Artificial Intelligence Innovation and Product Quality: Evidence from Food Recalls in China*

Fei Nie† Jianwei Ai‡ Lei Li§ Tao Xiong¶ Wendong Zhang‖

June 5, 2026

Abstract

Artificial intelligence (AI) is increasingly reshaping firm decision-making and transforming the production of goods. This paper studies the impact of AI on product quality, exploiting food recall as a revealed measure of quality failure. Using data on Chinese agri-food firms from 2007 to 2023, we find that doubling AI patent applications reduces food recall probability by 5.5 percent. AI strengthens quality control across suppliers, production, and marketing, with effects amplified by corporate social responsibility. We also document spillovers through competitive and supply chain channels: AI innovation by competitors, suppliers, and customers, each independently reduces focal firm recall risk. The results indicate that AI improves quality through enhanced organizational monitoring and coordination rather than automation alone.

Keywords: Artificial Intelligence; Product Quality; Food Safety; Product Recall.
JEL Codes: Q13, D21, L15.

*We gratefully acknowledge financial support from the National Social Science Foundation of China (Grant No. 19CJY049; 22&ZD079), National Natural Science Foundation of China (Grant No. 72173052; 72473048; 72171099), the U.S. Department of Agriculture's National Institute of Food and Agriculture project award No. 2022-67023-36727, the Guiding Project of Scientific Research Plan of Hubei Provincial Department of Education (Grant No. 23G061), the Fundamental Research Funds from the Central Universities of China (Grant No. 2662024JC007; X2662024JGPY006), and National Collaboration Program (Grant No. G2023157001L). All errors are our own.

†College of Economics and Management, Huazhong Agricultural University. E-mail: nie.fei@mail.hzau.edu.cn.

‡Charles H. Dyson School of Applied Economics and Management, SC Johnson College of Business, Cornell University. E-mail: jianwei.ai@cornell.edu.

§School of Economics, Nankai University. E-mail: nklilei@nankai.edu.cn.

¶Laboratory for Intelligent Food Security Governance, Huazhong Agricultural University. E-mail: taoxiong@mail.hzau.edu.cn.

‖Charles H. Dyson School of Applied Economics and Management, SC Johnson College of Business, Cornell University. E-mail: wendongz@cornell.edu.

1 Introduction

The economic impact of artificial intelligence (AI) depends critically on whether AI technologies meaningfully improve the production of goods and accelerate their adoption through various mechanisms (Aghion et al., 2017; Acemoglu, 2025; Jones, 2026). Product quality is fundamental to economic welfare and market discipline, and this concern is particularly acute in food markets, where quality failures impose substantial welfare costs, provoke costly regulatory intervention, and can generate systemic risks. Foodborne illnesses, for example, have recently been a significant global public health burden, resulting in substantial economic losses, and the burden falls disproportionately on low- and middle-income countries (Grace, 2023).[1] Despite its importance, product quality is rarely observed directly in firm-level data, and much of the literature has focused on productivity rather than quality. This limitation is particularly salient in the context of AI, where claims about improved prediction, monitoring, and oversight remain largely disconnected from empirical evidence on how AI affects product quality.

This paper addresses this gap by studying the impact of AI innovation on product recalls, which we use as a revealed measure of quality failure. We employ firm-level data from publicly listed agri-food companies to examine whether and how AI improves product quality. The food industry provides an ideal empirical setting: production is inherently multi-stage, quality monitoring is costly, and quality failures are subject to mandatory regulatory disclosure. Agri-food firms have strong incentives to develop new quality-control technologies to fulfill their obligation to protect public health (Barbancho-Maya and López-Toro, 2022). AI innovation can enhance traceability, strengthen regulatory compliance, and improve supply chain transparency (Senoner et al., 2022; Reitano et al., 2025). We track product recalls among Chinese agri-food firms from 2007 to 2023, a period of rapid AI development. Our

[1] Low- and middle-income countries account for 41% of the global population but 53% of all foodborne illness cases and 75% of associated deaths, according to the World Health Organization. WHO estimates of the global burden of foodborne diseases: foodborne diseases burden epidemiology reference group 2007–2015. Available at: https://www.who.int/publications/i/item/9789241565165.

results indicate that firms' AI innovation improves product quality through enhanced controls over suppliers, production processes, and marketing, with stronger effects among firms with greater corporate social responsibility. Moreover, AI adoption by peers, suppliers, and customers could further reduce product recall risk through supply-chain spillovers.

