Quality Assurance and Safety of Crops & Foods, 2024; 16(3): 25–41

Agricultural economic security under the model of integrated agricultural industry development

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Received: 5 March 2024; Accepted: 15 June 2024; Published: 27 July 2024

RESEARCH ARTICLE

Abstract

As globalization and technological advancements progress, the integrated agricultural industry development model has become crucial for agricultural modernization. This model fosters inter-industry integration, enhancing agricultural competitiveness and sustainability. However, it also introduces new challenges, such as increased risk spillover and outdated regulatory mechanisms. This study employs a vector autoregression (VAR) model and a directed weighted risk spillover network for a quantitative analysis of risk dynamics within agricultural markets, identifying pathways and influencers of risk transmission across industry segments. A blockchain-based regulatory framework is proposed to improve traceability, regulatory efficiency, and data security in agricultural product management. This includes the development of registration processes, smart contracts, consensus mechanisms, and data upload protocols. The research expands the theoretical base of agricultural economic security and offers practical policy guidance, with substantial academic and practical implications. It highlights how blockchain can address market trust issues, mitigate information asymmetry, and reduce potential risks, contributing to the healthier development of agricultural economy.

Keywords: integrated agricultural industry; agricultural economic security; risk spillover effect; vector autoregression model; blockchain; regulatory mechanisms; data security

Introduction

As the pace of globalization accelerates and technological advancements continue, agriculture is undergoing an unprecedented transformation (Adnan *et al.*, 2024; Dhananjayan *et al.*, 2023; Gao *et al.*, 2023; Jiuhardi *et al.*, 2022; Kashina *et al.*, 2022; Kim and Kim, 2024; Lin and Hu, 2022; Mahler, 2020; Miralles-Garcia, 2023; Omodero, 2021; Safitri *et al.*, 2022; Song *et al.*, 2021; Taneja and Ozen, 2023; Vulevic *et al.*, 2022). The model of integrated agricultural industry development, a novel agricultural operation mechanism, is aimed at driving agriculture toward greater efficiency and sustainability through technological innovation and integration of the industry chain (Puri *et al.*, 2023; Shah *et al.*, 2023). However, this transformation inevitably introduces new challenges to economic security, especially under the backdrop of economic globalization where the interconnectedness of agricultural risk factors significantly increases, exerting profound effects on agricultural economic security (Bessonov and Suglobov, 2019; Shchutskaya and Kozhukhova, 2023; Xia *et al.*, 2023). The promotion of industry integration while ensuring agricultural economic security has become a crucial topic of the current research. Agricultural economic security is the cornerstone of national food safety, social stability, and sustained development (Li and Huang, 2020). In the context of agricultural industry integration, economic security issues present new characteristics and trends, making their study of significant practical importance (Karanina *et al.*, 2019; Wang *et al.*, 2023). Analysis of the risk spillover effect aids in understanding the dynamic connections and potential threats within the agricultural market, providing a scientific basis for formulating effective regulatory policies and risk prevention strategies (Li *et al.*, 2023a, 2023b; Zhao *et al.*, 2023). Furthermore, the exploration of blockchain technology in the regulation of agricultural economic security offers innovative and forward-looking solutions for enhancing the transparency of agricultural industry, traceability, and data security (Sarkar *et al.*, 2022a; Yu *et al.*, 2021; Zhang *et al.*, 2022b). However, traditional studies on agricultural economic security often focus on macroeconomic policies and case analyses, lacking quantitative assessment of economic risk spillover effect under the context of agricultural industry integration (Park *et al.*, 2020; Sarkar *et al.*, 2022b; Zhang *et al.*, 2023). Existing methods face limitations in dealing with the dynamic connections and risk propagation mechanisms in complex economic systems, struggling to comprehensively capture and explain the risk spillover paths within the agricultural market (Li *et al.*, 2021; Zhang *et al.*, 2022a). Additionally, research on the application of emerging technologies, such as blockchain in the regulation of agricultural economic security is relatively weak, without a mature and systematic implementation plan.

This paper aims to fill a knowledge gap in the current research field. First, it deeply analyzes the spillover effects of agricultural economic risks under the integrated agricultural industry development model by establishing a vector autoregression (VAR) model and a corresponding risk spillover-directed weighted network. Second, it examines a blockchain-based agricultural economic security regulatory scheme, detailing the registration processes for enterprises involved in agricultural product operations, smart contracts, consensus mechanisms, and data upload mechanisms. These studies not only provide new perspectives and tools for managing agricultural risks but also offer feasible solutions for achieving an efficient and transparent agricultural economic regulatory system. Therefore, this paper has significant theoretical and practical value, positively influencing guidance for practice and policy formulation.

The findings and propositions presented in this paper significantly influence the trajectory of agricultural risk management practices and regulatory frameworks, marking a pivotal step toward achieving a more resilient and sustainable agricultural industry.

Economic Risk Spillover Effect under the Integrated Agricultural Industry Development Model

In the current context of the widespread promotion of the integrated agricultural industry development model, the study of agricultural economic risk spillover effect is of significant research value. Such research not only reveals potential risk transmission mechanisms and impact paths during the process of industry chain integration, providing a basis for governments and enterprises to preempt and prevent systemic risks but also offers scientific decision-making tools for formulating agricultural economic security strategies adapted to the trend of industry integration.

In this study, the forecast error variance decomposition method based on the VAR model is employed to quantify the spillover effect of agricultural economic risks. The underlying principle involves using VAR to capture dynamic relationships between variables in time series data and determining the contribution of each variable to the variance of the forecast error by decomposing the variance of the model's forecast error. In essence, this method quantifies the portion of uncertainty in the future value of each variable caused by other variables, thereby measuring the intensity and direction of interactions between different segments within the agricultural industry. Suppose a selection vector is represented by r_u, where only the uth element is 1 and all other elements are 0, the coefficient matrix of the VAR model in its moving average form is represented by X_g, and the covariance matrix of the error terms in the VAR model is represented by Σ. The expression for the portion f_{uk}^{g} of the g-step forecast error variance of variable b_u that can be explained by b_k when subjected to an external shock is given by the following equation:

$$f_{uk}{}^{g} = \frac{\delta_{uk}{}^{-1}\sum_{g=0}^{G-1}\left(r_u' X_g \sum r_k\right)^2}{\sum_{g=0}^{G-1}\left(r_u' X_g \sum X_g' r_u\right)}, u,k = 1, \ldots v. \quad (1)$$

The error variance of variable u's fluctuation caused by variable k's volatility is characterized by the numerator of f_{uk}^{g}, while the overall forecast error variance looking g steps ahead is represented by f_{uk}^{g}'s denominator. Hence, the spillover intensity between markets is characterized by the proportion of variable u's fluctuation caused by the volatility of variable k, represented by $f_{uk}(g)$. After standardization, the volatility spillover matrix is obtained, represented by $F^g = [f_{uk}^{g}]$.

Compared to the total effect, the net effect provides a more precise measurement, clearly revealing the dominant direction of risk transmission and the net impact between the various segments of agricultural industry chain. The net effect not only aids in understanding which parts are the emitters and receivers of risk but also supports decision-making for optimizing resource allocation, enhancing the entire industry chain's resistance to risks, and formulating effective regulatory strategies. Thus, it ensures the safety and stability of agricultural economy while promoting the integration of agricultural industry.

