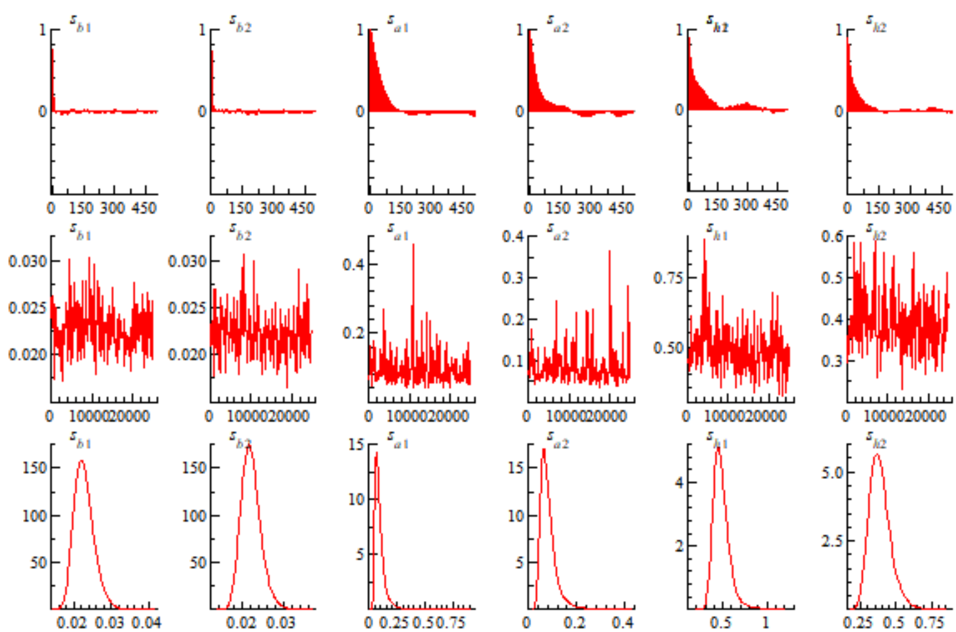

Figure 3 depicts the impulse response of GF and AI to ES. Initially, by analyzing the impact of GF on ES, several pivotal observations can be made. Specifically, in the initial phase, GF exerts a detrimental effect on ES. However, during the subsequent second and third phases, GF demonstrates a beneficial influence on ES.In the initial phase of implementing GF policy, namely the first phase, it exerts a detrimental effect on ES. This is primarily attributed to the hurdles posed by initial investments and resource reallocations. GF frequently necessitates substantial capital infusions, potentially sourced from the reallocation or adjustment of traditional energy ventures, thereby momentarily disrupting energy supply stability. Concurrently, the extended planning and construction timeframe of GF initiatives can diminish investments in traditional energy projects, further compromising the continuity of energy supply. Furthermore, the introduction of this novel policy necessitates a period of accommodation for market entities, who may not immediately grasp or embrace the new directives. Coupled with the inherent time delays in the approval, financing, and execution of GF projects, these factors collectively contribute to a delayed manifestation of policy efficacy.

Nonetheless, as the GF policy is implemented progressively-that is, entering the second and third stages-its impact on ES starts to move into a positive direction. This is largely driven by the evolution of the energy mix, with more funds channeled toward clean and renewable energy projects, hence reducing dependence on fossil fuels and enhancing diversity and stability in energy supply. In the meantime, GF projects also focus on holistic energy system planning and construction, enhancing resilience and reliability in the energy infrastructure, making energy supply more responsive and adaptable. These can quickly restore energy supplies during extreme weather conditions or other unexpected situations, reducing the risk of energy disruption. In addition, in the course of the continuous promotion of the policy and the gradual digestion and absorption by the market participants, the economic and social benefits of GF projects have gradually appeared, further promoting the improvement of ES standards, industrial development, and innovation, bringing more technical support and solutions to ES.