Our empirical strategy addresses several identification challenges. Product recalls may trigger defensive AI investment, generating reverse causality. Also, unobserved firm characteristics such as managerial quality or safety culture may simultaneously drive both AI innovation and recall performance. To address these concerns, we employ lagged AI measures, estimate specifications with firm and industry-year fixed effects, and implement instrumental variables estimation using provincial optical fiber density as an exogenous shifter of AI innovation costs. We also distinguish between internally developed and externally acquired AI patents to isolate genuine innovation capacity. Across all specifications, the estimated effect remains stable in sign and magnitude, alleviating concerns about spurious correlation.

This paper has three main empirical findings. First, we estimate the baseline relationship between firm-level AI innovation and food recall risk using discrete choice models with multiple robustness checks. Doubling in product-quality-related AI patent applications is associated with a 5.5% decline in the probability of food recalls, confirming the positive impact of AI innovation on product quality. Second, we investigate the underlying mechanisms through which AI reduces recalls. We document that AI innovation enhances quality control throughout the supply chain by improving supplier selection, standardizing production processes, and enabling data-driven marketing and inventory decisions. Corporate social responsibility (CSR) moderates AI's impact: firms with stronger CSR commitments exhibit larger recall reductions, suggesting that governance and ethical orientation complement technological deployment. Third, we examine heterogeneity and spillover effects, showing that effects are stronger for non-state-owned enterprises, in primary agriculture, and for mandatory recalls subject to stricter regulatory standards. We also document horizontal spillovers from competitor AI innovation and vertical spillovers from suppliers and customers, suggest-

ing that quality improvements propagate through supply chains.

China provides a particularly ideal setting for studying these questions. First, China is one of the world's largest agri-food markets, characterized by complex supply chains, rapid technological adoption, and stringent regulatory oversight following high-profile food safety incidents. Second, China has invested heavily in AI research and development, with publicly listed firms operating at the frontier of AI innovation in production and quality management. Critically, food recalls in China are subject to mandatory disclosure and regulatory oversight, generating systematic and comparable measures of quality failures that reflect economically meaningful events rather than voluntary reporting choices.

While our analysis focuses on the food industry, the findings are expected to generalize to other regulated sectors requiring monitoring of complex, multi-stage production. Pharmaceuticals, medical devices, and automotive manufacturing all share similar characteristics: stringent regulatory standards, costly quality failures with mandatory disclosure, and formal recall procedures (Back et al., 2024; Wang et al., 2023; Jumper et al., 2021; Abramson et al., 2024; Psarommatis and Azamfirei, 2024). These industries similarly manage intricate supply chains and must detect defects before market distribution. Economic theory and evidence on organizational information processing suggest that technologies enhancing prediction and detection capabilities can strengthen quality control and reduce operational risk. Our results thus contribute insights relevant to a broader class of regulated industries.

This paper contributes to three strands of literature. First, we provide systematic evidence on AI's impact on product quality, offering findings of agri-food firms actively deploying AI to optimize crop production, monitor supply chains, and track contaminants (Ben Ayed and Hanana, 2021; Javaid et al., 2023; Qian et al., 2023; Taneja et al., 2023). We show that AI also strengthens quality control in complex, multi-stage production, not just in automating routine tasks. Second, we advance understanding of how technology affects food safety. While food safety and product recalls have received attention in prior work (Pouliot and Sumner, 2013; Thomsen and McKenzie, 2001), robust empirical evidence on firm-level

innovation has been lacking. We decompose the channels through which AI enhances quality control and demonstrate that these mechanisms statistically mediate the relationship between AI innovation and recall reduction. Third, we document technology spillovers operating through competitive and supply chain channels, suggesting that social returns to AI innovation may substantially exceed private returns.