The net volatility spillover index refers to the total volatility spillover from the integrated agricultural market to other markets minus the total volatility spillover from other markets to the integrated agricultural market. This index reflects the net position of agricultural market in risk transmission, indicating whether it is a net emitter or receiver of risk. The expression for the net volatility spillover index from market u to market k is provided as follows:

$$OVT^{g}_{u\leftarrow k} = Z^{g}_{u\leftarrow k} - Z^{g}_{k\leftarrow u}, u \neq k. \tag{2}$$

Table 1 provides the volatility spillover index. The FROM column vectors of the spillover index table display the impact of volatility spillover from every other market experienced by the integrated agricultural market. It quantifies the contribution of external market movements to the volatility of integrated agricultural market as follows:

$$ST^{g}_{FR,u\leftarrow .} = \sum_{k} Z^{g}_{u\leftarrow k}, u \neq k. \tag{3}$$

The TO row vectors show the spillover impact of integrated agricultural market's volatility on every other market. It measures the role of integrated agricultural market in driving the volatility of other markets as follows:

$$ST^{g}_{SP;\leftarrow u} = \sum_{k} Z^{g}_{k\leftarrow u}, u \neq k. \tag{4}$$

The overall net volatility spillover index for the integrated agricultural market is defined as the total sum of volatility spillovers from the integrated agricultural market to all other markets minus the total sum of volatility spillovers from all other markets to the integrated agricultural market. This index reflects the comprehensive risk spillover position of the integrated agricultural market within the entire system. The expression for the overall net volatility spillover index for market u is as follows:

$$VET^{g}_{u} = ST^{g}_{SP;\leftarrow u} - ST^{g}_{FR,u\leftarrow .}, u \neq k. \tag{5}$$

The total effect of volatility spillover within the entire system represents the sum of volatility spillover effect between all markets within the system. It encompasses not only the impact of integrated agricultural market on other markets but also the influence of other markets on integrated agricultural market as well as the mutual influences between all markets, thereby providing a comprehensive perspective on systemic risk propagation. This is obtained by calculating the arithmetic mean value of all elements in either the FROM column or the TO row as follows:

$$\begin{aligned} TST^{g} &= \frac{1}{v}\sum_{u} ST^{g}_{SP;\leftarrow u} = \frac{1}{v}\sum_{u} ST^{g}_{FR,u\leftarrow .} \\ &= \frac{1}{v}\sum_{u}\sum_{k} Z^{g}_{k\leftarrow u}, u \neq k. \end{aligned} \tag{6}$$

To visually display the paths and intensities of risk transmission between markets, enabling decision-makers to intuitively identify the sources and convergence points of risk and thereby design-targeted interventions to reduce systemic risk, this study further constructs a directed weighted network based on the risk spillover index. Analysis of the network's topological structure reveals potential vulnerabilities and key transmission channels during the agricultural industry integration process, thus providing a scientific basis for enhancing the resilience and stability of agricultural industry chain.

Initially, based on empirical data, the risk spillover indices among markets are calculated, with each market designated as a node in the network. The risk spillover between markets serves as the edges between nodes, and the magnitude of the risk spillover index is used to assign weights to these edges, reflecting the strength of connections. Further, the directionality of the network is determined, that is, the direction of risk transmission, based on the sign of the net volatility spillover index, with positive values indicating that the market is a risk emitter and negative values indicating risk reception. Specifically, suppose the network of agricultural economic risk spillover under the model of integrated agricultural industry development is represented by $H(C, R)$, with nodes denoted by $N = \{1, 2, \ldots, v\}$ and the number of nodes by v, then the edges between nodes are represented by $R = \{r_{uk}, u = 1, 2, \ldots, v, k = 1, 2, \ldots, v\}$. In the directed network H, if $r_{uk} \neq 0$, it indicates an edge from node u to node k. If $r_{uk} > 0$, it implies that the edge represents

Table 1. Volatility spillover index.

	a_1	a_2	...	a_v	FROM
a_1	f^{j}_{11}	f^{j}_{12}	...	f^{j}_{1v}	$\sum_{u=1}^{v} f^{j}_{1k}$, $k \neq 1$
a_2	f^{j}_{21}	f^{j}_{22}	...	f^{j}_{2v}	$\sum_{u=1}^{v} f^{j}_{2k}$, $k \neq 2$
...	...	...	...	...	...
a_v	f^{j}_{v1}	f^{j}_{v1}	...	f^{j}_{vv}	$\sum_{u=1}^{v} f^{j}_{vk}$, $k \neq n$
TO	$\sum_{u=1}^{v} f^{j}_{u1}$, $u \neq 1$	$\sum_{u=1}^{v} f^{j}_{u2}$, $u \neq 2$	...	$\sum_{u=1}^{v} f^{j}_{uv}$, $u \neq n$	$\sum_{u=1}^{v} f^{j}_{uk}$, $u \neq k$

spillover from market k to market u. If $r_{uk} < 0$, it implies that the edge represents spillover from market k to market u.

Finally, network analysis tools and graph theory methods are utilized to study the structural characteristics of the network. For instance, by calculating the in-degree and out-degree of nodes to analyze the influence and the degree to which markets are affected, identify the clusters of risk spillover. It is assumed that there can be only one edge between any two nodes, let $R^g = F^g - F^{gS}$, where the net spillover effect of element k on u is represented by $r^g_{uk} = f^g_{uk} - f^g_{ks}$, taking only its lower triangular matrix:

$$F^g = \begin{bmatrix} f^g_{11} & f^g_{11} & \cdots & f^g_{11} \\ f^g_{21} & f^g_{22} & \cdots & f^g_{2v} \\ \vdots & \vdots & \ddots & \vdots \\ f^g_{v1} & f^g_{v2} & \cdots & f^g_{vv} \end{bmatrix}, \tag{7}$$

$$R^g = \begin{bmatrix} 0 & 0 & \cdots & 0 \\ r^g_{21} & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ r^g_{v1} & r^g_{v2} & \cdots & 0 \end{bmatrix}. \tag{8}$$

Implementation of Blockchain-Based Agricultural Economic Security Regulatory Schemes

Figure 1 illustrates the structure of blockchain-based agricultural economic security regulatory schemes. The design of blockchain-based agricultural economic security regulatory schemes should follow principles similar to those of drug traceability and regulatory platforms, ensuring the traceability, authenticity, and security of agricultural product data. The following are specific implementation requirements to meet agricultural economic security regulation:

(a) *Traceability of agricultural product data*: The integrated agricultural industry development model necessitates that data from every segment of agricultural products, from planting, breeding, and processing to sales, should be recorded and are traceable. This means that the scheme must ensure the complete recording of each item of agricultural product data and be able to trace quickly every segment for efficient supervision and management. Through the immutability of blockchain, each addition of data becomes a block in the chain, ensuring