Mainly, there are a number of factors contributing to a lagged effect of GF on ES, including a policy implementation timeline, market accommodation and adjustment process, project construction, and operational cycles. From policy formulation and introduction down to the implementation and significant accomplishment, there is a certain time required. It takes time for the market participants to learn about and accommodate new policies and further adjust their business strategies and orientation of investment. Moreover, GF projects usually involve lengthy planning and construction periods, including the approval of projects, financing, construction, commissioning, and other stages, the time lags of which will affect the appearance of policy effects. Consequently, when assessing the impact of GF policies on ES, it is imperative to comprehensively consider the inherent delays to gain a thorough and accurate understanding of policy outcomes.

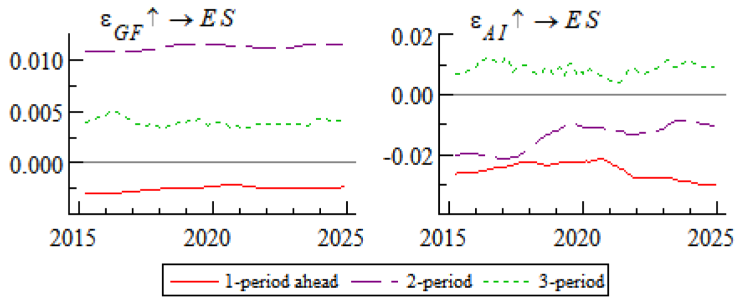

Figure 3. Impulse responses of GF and AI on ES

Next, we delve into the impact of AI on ES, particularly the underlying reasons for its transition from negative to positive. In the first and second phases, AI has a negative impact on ES, which is caused by multiple factors. On the one hand, the initial application of AI technology in the energy field indeed necessitates substantial research and development funds and technical investment. Basic algorithm explorations, model training, data processing, and many other activities require these funds. Also, technological innovations and adaptation to realize seamless integration in particular energy scenarios require funding. It is difficult to translate such high investments in the short term into enhanced ES. Instead, they could cause some type of instability or disruption in the 'analog' structures of energy supply and management, since resources are redistributed and/or the technology of sustainable resources is at an experimental stage and might have a negative effect on ES. On the other hand, AI technology faces a series of technical problems in their deploy ability in the energy sector. For example, there is the issue of how best to integrate AI algorithms with the operational reality of the energy systems for exacting predictions and optimal control. Then, there is the challenge of processing and analyzing massive volumes of energy data to extract valuable insights from them. Safety and reliability are also concerns to be taken seriously with the AI systems to avoid any sort of technical malfunction or security breach that could result in the disruption of energy supplies. All these challenges and issues require time and experience to get sorted out and thus can affect ES negatively during the initial phases.

In the third phase, though, the influence of AI starts getting positive on ES. This transformation is mainly caused by constant maturity and the increase in the scope of application of AI technology. While algorithms of AI technology are being continuously optimized and more training data is available, the effectiveness of AI systems in this energy sector steadily sets in. From the perspective of energy production, AI technology reveals its remarkable edge in enhancing production efficiency, perfecting energy allotment, and predicting energy needs. Accurately forecasting energy demand, AI systems help the energy provider in planning and managing energy supply. In addition, this will also reduce the risks of wasting and shortages in energy. At the same time, AI technology optimizes energy allocation, promotes the effective use of energy, reduces energy consumption cost, hence enhancing the security and stability of the energy system.

Comparing to GF, the lagged impact of AI on ES is stronger. This may be attributed to the complex and innovative characteristics of AI technology. As an emerging field, artificial intelligence involves ongoing experimentation and iterative improvement throughout its development and deployment, requiring extended periods to substantiate its real-world effectiveness. Furthermore, the implementation of AI technology in the energy sector must consider the interplay and dynamic shifts of numerous factors, such as fluctuations in energy market prices, changes in the policy environment, and advancements in energy technology. These factors introduce complexity and uncertainty into assessing the impact of AI technology on ES.

Figure 4 demonstrates the impulse responses between GF and AI. Specifically, GF exerts a positive influence on AI, whereas AI, in turn, positively impacts GF during the initial phase. In the subsequent second and third phases, the influences of AI on GF exhibit both negative and positive dynamics. The positive influence of GF on AI constitutes a multi-faceted and deeply ingrained process, manifesting in the following dimensions: Firstly, GF offers the requisite financial backing for AI technology research and development. By funneling investments into eco-friendly, low-carbon, and sustainable ventures, GF not only fosters rapid advancements in these domains but also assures ample financial security for the research, development, and innovation of AI technologies. Of the funds, support is given for AI algorithm research and development, data collection and processing, model creation, and optimization in order to accelerate the maturation of AI technologies.