The remainder of this paper is organized as follows. Section 2 develops the theoretical foundations and main hypotheses. Section 3 describes the data sources, variable construction, and descriptive statistics. Section 4 outlines the empirical methodology and identification strategy. Section 5 presents the main findings, including baseline results, mechanism analysis, and robustness checks. Section 6 investigates horizontal and vertical spillover effects. Section 7 concludes with implications for policy and future research.

2 Literature Review and Hypotheses Development

This section develops the theoretical foundation for understanding how AI innovation affects product quality in the agri-food sector and presents our main hypotheses.

2.1 Impact of AI Innovation on Product Quality

AI technologies can improve product quality through three mechanisms. First, AI strengthens traceability systems that track contaminants, monitor environmental conditions, and detect fraud (Qian et al., 2023; Senoner et al., 2022; Taneja et al., 2023). Second, AI applications in crop production and livestock management increase operational precision (Ben Ayed and Hanana, 2021; Javaid et al., 2023). Third, AI enables real-time supply chain monitoring, helping firms meet regulatory standards while maintaining transparency (Acemoglu and Lensman, 2024). By automating quality control procedures, AI reduces inconsistencies in safety protocols and enables firms to transition from reactive problem-solving to predictive risk management.

Firms progressively adopt AI technologies of increasing sophistication (Aghion et al., 2015; Acemoglu, 2025). As agri-food firms move up this technology ladder, their capacity to implement comprehensive quality control across the supply chain improves. The impact manifests through both substitution effects, where AI replaces error-prone manual inspections with automated systems, and complementarity effects, where AI enhances human decision-making through data-driven insights.

When quality failures occur, firms face a strategic choice: pay regulatory penalties or conduct a product recall. Although penalties may involve lower immediate financial costs, the long-term consequences of quality failures substantially exceed direct penalties (Ferrier and Lamb, 2007). These consequences include erosion of consumer trust, legal liability, and brand depreciation. In complex global food supply chains subject to stringent regulatory oversight, firms face intensifying pressure to maintain product safety while preserving consumer confidence. AI-enabled systems allow firms to detect potential defects early by analyzing data from suppliers, production processes, and customer feedback (Naseem and Rizwan, 2025; Ziani et al., 2025). This early detection capability allows firms to initiate proactive recalls before regulatory enforcement, reducing both fines and reputational damage. AI-driven quality control enhances precision in risk assessment, facilitates root cause analysis, and improves operational efficiency in recall execution (Taylor et al., 2016). Consequently, firms increasingly invest in AI technologies that enable comprehensive quality monitoring as a core element of business strategy. This logic motivates our primary hypothesis:

Hypothesis 1. AI innovation reduces food recall risk by enabling earlier detection and prevention of quality failures.

2.2 Quality Control Across the Production Process

AI improves product quality through a full-process quality control framework operating across three stages: supplier management, production, and marketing (Mac Clay et al.,

2024; Ziani et al., 2025). This framework aligns with AI's core management functions: task allocation, process direction, cross-unit coordination, stakeholder motivation, and organizational learning (Koehler and Sauermann, 2024). We examine each channel through which AI innovation reduces quality failures in agri-food production (Naseem and Rizwan, 2025; Qian et al., 2023; Senoner et al., 2022).

Supplier quality control. AI enhances supplier selection and material verification through automated systems that identify high-quality suppliers and monitor input quality (Song et al., 2024; Toorajipour et al., 2021). Real-time supply chain monitoring detects deviations before they compromise production. Continuous learning from operational data enables these systems to improve supplier assessments over time (Alekseeva et al., 2020). By ensuring that inputs meet quality standards before entering production, AI substantially reduces downstream defect risk.