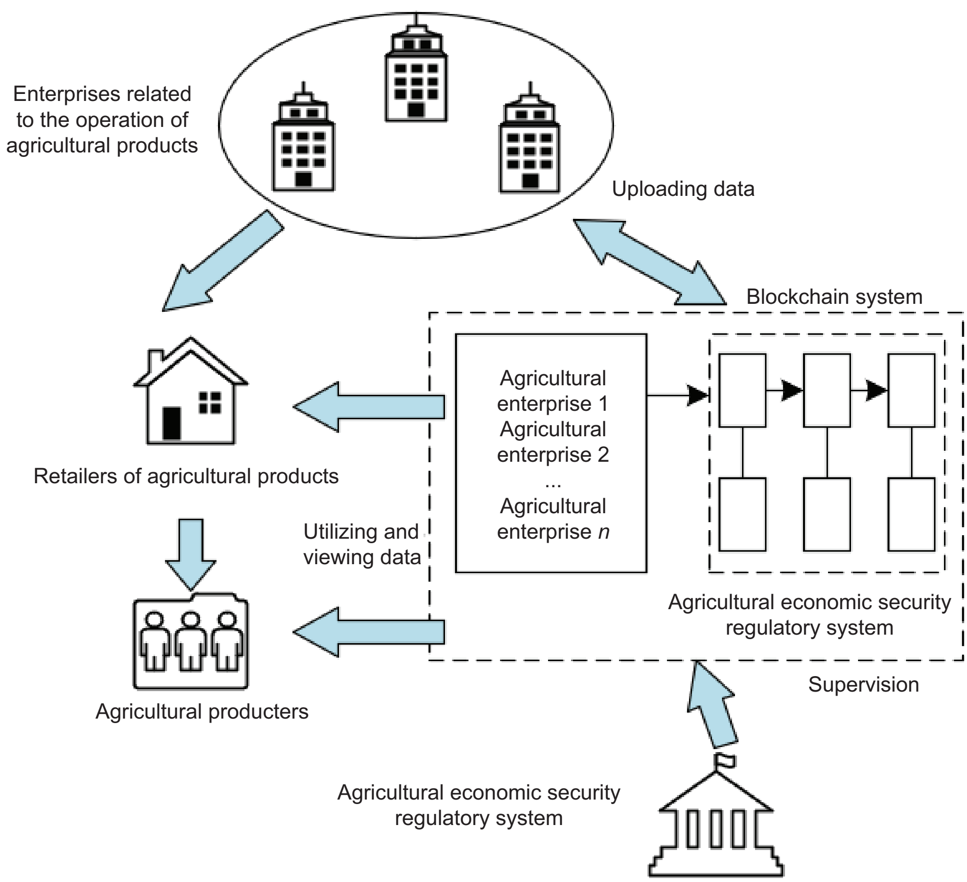

Figure 1. Blockchain-based agricultural economic security regulatory schemes.

that every operation from the source to the final consumer is queried and verified, thus achieving transparency and efficient traceability throughout the entire process.

(b) *Authenticity of agricultural product data*: To guarantee the authenticity of agricultural product data, the blockchain platform needs to integrate advanced data entry and verification technologies. This may include Internet of Things (IoT) devices, such as temperature and humidity sensors, location trackers, etc., to automatically collect and upload data to the blockchain, reducing data inaccuracies or fraud caused by human intervention. Simultaneously, smart contracts are utilized to execute automatically the data verification processes based on preset conditions, ensuring that only verified data are added to the blockchain, thus enhancing the authenticity and reliability of the data.

(c) *Security of agricultural product data*: In a regulatory platform involving multiple agricultural enterprises, blockchain technology should ensure the security and privacy of all sensitive data. This is achieved through encryption technologies, ensuring that data are encrypted during storage and transmission on the blockchain, and only authorized users can decrypt and access the data. Additionally, a permission management system is established to control the data access rights of different participants (such as farmers, processing enterprises, regulatory agencies, etc.), ensuring that relevant data are accessed only under specific conditions, thereby protecting the commercial secrets of agricultural enterprises and the personal information of consumers.

Registration process design of enterprises related to agricultural product operation

Figure 2 demonstrates the schematic structure of the blockchain for enterprises related to the operation of agricultural products. Agricultural enterprises initiate a join request through the user interface of regulatory platform. The application includes basic information about the enterprise, such as the enterprise name, address, legal representative, and scope of business. Upon submission of the application, enterprises must agree to comply with the rules and standards of the blockchain platform, including data-sharing and privacy protection policies. The registration information (l_{l1}, l_{l2}, ..., l_{lv}) submitted by agricultural enterprises is packaged into a transaction set L_{TRFl} = (TR_{l1}, TR_{l2}, ..., TR_{lv}), and temporarily stored in the blockchain system's data buffer area. This buffer is a temporary storage area used for preliminary format and integrity checks of information before it is officially written into the blockchain. Transactions within the blockchain are saved in the form of a Merkle tree, with its structure shown in Figure 3. A Merkle tree is a data structure widely used in blockchain technology, primarily serving to verify the integrity and validity of data, thereby ensuring the security and reliability of transactions. Merkle trees can efficiently store and verify large volumes of data, requiring only the storage of the root hash, rather than the hashes of all data blocks, thus saving storage space.

A unique identification number $UF_f \in \{0, 1\}^*$ is generated for agricultural enterprises by the system, identifying the enterprise throughout the entire blockchain system. Simultaneously, the system generates a pair of public and private keys for the agricultural enterprise to calculate $T_{UFf} = G_1(UF_f) \in GH_1^*$, with the private key represented by $tj_l = e^*T_{UFf}$ and the public key represented by $oj_l = h^{tjl}$. The public key, being public, is used for identifying the enterprise and verifying its signatures; the private key, kept confidential, is used for signing transactions and data, ensuring the security of information.

The registration information is signed by agricultural enterprises using their private key to prove the origin and authenticity of the information. The system uses the corresponding public key to verify the signature, ensuring that the information has not been tampered with and indeed originates from the said agricultural enterprise. Only after the signature is successfully verified, the information is moved to the next stage of processing.

The leadership department of agricultural enterprise OG_X is represented by F_l, corresponding to department nodes in the blockchain system, denoted by $\{F_{t1}, F_{t2}, ..., F_{tv}\}$. The signature of the leadership department is represented by $SI_l = G_1(L_{TRFt})^{tjl}$, and the formula for verifying the authenticity of the signature is given as follows:

$$r(SI,h) = r(G_1(L_{TRFt}),oj_i). \tag{9}$$

Once verified, the system assigns an identity code $UF_{tv} \in \{0,1\}^*$ to the agricultural enterprise. This code is unique within the platform, allowing other enterprises or regulatory authorities to query and verify the identity of the agricultural enterprise. The identity code, along with the enterprise's unique number, the public and private keys $\{tj_{tv}, oj_{tv}\}$ of the department node, and other relevant information, is recorded on the blockchain, creating an immutable registration record. This record provides public proof of the enterprise's identity without exposing sensitive information about the enterprise.

Through this process, the registration information of agricultural enterprises is reliably recorded on the blockchain, laying foundation for subsequent