The second point is that GF opens vast avenues to the deployment of AI technology: as the ethos of environmental conservation and sustainable development is deeply rooted in people’s consciousness, more and more sectors are willing to apply AI technology to realize highly effective and intelligent production and management. For instance, AI technology can be used in the energy sector for the construction and management of smart grids with a view to improving energy efficiency. On the one hand, AI technologies can be applied in environmental protection for environmental monitoring and data analysis, providing a scientific basis for the promulgation of some environmental policies. On the other hand, in the field of smart city construction, AI technologies can be applied in urban traffic management, public safety surveillance, etc., to improve the quality of urban governance.

Third, GF provides policy direction and support for the innovative application of AI technology. By formulating relevant policies, the government advocates for the integration of green finance and AI technology to accelerate the formation of new economic growth poles. For instance, the government can set up special funds to support application and innovation in the field of AI technology in the GF sector. It can introduce relevant policies to encourage enterprises to use AI technology in raising production efficiency and reducing operational costs. In addition, it promotes international cooperation and enables the whole world to share and communicate AI technology.

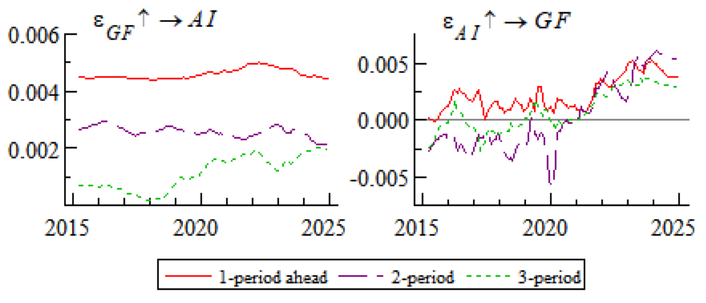

Figure 4. Impulse responses of GF and AI

Conversely, in the first phase itself, AI technology has immensely helped in increasing investments in GF projects by decreasing the associated risk in investments and allowing more accurate allocation of funds for environmental and sustainable development. Its role in the assessment and evaluation of risk has been pivotal for investors to decide wisely and limit their losses as much as possible. Besides, AI technology has innovatively diversified the varieties of green financial products. Traditional green financial products have been restricted to fixed environmental protection industries. However, this situation has changed since the development of AI technology. Using intelligent algorithms and machine learning, AI technology designs more personalized and diversified green financial products that can satisfy the market demand and different investor preferences. This approach meets various investors' needs but simultaneously creates a broader market for GF. More importantly, AI technology applied in the GF has been driving the establishment and perfection of the industry standards; with the promotion and application of AI technology, the standards for the evaluation of green finance projects and the risk management process could be further optimized and upgraded. This will be conducive to enhancing the competitiveness and influence of the whole GF industry, promoting it to develop faster and more stably.

In its second and third development stages, GF relies more strongly on AI technologies which become quite multilevel and interrelated. Along with deeper development, several risks and problems of a latent character began to show up gradually. First, such factor as data security becomes quite key. It is about a tremendous volume of environmental information, investors, and other classified details. Any leakage or misuse of these data could bring huge losses to the project and investors. In addition, privacy protection is an urgent issue to be solved. In using AI technology in data analysis, guaranteeing that personal privacy is not infringed upon has become an extremely important topic. Moreover, the algorithm bias also cannot be neglected as a risk point. If biases are already part of the design and training of AI algorithms, their predictions and decision results will be biased, too, thus bringing inequity into GF projects. On the other hand, some of the positive impacts of AI technology are gradually showing up. With the continuous maturation and refinement in technology, the application of AI in green finance has gone further and deeper. For example, AI technology can be applied to smart grid construction and management in the energy sector, which promotes energy efficiency and reduction of carbon emissions. AI can be applied to environmental protection for environmental monitoring and data analysis, providing a scientific basis for the formulation of environmental policy. In addition, in terms of urban planning and management, AI can be incorporated into urban traffic management and waste treatment to improve the level of sustainable urban development. All these applications will not only help the sustainable development of GF but also create more green well-being for society.