Production quality control. AI drives production standardization through three complementary mechanisms. First, real-time monitoring via sensors and automated processes maintains consistent adherence to quality specifications. Second, predictive maintenance uses historical data to identify equipment failures before they occur, preventing contamination and product defects (Raisch and Krakowski, 2021). Third, AI-enabled traceability systems create transparent records of each production stage, enabling rapid identification of contamination sources and accelerated recall execution (Nucci et al., 2023). These capabilities permit firms to transition from reactive problem-solving to preventive quality assurance.

Marketing quality control. AI enables dynamic analysis of consumer behavior and demand patterns. By processing large-scale customer data, AI optimizes inventory management, reducing overstock and stockout risk while aligning production with actual demand. Continuous analysis of customer feedback guides product optimization and portfolio diversification (Abrardi et al., 2022). This real-time responsiveness to market signals permits firms to align product quality with consumer expectations (Prentice and Nguyen, 2020). Through data-driven decision-making, AI enables firms to deliver higher-quality products that better

satisfy consumer preferences.

These three mechanisms jointly constitute the full-process quality control framework through which AI reduces food safety failures. This analysis motivates our second hypothesis:

Hypothesis 2. AI innovation reduces food recall risk by improving quality control across suppliers, production processes, and marketing activities.

2.3 The Role of Corporate Social Responsibility

Corporate social responsibility may amplify AI's impact on product quality through two mechanisms. First, CSR functions as organizational insurance that protects firm value during adverse events (Godfrey et al., 2009). When firms encounter product quality failures, strong CSR commitments amplify reputational costs and regulatory scrutiny, creating stronger incentives to invest in preventive technologies. Second, CSR raises stakeholder expectations regarding supply chain integrity, process standardization, and product safety. These heightened expectations increase the marginal return to AI-enabled quality monitoring and control systems.

The moderating effect operates through channels aligned with our full-process quality control framework. In supplier management, CSR-conscious firms face stronger pressure to ensure supply chain integrity, increasing incentives to deploy AI-driven supplier vetting and material monitoring systems. In production, CSR commitments to worker safety and process standardization motivate investments in AI-enabled real-time monitoring and predictive maintenance. In marketing, firms with robust CSR records recognize that product recalls impose substantial reputational damage beyond immediate financial penalties, encouraging deployment of AI-powered traceability and inventory management systems.

In essence, CSR amplifies the effectiveness of AI-driven quality control by raising the perceived costs of quality failures and strengthening organizational commitment to comprehensive risk management. Firms with higher CSR engagement view AI innovation as a