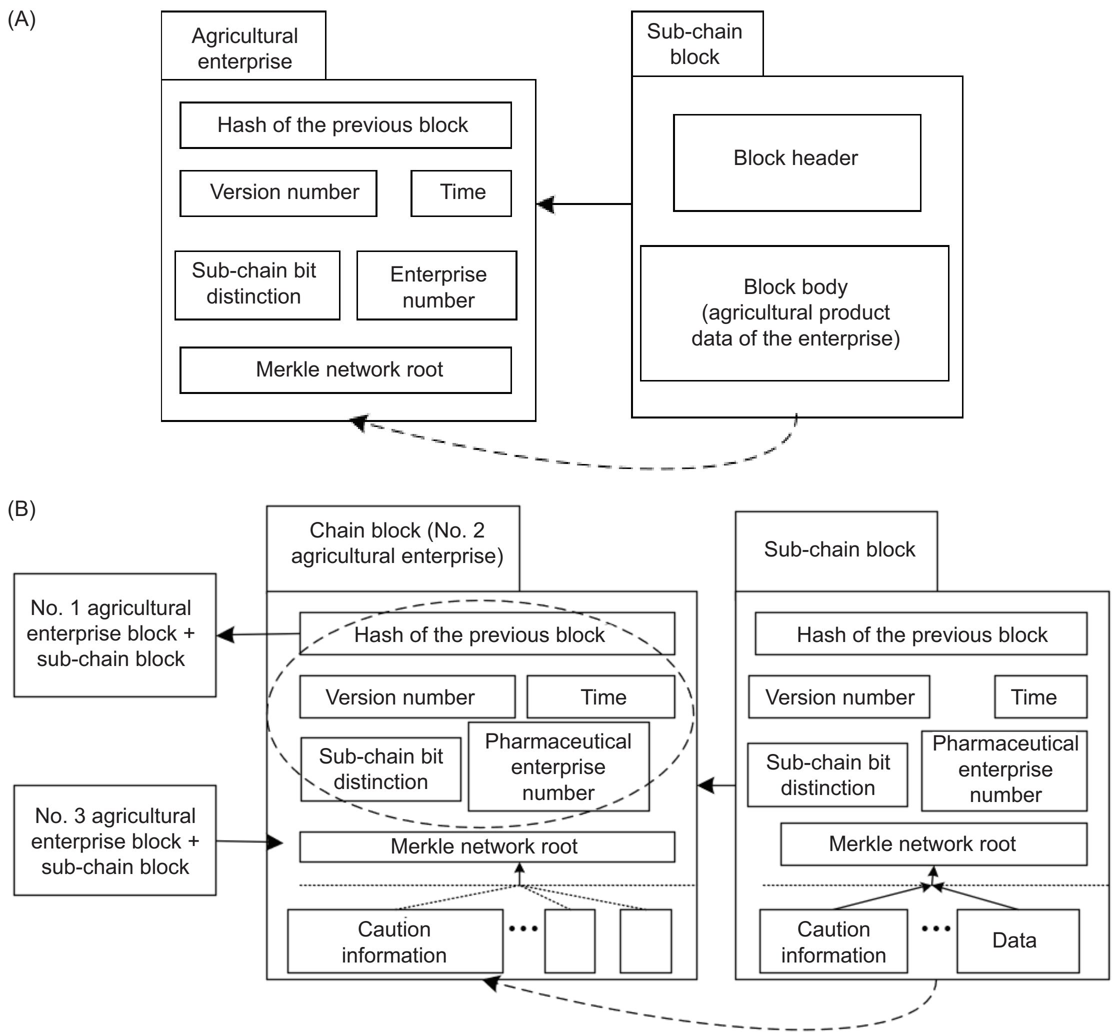

Figure 2. Blockchain structure of enterprises related to agricultural product operation. (A) Agricultural enterprise block + sub-chain block. (B) Main chain block + sub-chain block.

traceability, verification, and transactions. This enhances the transparency of the entire agricultural economic security regulatory system and guarantees the traceability and authenticity of agricultural products' data. Simultaneously, it protects the commercial privacy of agricultural enterprises, preventing unauthorized data access and tampering.

Smart contract design

In the blockchain-based agricultural economic security regulatory scheme, smart contracts are computer programs that automatically execute, control, or document legal events and actions in accordance with the terms of a contract. Based on business logic and the needs of the integrated agricultural industry development model, this paper defines the following two types of smart contracts:

Main chain smart contracts

Main chain smart contracts are deployed on the blockchain's main network and typically handle global core business logic and rules. Within the agricultural economic security regulatory scheme, main chain smart contracts are responsible for the following:

- *Agricultural enterprise registration and identity verification*: Managing the entire process of agricultural enterprises joining the regulatory platform, including identity verification, qualification review, and the allocation of public and private keys.

- *Traceability and transparency assurance*: Ensuring that information about agricultural products (such as planting, production, processing, transportation, and sales records) is recorded and traceable throughout the supply chain.

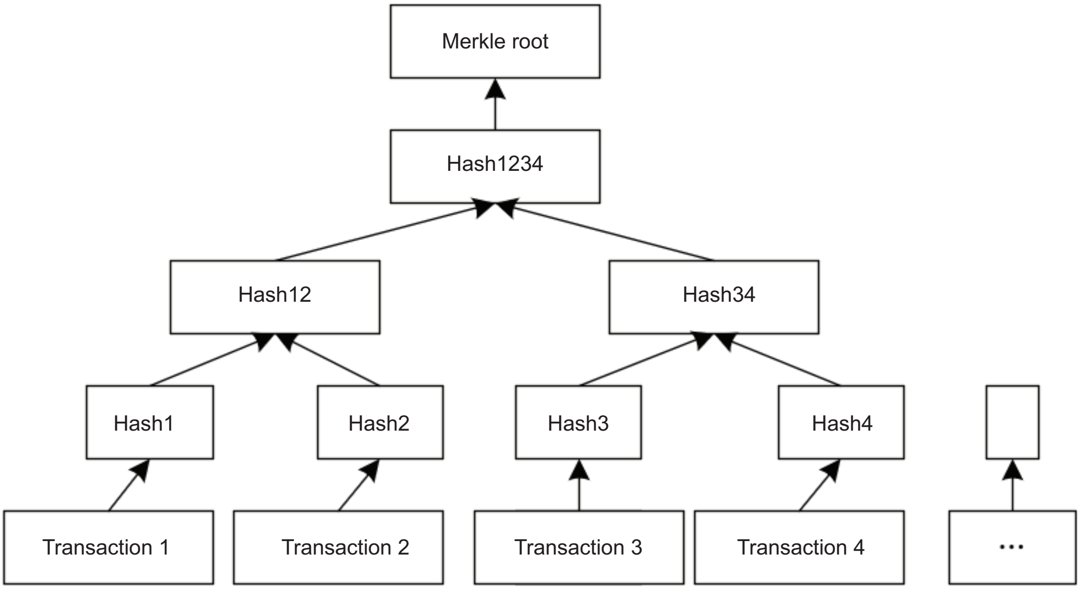

Figure 3. Schematic structure of a Merkle tree.

- *Data integrity verification*: Ensuring the security and immutability of data during transmission and storage through encryption algorithms.
- *Transaction and settlement processing*: Managing the confirmation, recording, and execution of payments related to agricultural product transactions.
- *Permissions and rule management*: Setting and maintaining the system's permission hierarchy and operational rules, including data access control and user behavior standards.

Sub-chain smart contracts

Sub-chain smart contracts typically operate on auxiliary chains that branch off from the main chain, carrying specific business logic and providing customized services for different segments or regions of agricultural industry chain. Within the agricultural economic security regulatory scheme, sub-chain smart contracts focus on the following:

- *Regional business processing*: Business logic implemented for specific areas or specific agricultural products, such as the certification process for products with geographical indications.
- Specific segment monitoring: Monitoring processes, such as the processing of agricultural products or quality control, achieving data collection, and processing for specific segments.
- *Microeconomic activities*: Supporting specific business needs of small-scale agricultural enterprises or cooperatives, such as microcredit management, local market transactions, etc.
- *Targeted data analysis*: Conducting data analysis based on the specific needs of agricultural industry chain, providing decision support and business insights.
- *Customized cooperation agreements*: Supporting cooperation between agricultural enterprises, such as joint purchasing, sales agreements, or shared resource platforms.

In summary, main chain smart contracts are responsible for maintaining the blockchain regulatory platform's infrastructure and core business processes, while sub-chain smart contracts provide more flexible, need-specific solutions. Together, they support the framework of the entire agricultural economic security regulatory scheme. Through this design, the blockchain regulatory platform is able to adapt to diverse and regionalized agricultural development needs while ensuring global consistency and security.