Figure 5 illustrates the impulse response of WUI to ES. This interplay manifests a multifaceted and dynamic influence, positively inciting advancements in technological innovation and promoting the diversification of energy sources. Conversely, it adversely impacts the potential for energy price volatility and disruptions within supply chains. The congruence of these effects with empirical observations underscores the rationale for selecting WUI as a control variable in this research endeavor.

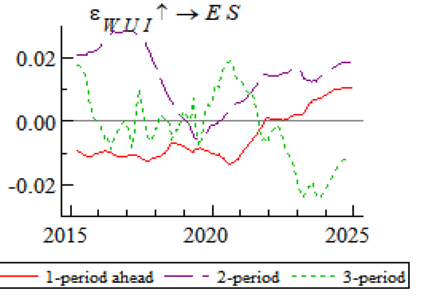

Figure 5. Impulse responses of WUI on ES

6. Conclusion

Utilizing a methodology that incorporates the GF, AI, ES, and WUI, we can obtain estimated coefficient values, autocorrelation samples, trajectories, and posterior probability densities for the TVP-VAR-SV model. This technique enables us to accurately capture the evolving relations among the chosen indicators, thereby delving into the intricate dynamics between GF, AI, and ES. We find that in the initial stage, GF has a negative impact on ES, but in the second and third stages, it turns into a positive impact, showing the lag of its impact. The influence of AI on ES is negative in the early stage and the second stage, and it turns positive until the third stage, and the lag of its influence is more obvious. GF has shown a continuous positive promoting effect on AI. However, the influence of AI on GF is positive in the first phase, and showed a complex situation of interweaving positive and negative influences after entering the second and third phases. In addition, WUI has both positive and negative effects on ES, which verifies its rationality as a control variable to a certain extent. Through a detailed analysis of the dynamic relationships among GF, AI and ES, this study concludes that both GF and AI contribute positively to ES, although their influences exhibit inherent time lags.

Following the aforementioned conclusions, a set of policy recommendations are put forth to safeguard energy security. Firstly, the government ought to augment its policy support and financial allocations for green finance, encompassing but not limited to the provision of incentives such as tax reliefs, subsidy schemes, and the establishment of dedicated funds. These measures are aimed at encouraging a greater influx of social capital towards green energy initiatives. This strategy will not only expedite the development and deployment of green energy technologies but also foster the construction of clean energy infrastructure, thereby laying a solid foundation for sustainable development. Meanwhile, it is necessary to establish and improve the green financial supervisory mechanism. Based on the formulation of environmental impact assessment standards and disclosure methods for publicly offering information, we can ensure that every green investment yields a win-win result in environmental and economic benefits while ensuring appropriate fund use and smooth project operation.

Another key development toward a more energy-efficient future is the widespread dissemination of AI technology in the energy sector. For instance, smart grids using AI technology can adopt automatic grid scheduling, predict faults, and quickly respond to improve efficiency and stability in the energy system. In addition, AI can guarantee optimal distribution, reduce energy wastage, and balance supply and demand. In this regard, the government should further escalate support for research, development, and innovation in

AI technology, develop industry-university-research cooperation, cultivate professionals, and actively promote the application of new AI technologies in energy security continuously. This includes the forecast of energy demand by big data analysis and the optimization of energy production strategies through machine learning.

Finally, the government should build a comprehensive policy framework for energy that could combine green finance with artificial intelligence development to capture synergies: setting up precise targets for energy transition, developing practical implementation paths and roadmaps, setting up crossdepartmental coordination mechanisms to ensure a coherent and efficient implementation of varied policies. The policy framework should also consider the balance between traditional and renewable energy development, ensuring the stability and security of energy supply. Strengthening international cooperation is equally important to achieve the long-term goal of energy security. In the face of global energy challenges, countries should increase experience sharing, technology exchanges, and market openness, promoting the global energy transition, addressing climate change, and achieving sustainable development goals together. This includes participation in international energy organizations, the signing of agreements on climate change, and facilitating cross-border collaboration on green energy projects to jointly build a greener, smarter, and safer global energy system.

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