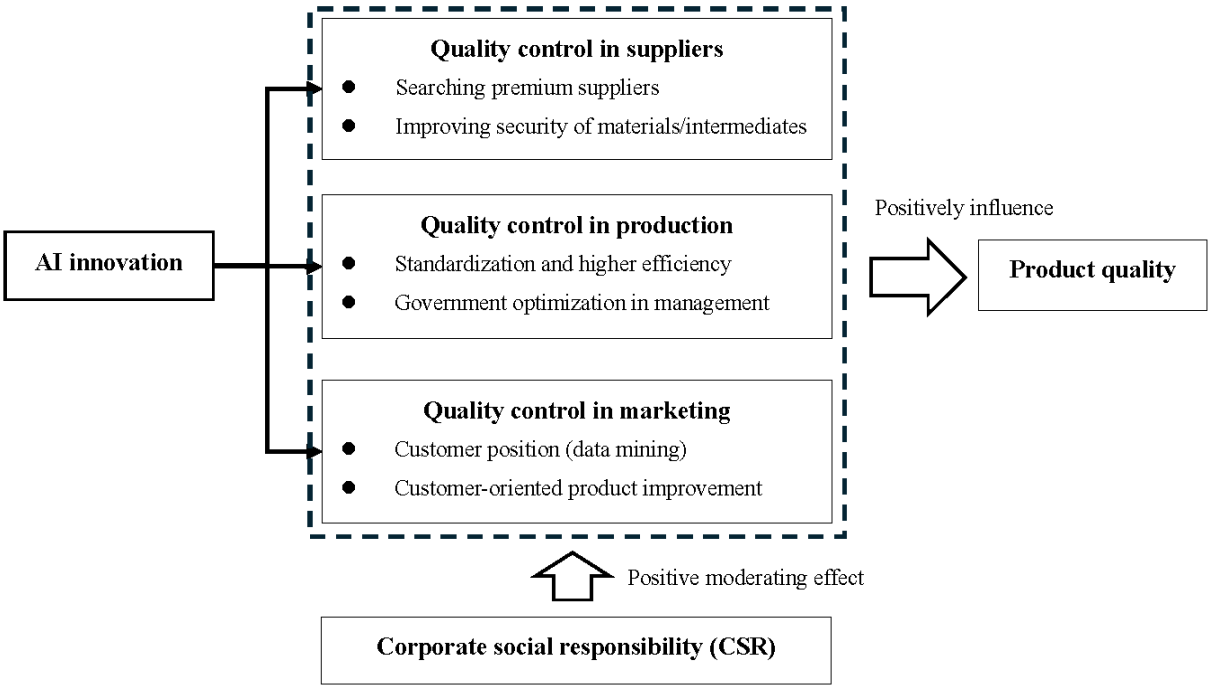


Figure 1: Conceptual Framework: Mechanisms Linking AI Innovation and Product Quality

Notes: AI innovation enhances quality control at three stages of the supply chain: suppliers, production, and marketing. It improves supplier selection and material security, increases production standardization and managerial efficiency, and enables data-driven customer positioning and product improvement. These mechanisms jointly contribute to improved product quality. Corporate social responsibility (CSR) plays a positive moderating role that strengthens the impact of AI-enabled quality control on product quality.

complement to their stakeholder commitments rather than merely a cost-minimization tool. This synergy suggests that quality improvements from AI innovation should be larger among firms demonstrating strong social responsibility. Figure 1 illustrates the full-process quality control framework and the moderating role of corporate social responsibility.

Hypothesis 3. Corporate social responsibility amplifies the impact of AI innovation on product quality by strengthening organizational incentives for quality control across suppliers, production, and marketing.

3 Institutional Background and Data

This section describes China's mandatory food recall disclosure system and presents our firm-level panel dataset. We document the regulatory institutions that generate systematic measures of quality failures, describe the characteristics of China's agri-food sector, and present variable construction and descriptive statistics.

3.1 Food Recalls in China

China's food safety regulatory framework has evolved substantially over the past two decades, driven by high-profile contamination incidents that exposed systemic vulnerabilities in production monitoring and supply chain oversight. The 2008 melamine scandal, in which infant formula manufacturers adulterated milk powder with melamine to artificially inflate protein readings, killed six infants and sickened approximately 300,000 children nationwide. This crisis catalyzed comprehensive regulatory reforms, establishing mandatory disclosure requirements for food recalls and creating institutional accountability mechanisms (Pei et al., 2011).

The regulatory architecture governing food safety rests on several foundational statutes. The *Food Safety Law of the People's Republic of China*, revised in 2015 and 2018, establishes firm-level responsibility for product quality and mandates immediate reporting of safety incidents to regulatory authorities. The *General Administration of Market Regulation*, established in 2018 through the consolidation of several agencies, enforces these requirements and maintains a comprehensive food recall database. Critically, firms must disclose recalls publicly within specified timeframes, generating systematic records of quality failures. This institutional feature of mandatory public disclosure provides the empirical foundation for our study.

Food safety standards in China are defined through multiple channels. The Ministry of Agriculture and Rural Affairs establishes agricultural product quality standards for primary

production. Industry associations publish supplementary standards reflecting best practices. Regulatory enforcement is decentralized: provincial, municipal, and district-level market supervision bureaus conduct inspections, testing, and enforcement actions, creating a multi-layered oversight system.[2]

An important institutional feature distinguishes between mandatory and voluntary recalls. Mandatory recalls are initiated when regulatory authorities detect violations of food safety standards during inspections or testing. These recalls reflect the detection of objective quality failures by independent regulatory agents. Voluntary recalls occur when firms proactively identify defects through internal quality control systems and announce recalls before regulatory discovery. The 2008 reforms strongly incentivized voluntary recalls by reducing penalties for firms that self-identify and promptly remediate safety failures, whereas firms concealing known defects face substantially larger fines and reputational sanctions (Kong et al., 2019). This institutional design aligns firm incentives with public health objectives.