Consensus mechanism design

In the blockchain-based agricultural economic security regulatory scheme, Delegated Proof of Stake (DPoS) is selected as the consensus mechanism, tailored to the characteristics of agricultural industry. The improvement in the consensus mechanism involves setting specific election and reward systems to ensure that nodes of different roles can participate effectively and fairly in the maintenance of blockchain network. For example, general nodes can gain voting rights based on their participation and contribution to various segments of agricultural production, processing, and distribution. Candidate nodes refer to those willing and meeting certain criteria to partake in the blockchain verification process, with witness nodes being elected through voting by general nodes. Witness nodes are responsible for the actual creation and verification of blocks, with their election process involving all nodes to ensure the network's decentralization and democratization. To enhance system efficiency and reduce the potential for malicious attacks, the number of witness nodes can be limited, and necessary incentives can be established to encourage active and honest participation by nodes.

When implementing blockchain technology as a framework for agricultural economic security regulation, it is necessary to consider comprehensively its feasibility and effectiveness. The scalability of blockchain technology is a crucial factor, especially when handling large-scale agricultural product transactions and regulatory data, ensuring that the system can support high concurrency and large-scale data processing. Additionally, the accessibility of stakeholders is the key, as it is essential to ensure that different parties can easily access and use regulatory system, promoting information-sharing and transparency. At the same time, it is important to recognize the challenges that may arise with the adoption of blockchain technology, such as the establishment of technical standards, data privacy protection, and network security issues, and to take appropriate measures to address them. By considering these factors, we can better assess the feasibility and effectiveness of implementing blockchain technology in agricultural regulatory framework, providing a more reliable solution for agricultural economic security regulation.

In the integrated development model of agricultural industry, the consensus stage of the blockchain system involves the following three types of entity nodes:

(a) *General nodes*: Representing ordinary participants in the blockchain network, these can be farmers, agricultural enterprises, distributors, retailers, consumers, and other participants in agricultural economy. The primary functions of general nodes are to initiate transactions, and to verify and record information. They initiate transaction requests in the network, upload data related to agricultural production and distribution, and validate data uploaded by other nodes. Within the consensus mechanism, general nodes possess voting rights, allowing them to vote for candidate nodes and select trusted nodes to become witness nodes.

(b) *Candidate nodes*: Wishing to participate in the core consensus process of blockchain network, these nodes typically need to meet certain eligibility criteria, such as owning a specified amount of tokens, having a good reputation record, and possessing high-performance computing resources. Candidate nodes declare their intention to the network and obtain qualification to become witness nodes through voting by general nodes. In the integrated model of agricultural industry, candidate nodes are large agricultural enterprises, cooperatives, agricultural research institutions, etc., capable and willing to maintain the stability and security of network.

(c) *Witness nodes*: Witness nodes are elected to be responsible for the actual production, verification, and packaging of blocks. They play a crucial role in the consensus process, ensuring the swift and accurate handling of transactions and blocks. Witness nodes must maintain a high level of reliability and integrity, as their actions directly affect the trustworthiness and efficiency of blockchain. In the integrated development model of agricultural industry, witness nodes represent regional agricultural industry clusters, government regulatory agencies, industry associations, etc., collectively ensuring that the traceability and regulatory information of agricultural products are authentic and complete.

Specifically, the consensus stage includes a voting phase, witness election phase, and witness working phase, each with its specific functions and operational steps.

The voting phase marks the beginning of the consensus process, where all general nodes can participate in voting. Each node accumulates a certain amount of voting rights based on system rules and its economic activities. These voting rights are used to support candidate nodes, those wishing to become witnesses. This process often requires nodes to stake equity, that is, to lock a certain amount of tokens on blockchain, indicating their commitment to the network and willingness to contribute. Voting is usually based on each node's assessment of candidate nodes' trustworthiness and contributions, with these assessment criteria being tailored to the specific needs of agricultural industry, such as contributions to agricultural knowledge, assurance of agricultural product quality, etc.

After conclusion of the voting phase, the system elects a certain number of witness nodes from candidate nodes. These witness nodes are tasked with creating new blocks and verifying transactions. Within the integrated development model of agricultural industry, the election of witnesses ensures the accuracy and completeness of agricultural data, as they are typically entities with high credibility and expertise in agricultural field, such as large agricultural enterprises, technologically advanced cooperatives, or regulatory bodies appointed by the government. To ensure the fairness of voting, this study introduces a weight composed of two significant factors, S_{ER} and CO_{og}, into the final vote tally calculation. The number of errors or mistakes in witness work, S_{ER}, represents the credibility of leading nodes while working as witness nodes, and the number of votes originating from agricultural enterprises, CO_{og}, represents the fairness of voting. The weight calculation formula is given as follows:

$$WE_u = \frac{CO_{og}}{e_f + S_{ER}} \tag{10}$$

Once witnesses are elected, they begin the process of validating and packaging transactions into new blocks, which are then added to the blockchain. During this stage, witnesses must maintain a high level of network connectivity and computational capacity to respond quickly to network demands. The transactions they verify include data from various stages of agricultural products' lifecycle, such as production, processing, transportation, and sales. Once these data are recorded in blocks, they are broadcast throughout the network, verified by other nodes, ensuring immutability and transparency. In the agricultural economic security regulatory scheme, the work of witnesses encompasses not only technical operations but also adherence to agricultural regulatory rules and standards, ensuring the authenticity of agricultural data. This is crucial for food traceability, quality control, and the construction of market trust.

Design for uploading agricultural product data

When an agricultural producer creates a new product, a production data record is automatically generated using IoT devices. This data includes information about the product type, yield, production date, seeds, or feed used, and fertilization and feeding details. Within the integrated development model of agricultural industry, this data also encompass information related to other industry segments (such as processing, logistics, etc.) to form a complete industry chain data. The production data is packaged into a 'transaction' $TR = \{ZS, TO\mathbf{D}_R, UF_f, \delta_r\}$, ready to be uploaded to the blockchain. Each transaction includes metadata, such as timestamps, production batches, and links to detailed records of the production process.

To ensure the uniqueness and verifiability of data's origin, the system generates a unique identity token TO_{DR} for each product and a unique enterprise number UF_f for each production enterprise or individual. These unique identifiers aid in subsequent traceability and identity verification. Before submission to the blockchain, the transaction is signed $SI_t = G_1(TR)^{tjtv}$ with the private key of the product producer, ensuring the authenticity and non-repudiation of the transaction. After signing, anyone can use public key to verify authenticity of the signature, but cannot forge it. The signature verification formula is given as follows:

$$r(SI_t,h) = r(G_1(TR),oj_{tv}) \tag{11}$$

The data included in transactions are processed through hashing to generate a hash fingerprint. This fingerprint encrypts integrity of the data, ensuring that any slight modification to the data results in a significant change in hash fingerprint, thereby guaranteeing immutability of the data. When a transaction is ready to be added to the chain, it is sent to one or more witness nodes. Witness nodes, elected through the consensus mechanism, are responsible for verifying the validity of transactions. They check the transaction's signature, enterprise number, hash fingerprint, and other information to ensure the transaction's legality and consistency. Once verified, the transaction is packaged into a new block and broadcast by witness nodes to other network nodes. Once the block is accepted by the majority of nodes, the new block is added to the blockchain, the transaction is confirmed, and the data are recorded permanently.

Enhancing the traceability of agricultural products and strengthening data security mechanisms play a critical role in reducing risks and ensuring integrity of the entire supply chain. By establishing a blockchain-based regulatory framework, it is possible to achieve comprehensive tracking and recording of the production, distribution, and sales processes of agricultural products, ensuring the authenticity and credibility of information, thereby effectively reducing the occurrence of food safety incidents and frauds. Additionally, enhancing data security measures, utilizing encryption technologies, and implementing access control mechanisms help protect sensitive information from unauthorized access and tampering, thus ensuring integrity and confidentiality of the data, and enhancing reliability and security of the entire supply chain.