The food industry in China is characterized by substantial fragmentation and complexity. Production occurs across multiple stages: primary agriculture, intermediate processing, and final processing, with hundreds of thousands of firms operating at each stage. This multi-stage structure, combined with China's continental geography and regulatory federalism, creates variation in food safety risks and regulatory oversight intensity that our empirical analysis exploits.

3.2 Data

Our analysis uses a panel dataset of 265 Chinese publicly listed agri-food firms covering 2007 to 2023. We construct this dataset by integrating information from three sources: (1) AI innovation data from the Chinese Research Data Services Platform (CNRDS); (2) food recall information from the WIND Economic Database; and (3) firm-level financial data from the China Stock Market & Accounting Research (CSMAR) database. Following the industrial

[2]For details, see https://www.mee.gov.cn/zcwj/zyygwj/201912/t20191225_751544.shtml.

classification for national economic activities, we classify firms into three sectors: primary agriculture, agri-sideline production, and food manufacturing.

We follow a systematic data processing procedure. First, we merge financial data, food recall records, and AI patent data, matching firms by stock code, name, and location. Second, we exclude firms designated as special treatment (ST or *ST), which indicates either consecutive annual losses or pending delisting proceedings.[3] Third, we remove firms with significant missing values or data anomalies inconsistent with Chinese accounting standards. Finally, we winsorize all continuous variables at the 1st and 99th percentiles to mitigate the influence of outliers.

Our final sample consists of 265 listed firms distributed across agri-food sectors as shown in Table A.4. Primary agriculture accounts for 67 firms, while agri-sideline and food manufacturing together comprise 198 firms. Observations from agri-sideline and food industries represent approximately 74.16% of our total sample, roughly 2.8 times the observations from primary agriculture. This distribution reflects the concentration of publicly listed firms in downstream processing activities relative to primary production.

3.3 Measurements

3.3.1 Food Recalls

The dependent variable is a binary indicator for whether firm i experiences a food recall in year t, denoted $Recall_{i,t}$, which equals one if a recall occurs and zero otherwise (Thomsen and McKenzie, 2001). Following Kong et al. (2019), we collect recall data from announcements issued by the Shanghai and Shenzhen Stock Exchanges and reports published by authoritative media outlets such as Xinhua News, China Food Safety News, and Sina News. We identify 38 firms that issued 56 food recall announcements from 2007 to 2023.[4] Figure A.1

[3]We exclude special treatment firms because their elevated delisting risk and potential financial data manipulation would introduce substantial measurement error. Following standard practice in Chinese equity markets research, we treat these firms as extreme observations that would distort regression estimates.

[4]We validate our identification by comparing with Kong et al. (2019), who documented 35 listed firms that posted recall announcements in the food industry from 2008 to 2016.

presents the number of food recalls among agri-food listed firms during our sample period.

Recalls are categorized as either mandatory or voluntary. A mandatory recall is initiated when regulatory authorities or media pressure compel a firm to retrieve defective products. A voluntary recall occurs when a firm independently identifies a defective product and proactively announces its recall. We observe only two voluntary recalls in our sample. This distribution indicates that regulatory authorities and public pressure predominantly drive China's food recalls, with limited scope for discretionary firm decisions. Table A.5 provides details for each recall event.