Regulatory compliance is a critical issue, particularly when it comes to requirements related to data privacy and personal information protection. It is necessary to ensure that the proposed system complies with relevant regulations and standards to avoid potential legal risks and compliance issues. Moreover, technical infrastructure requirements are another key consideration, including needs for network bandwidth, security, data storage, and processing capabilities, to ensure that the system can meet the demands of practical applications and maintain stable operation. The acceptance of stakeholders is also a crucial factor. It is essential to promote actively the participation and support of all parties, including agricultural producers, government regulatory agencies, and financial institutions, to ensure the smooth implementation and long-term sustainable development of the proposed regulatory framework. Considering these factors comprehensively can more fully assess the feasibility of implementing the proposed regulatory framework, providing effective solutions to practical challenges in agricultural economic security regulation.

The proposed policy needs to align with the existing regulatory framework to ensure its smooth implementation and gain the support of stakeholders. This includes fitting with current laws, standards, and regulatory practices to ensure legal, institutional, and procedural compliance of the proposed policy. Simultaneously, assessing the potential impacts of the proposed policy on stakeholders and market dynamics is also crucial. Policy implementation may affect various stakeholders, such as agricultural producers, businesses, and regulatory bodies, hence a comprehensive assessment of their interests and impacts is necessary. Furthermore, the proposed policy might have positive or negative effects on market dynamics, such as enhancing market transparency and improving liquidity, but it may also trigger industry transformations and market volatility. Therefore, when formulating and implementing the proposed policy, it is vital to consider fully its impact on stakeholders and market to achieve policy sustainability and market stability.

Experimental Results and Analysis

This paper utilizes a variety of software tools to support the research. In building a VAR model and the risk spillover-directed weighted network, the study employs statistical software packages, including the stats models library in Python, which are used for data processing, model fitting, and analysis. This software provides a rich set of statistical analysis tools and functions that help quantify the spillover effects of agricultural economic risks under the integrated agricultural industry development model. In discussing the blockchain technology-based agricultural economic security regulatory scheme, the research uses blockchain platform development tools and smart contract programming languages as well as development tools, such as Truffle and Remix, for contract deployment and testing. Additionally, blockchain explorers and other tools are used to monitor and verify transaction execution.

In the paper, validating the generation and efficiency of models is crucial. First, the paper conducts validation of the constructed VAR model and the risk spillover-directed weighted network to ensure their accuracy and effectiveness. This includes using various statistical methods and tests to assess the model's fit and predictive ability, such as the Wald test, Wooldridge test, and Frees test. Through these validation steps, it is possible to determine whether the model can accurately capture the spillover effects of agricultural economic risks under the integrated agricultural industry development model. Second, for the blockchain technology-based agricultural economic security regulatory scheme, it is necessary to verify its efficiency and feasibility in practical applications. This may involve field testing and evaluation of various aspects, such as registration processes, smart contracts, consensus mechanisms, and data upload mechanisms. Key focuses include the operational convenience, data security, and transaction speed performance indicators of the scheme. Through these validation efforts, it is possible to assess whether the scheme can effectively enhance the efficiency of agricultural economic regulation and provide feasibility assurance for practical applications.

In constructing a VAR model and the corresponding risk spillover-directed weighted network, an in-depth quantitative analysis of agricultural economic risk spillover effect under the integrated development model of agricultural industry was conducted. Table 2 provides the descriptive statistics of variables, including mean value, standard deviation (SD), minimum, maximum, and level of statistical significance (P value). It is evident from Table 2 that the mean of the agricultural economic risk index is close to 0, indicating that, on average, the agricultural economic risk index slightly falls below the risk baseline during the sample period. A large SD indicates significant fluctuation around mean value; $P = 0.0000$ signifies that statistically this variable is highly significant. The mean value of agricultural industry integration index is 0.092, indicating positive growth in integration levels, but a relatively small SD suggests minor variation in integration levels across the sample. $P = 0.0000$ indicates that differences in the level of agricultural industry integration are statistically significant. Among control variables, $P < 0.05$ for the ratio of agricultural technology investment, market access degree, agricultural insurance coverage rate, government support, climate change index, availability of agricultural financial services, and agricultural labor force quality index, implying statistical significance. These control variables significantly impact agricultural economic risk index. Based on the above-assumed descriptive statistics and positive test results, it is concluded that the agricultural industry integration index significantly affects the agricultural economic risk index, and the control variables are also statistically significant. This suggests that the integrated development model of agricultural industry contributes to reducing or controlling agricultural economic risks.

Table 2. Descriptive statistics of variables.

Variable	(1) Mean	(2) Standard deviation	(3) Minimum	(4) Maximum	(5) *P* value
Agricultural economic risk index	–0.042	0.884	–1.698	1.012	0.0000
Agricultural industry integration index	0.092	0.073	–0.051	0.412	0.0000
Ratio of agricultural technology investment	9.845	1.125	6.623	12.365	0.0018
Market access degree	2.789	2.541	–1.234	14.265	0.0000
Agricultural insurance coverage rate	8.23*e*-05	1.362	–1.548	5.784	0.0000
Government support	6.784	4.121	2.154	25.361	0.0312
Climate change index	52.361	16.598	21.365	104.265	0.0022
Availability of agricultural financial services	0.135	3.658	–9.325	11.265	0.0389
Agricultural labor force quality index	0.158	0.689	–1.235	1.124	0.0000

Table 3 presents the results of three different panel data statistical tests, including the Wald test, Wooldridge test, and Frees test. These tests are commonly used in panel data analysis to ensure that the assumptions of the model are met, allowing for valid inferences. As shown in Table 3, $P < 0.01$ for Wald test, strongly rejecting the null hypothesis of homoscedasticity of residuals, indicating significant between-group variance; $P < 0.01$ for Wooldridge test, meaning that the null hypothesis of no autocorrelation is rejected, indicating significant within-group autocorrelation; and $P < 0.01$ for Frees test, rejecting the null hypothesis of no cross-sectional correlation, indicating significant cross-sectional correlation. The test results in Table 3 indicate that there are key issues with panel data characteristics in the constructed VAR model, such as between-group variance, within-group autocorrelation, and cross-sectional correlation. These issues need to be considered in the estimation of VAR model, otherwise it could lead to inconsistent model estimates and invalid inferences.

Table 3. Test results.

Test method	Statistic	*P* value	Conclusion
Wald test	$Chi^2(15)$~475.23	0.000	Significant between-group variance
Wooldridge test	*F*(1,15)-14.258	0.0013	Significant within-group autocorrelation
Frees test	1.569	<0.01	Significant cross-sectional correlation

The analysis indicates that in these tests, $P < 0.01$, which means that the corresponding null hypotheses are strongly rejected statistically. Specifically, the Wald test indicates the presence of significant between-group heteroscedasticity, the Wooldridge test shows significant within-group autocorrelation, and the Frees test reveals significant cross-sectional correlation.