3.3.2 AI Innovation

The independent variable is measured by the annual number of firm-level product-quality-related AI patent applications, denoted $AI_patents_{i,t}$ (Zhai and Liu, 2023).[5] To identify AI patents, we match listed agri-food firms to the national patent database and extract detailed patent information, including International Patent Classification (IPC) codes. Using the Strategic Emerging Industries Classification and IPC Correspondence Table (2021) issued by the China National Intellectual Property Administration (CNIPA), we identify patents classified under AI-related IPC codes.

From 1.37 million patents held by listed firms, we identify over 43,000 AI patents and restrict the sample to those belonging to agri-food firms. Because not all AI patents relate to product quality, we further screen patents using the Foodmate IPR Service Center (FISC), which links AI patents to the China Food Industry Patent Database (CFIPD). Patents whose application scope includes quality monitoring, management, inspection, or traceability are classified as product-quality-related AI patents.

Finally, we aggregate these patents at the firm-year level to construct the annual count

[5]According to the 2022 Report on the Chinese AI Market released by the China Economic Industry Information Research Network, approximately 58 percent of Chinese enterprises have adopted AI technologies, ranking among the highest globally. In the agri-food sector, listed firms have implemented AI applications in smart breeding, precision agriculture, automated sorting, and digital supply chain management. This widespread adoption indicates that AI technologies are economically relevant in the industry we study.

of product-quality-related AI innovation. In total, 173 agri-food firms, representing 65.28 percent of the sample, filed such patents during our sample period, consistent with Chen et al. (2024). Table A.6 provides an overview of IPC codes and keywords for product-quality-related AI patent applications.

3.3.3 Full-Process Quality Control

The mechanism variables capture quality control across suppliers, production, and marketing. We construct these measures using data from annual reports of agri-food listed firms in the WIND Economic Database and the CSMAR database.

Supplier quality control is measured by two indicators reflecting supply chain risk: procurement concentration ($Pcd_{i,t}$) and administrative penalties imposed on suppliers ($Aps_{i,t}$). Procurement concentration is the ratio of a firm's purchases from its top five suppliers to total procurement expenditures. Administrative penalties are the number of penalties imposed by the State Administration for Market Regulation (SAMR) on a firm's top five suppliers within a fiscal year.[6] Firms relying heavily on a concentrated supplier base face greater supply chain risk, particularly when suppliers are subject to regulatory penalties for material quality issues (Bauer et al., 2018; Robinson and Malhotra, 2005).

Production quality control is measured by two indicators reflecting standardization: total factor productivity ($TFP_{i,t}$) and monitoring cost ($Cost_{i,t}$). Productivity is estimated using the Levinsohn-Petrin method (Levinsohn and Petrin, 2003). Monitoring cost is operationalized as the cost-to-revenue ratio, measuring inputs per unit of output. Higher standardization is associated with increased productivity and reduced monitoring costs (Aobdia, 2020; Kaynak, 2003).

Marketing quality control is measured by customer concentration ($Ccd_{i,t}$) and inventory turnover ($Inv_{i,t}$). Customer concentration is the ratio of a firm's revenue from its top five customers to total revenue. Inventory turnover is measured by the inventory turnover ra-

[6]Data are manually compiled from the China Market Supervision Administrative Penalty Document Network. Available at: http://cfws.samr.gov.cn.

tio. Customer-oriented marketing strategies that emphasize quality control can expand the customer base, reducing customer concentration, and accelerate product turnover (Achilleas and Anastasios, 2008; Dalgic, 2013; Lai and Cheng, 2005).

3.3.4 Corporate Social Responsibility

The moderating variable, corporate social responsibility ($CSR_{i,t}$), is measured using the CSR index from the Shanghai National Accounting Institute's (SNAI) social responsibility rankings for listed firms. This index has been extensively employed in academic research on CSR practices among Chinese listed firms (Kong, 2012). Because the CSR index contains negative values for several firms, we apply the log-modulus transformation method proposed by John and Draper (1980) to preserve all observations. Higher values of the SNAI CSR index reflect greater CSR engagement among agri-food listed firms. Firms that did not publish independent CSR reports by the end of the fiscal year received no score.