Table 4 provides regression model results, employing a comprehensive Feasible Generalized Least Squares (FGLS) estimation method for panel data, suitable for addressing between-group variance, within-group autocorrelation, and cross-sectional correlation. Each model incrementally introduces new control variables based on the basic model. The constant term is highly significant across all models, indicating statistical significance of the model. The core explanatory variable, the agricultural industry integration index, has coefficients ranging from -0.017 to -0.055, nearly all significant (at least at the 5% level). Negative signs indicate a negative correlation between increase in agricultural industry integration index and agricultural economic risk index, suggesting that enhanced industry integration contributes to the reduction of agricultural economic risk. Coefficients for the ratio of agricultural technology investment are positive (0.043–0.066) and statistically significant, indicating a positive correlation with agricultural economic risk. Coefficients for market access degree are mostly negative and significant, indicating that improvements in market access help reduce agricultural economic risk. Coefficients for agricultural insurance coverage rate transition from insignificance to significant positive correlation, suggesting that increased insurance coverage can, to some extent, increase agricultural economic risk because of risk transfer. Coefficients for government support are significantly negative, indicating that government support helps mitigate agricultural economic risk. The climate change index is negatively significant, implying a complex relationship between climate change and agricultural economic risk. Coefficients for the availability of agricultural financial services are significantly positive, indicating that improvements in financial services increase agricultural economic risk because of increased market volatility. The agricultural labor force

Table 4. Basic model regression results.

Variable	(1) Agricultural economic risk index	(2) Agricultural economic risk index	(3) Agricultural economic risk index	(4) Agricultural economic risk index	(5) Agricultural economic risk index	(6) Agricultural economic risk index	(7) Agricultural economic risk index	(8) Agricultural economic risk index
Agricultural industry integration index	–0.017* (-4.89)	–0.005 (–0.58)	–0.018* (–3.15)	–0.032* (–3.68)	–0.055* (–6.12)	–0.055* (–6.08)	–0.052* (–4.78)	–0.055* (–5.65)
Ratio of agricultural technology investment		0.066* (15.62)	0.065* (14.58)	0.062* (13.69)	0.051* (9.21)	0.043* (7.56)	0.051* (9.22)	0.048* (9.36)
Market access degree			–0.028* (–12.36)	–0.023* (–8.58)	–0.022* (–5.53)	–0.018* (–4.23)	–0.021* (-4.75)	–0.022* (–4.89)
Agricultural insurance coverage rate				0.001 (1.23)	0.002 (2.14)	0.002 (1.48)	0.003* (2.78)	0.003* (3.14)
Government support					–0.032* (–8.78)	–0.033* (–9.56)	–0.051* (–13.69)	–0.052* (–13.56)
Climate change index						–0.042* (–3.36)	–0.025 (–2.13)	–0.025 (–2.45)
Availability of agricultural financial services							0.265* (4.62)	0.254* (4.58)
Agricultural labor force quality index								–0.012* (3.12)
Constant	0.987* (201.56)	0.245* (5.78)	0.269* (5.98)	0.321* (6.23)	0.457* (7.22)	0.546* (8.25)	0.512* (8.57)	0.528* (9.56)
Observations	230	230	230	230	230	230	230	230
Number	15	15	15	15	15	15	15	15

quality index is significantly negative, suggesting that improved labor quality helps reduce agricultural economic risk. Overall, results in Table 4 show that the agricultural industry integration index is generally negatively correlated with the agricultural economic risk index, indicating that industry integration contributes to risk reduction. Other control variables, such as market access degree, government support, and agricultural labor force quality index, are also positively correlated with risk reduction, while increase in the ratio of agricultural technology investment and availability of agricultural financial services elevates risk.

Policymakers should consider how to manage and reduce agricultural economic risk by promoting industry integration, improving market access, providing appropriate government support, and enhancing labor quality. Meanwhile, attention should be paid to the potential risks brought about by improvements in technology investment and financial services to ensure the stable development of agricultural sector.

Table 5 presents the comparison of four different agricultural economic security regulatory schemes for experimental purposes, all based on blockchain technology. Each scheme differs in architecture, data security, smart contracts, system robustness, supervisability, and traceability. It is evident from the table that the scheme proposed in this paper provides the most comprehensive set of characteristics, enhancing data security, implementing automated regulation through smart contracts, ensuring system robustness, and featuring supervisability and traceability. This comprehensive feature set theoretically makes the proposed scheme the most reliable choice.

Figure 4 illustrates the time consumption during the testing phase of different agricultural economic security regulatory schemes with increase in the number of

Table 5. Comparison of agricultural economic security regulatory schemes.

Scheme	Architecture	Data security	Smart contract	System robustness	Supervisability	Traceability
Reference scheme 1	Blockchain	×	×	×	√	√
Reference scheme 2	Blockchain	×	√	×	×	√
Reference scheme 3	Blockchain	√	×	√	×	√
Scheme proposed in this study	Improved blockchain	√	√	√	√	√

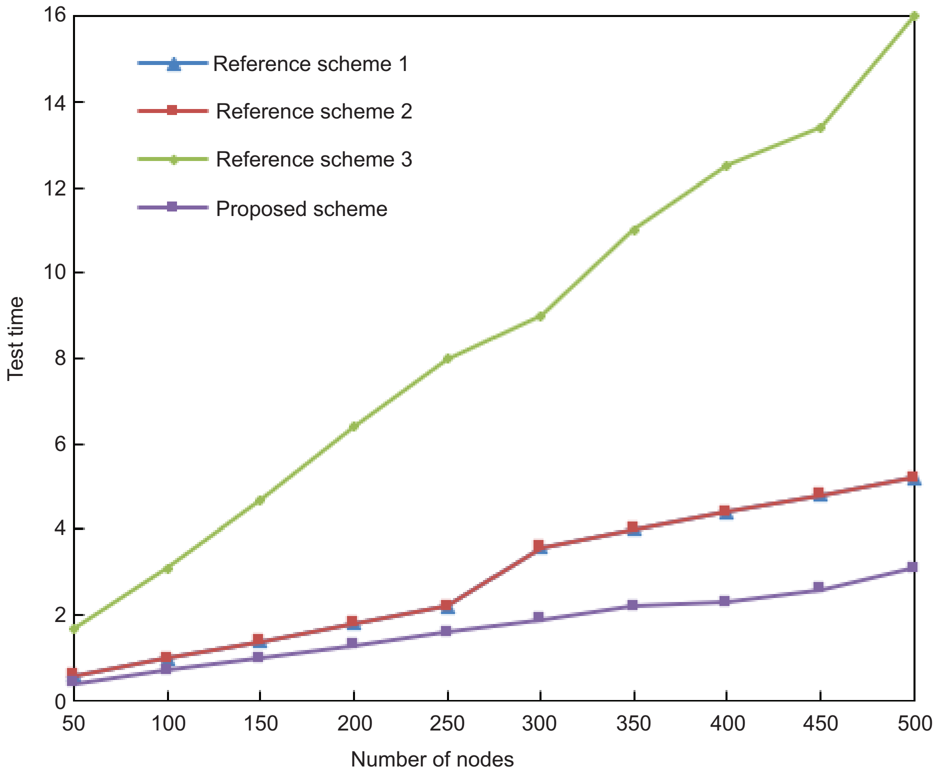

Figure 4. Time consumption comparison of different agricultural economic security regulatory schemes during the test stage.

nodes. Analysis of these data helps understand each scheme's scalability and efficiency. It is noted that the time consumption for reference schemes 1 and 2 grows linearly with increase in node numbers. When the number of nodes increases from 50 to 500, the time consumption increases from 0.6 s to 5.2 s. This indicates that these two schemes, with similar architecture and performance characteristics, have good stability and predictability with the increase in node numbers but may impact applications with high real-time demands under high load. The time consumption for reference scheme 3 increases significantly with the number of nodes, more steeply increasing from 1.7 s to 16 s. This indicates scalability issues with reference scheme 3, or its processing mechanisms become more complex and time-consuming with increase in the number of nodes. The time consumption of this paper's scheme grows linearly with increase in node numbers but at a slower rate than other three schemes. At 500 nodes, its time consumption is only 3.1 s, significantly lower than other schemes. This demonstrates higher efficiency and better scalability of the scheme proposed in this paper when handling a large number of nodes.

It is concluded that the regulatory scheme proposed in this paper offers the best performance, even as the number of nodes increases significantly, the rise in time consumption remains lowest. This indicates that the proposed scheme outperforms other schemes in handling concurrent operations and maintaining system efficiency. Within the context of agricultural economic security regulation, such efficiency is crucial as it allows

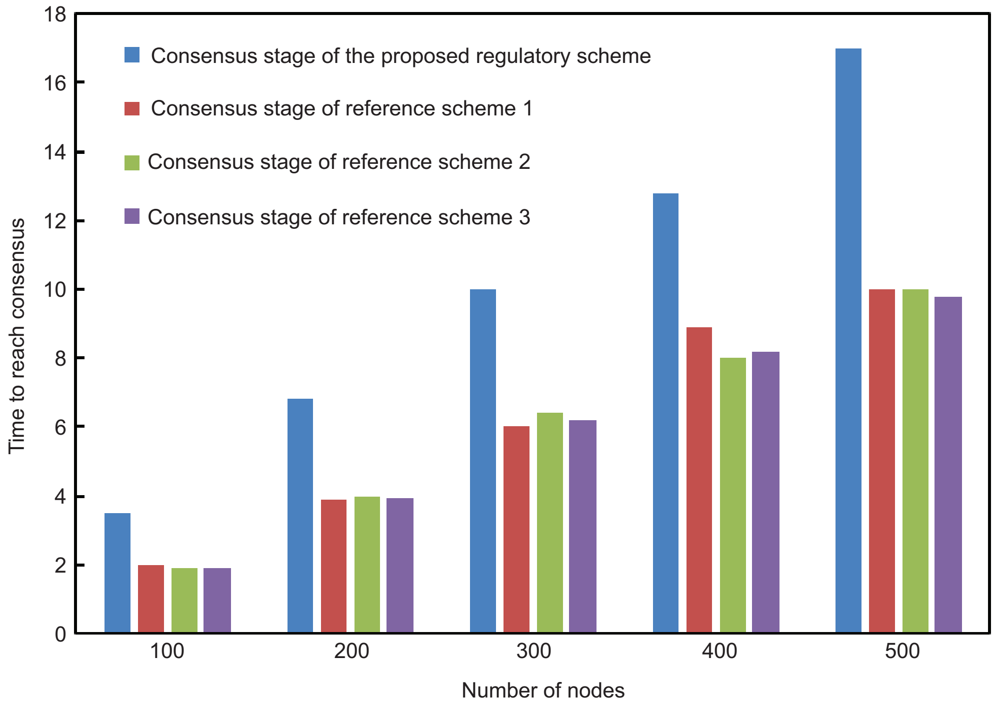

Figure 5. Time consumption comparison of different agricultural economic security regulatory schemes during the consensus stage.

more participants to join the system in real time without significantly impacting the overall performance of the system. The high efficiency of the proposed scheme demonstrates its effectiveness in practical applications, providing a scalable and responsive blockchain solution for agricultural economic security regulation. Assessing the external validity of research findings is a crucial aspect to ensure that the results are generalizable to other scenarios or populations. In this study, it is important to focus on whether the selected models of integrated agricultural industry development and the regulatory framework are applicable to agricultural systems in different regions or countries, and whether the results can be validated in different environments. Additionally, the universality and reproducibility of research methods are to be considered to ensure that other researchers can replicate the results in different contexts.

Figure 5 displays the time consumption of different agricultural economic security regulatory schemes during the consensus phase with increase in the number of nodes. These data analyses help assess the efficiency of each scheme in achieving consensus. According to the data in Figure 5, we observe that the time consumption of the regulatory scheme discussed in this paper shows a rapidly increasing trend with increase in the number of nodes, while time consumption for reference schemes 1–3 increases relatively slowly. Specifically, the regulatory scheme in this paper consumes significantly more time when the number of nodes increases to 500, compared to other schemes, indicating potential performance bottlenecks in scaling of the system. In contrast, reference schemes 1–3 show more stable growth in time consumption during the consensus phase, especially reference scheme 3, which demonstrates the best performance, maintaining lower time consumption even with a larger number of nodes. Therefore, although the regulatory scheme discussed in this paper may have some shortcomings in time efficiency, it is advantages in other aspects, such as higher security, better decentralization, and better adaptability. Thus, while making choice of schemes, it is necessary to consider various factors and weigh pros and cons based on specific needs.

Conclusions

This study, through the establishment of a VAR model and the corresponding risk spillover-directed weighted network, quantitatively analyzes the economic risk spillover effect under the integrated development model of agricultural industry, offering a new perspective for understanding and assessing agricultural economic risks. The study meticulously designed a blockchain-based agricultural economic security regulatory scheme, including enterprise registration, smart contracts, consensus mechanisms, and data upload mechanisms.

These designs are significant for enhancing the transparency and security of agricultural product operations.

The appropriateness of VAR modeling and risk spillover-directed weighted network methods used in the text for research objectives is reflected in two aspects. First, the VAR model can capture the spillover effects of economic risks under the integrated agricultural industry development model. By analyzing dynamic relationships between different variables, it reveals transmission and impact mechanisms of economic risks across various agricultural sectors, providing a new perspective for a deeper understanding and assessment of agricultural economic risks. Second, the risk spillover-directed weighted network method allows for a more comprehensive quantification of risk spillover effects within the agricultural economic system. By incorporating the paths and extent of risk transmission, it helps to assess more accurately the impact of risk spillover on the entire economic system, thus providing effective tools and methods for managing agricultural economic risks.

Regarding experimental results, variable descriptive statistics were implemented, and Wald, Wooldridge, and Frees tests were conducted to ensure the model's validity and data consistency. Stepwise regression analysis was performed using a comprehensive FGLS estimation method, aiding in identifying key factors and their impact levels within agricultural economic security regulation. A comparative analysis of the agricultural economic security regulatory schemes participating in the experiment was conducted, evaluating their time consumption during testing and consensus stages, thereby assessing efficiency.

This research provides new quantitative analysis tools and perspectives for agricultural risk management, advancing the application research of blockchain in agricultural economic security regulation. However, this study has limitations regarding model settings, such as the selection of lag periods for VAR model and assumptions about the structure of risk spillover network. Experimentally, the proposed scheme was not efficient in terms of consensus efficiency, thus limiting performance in large-scale application scenarios.

In order to further refine the study, the following aspects could be included:

(1) Strengthen the deep understanding of the integrated agricultural industry development model and risk transmission mechanisms. This can be done by expanding research framework through more dimensions and a broader range of data samples to capture more potential factors and complex correlations.

(2) Further optimize the design of regulatory framework, taking into account the needs of various stakeholders and the feasibility of practical operations, to ensure the effectiveness and sustainability of regulatory system. At the same time, integrate blockchain technology with other cutting-edge technologies to enhance the intelligence and efficiency of regulatory system.

(3) Strengthen connection with actual regulatory practices by collaborating with government departments, agricultural enterprises, and financial institutions to apply research findings to actual agricultural economic security regulation. Continuously optimize and improve regulatory policies and technical methods to achieve more effective risk management and economic stability.

Data Availability Statement

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declared no conflict of interest. The funders had no role in the design of the study, collection, analyses, or interpretation of data, writing of the manuscript, and in the decision to publish the results.

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