Given that food recalls may be associated with firm characteristics, we include a set of control variables sourced from the CSMAR database. Control variables include firm size ($Size_{i,t}$), firm age ($Age_{i,t}$), return on assets ($Roa_{i,t}$), leverage ratio ($Lev_{i,t}$), asset growth ($Tagr_{i,t}$), equity concentration ($Ten_{i,t}$), cash flows ($Cash_{i,t}$), and industry concentration ($HHI_{i,t}$). Table A.7 provides detailed definitions of all control variables.

3.4 Sample Construction and Summary Statistics

Our final sample is an unbalanced panel of agri-food firms spanning 2007 to 2023, constructed by merging the CSMAR database, the WIND Economic Database, and the CNRDS. The sample comprises 38 recalling firms with 486 observations and 227 non-recalling firms with 2,089 observations. Table 1 presents descriptive statistics for the main variables by recall status. The mean number of product-quality-related AI patent applications is lower for recalling firms than for non-recalling firms, with a difference of -0.032.

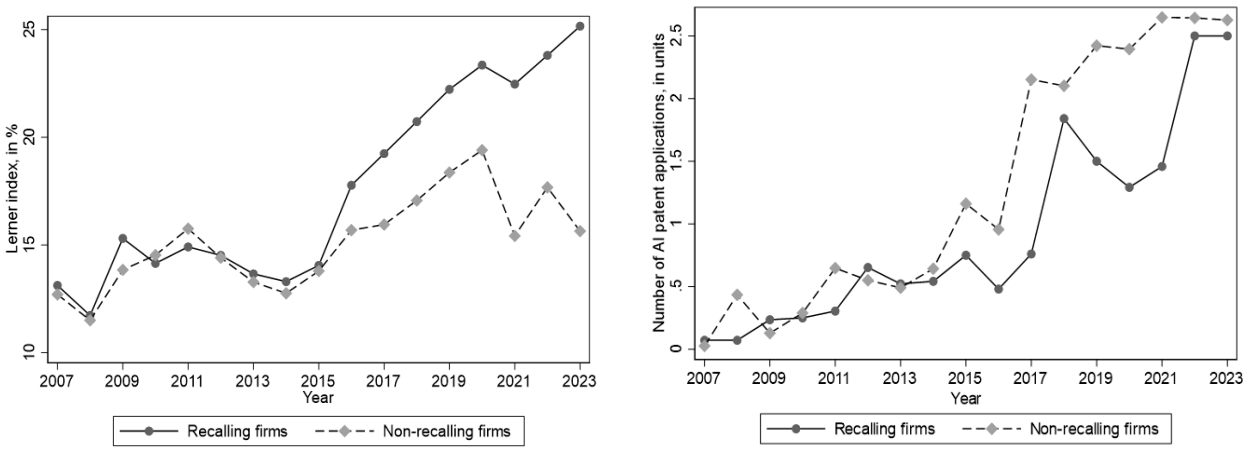
A central concern is whether 56 food recalls across 38 firms accurately reflect the food

Table 1: Summary Statistics by Recall Status

	Recalling firms			Non-recalling firms			Difference
Variable	Obs.	Mean	Std. dev.	Obs.	Mean	Std. dev.	
AI_patents	486	0.365	0.758	2,089	0.397	0.707	−0.032**
Pcd	486	0.325	0.197	2,089	0.241	0.161	0.083***
Aps	486	2.567	6.285	2,089	1.434	4.787	1.133***
TFP	486	6.427	0.834	2,089	6.982	0.682	−0.555***
Cost	486	0.709	0.202	2,089	0.650	0.201	0.059***
Ccd	486	0.236	0.192	2,089	0.135	0.101	0.101***
Inv	486	4.459	4.048	2,089	5.778	5.028	−1.319***
CSR	486	5.296	1.957	2,089	5.505	2.008	−0.209*
Size	486	22.567	1.112	2,089	21.789	1.129	0.778***
Age	486	2.966	0.332	2,089	3.010	0.303	−0.044**
Roa	486	0.054	0.077	2,089	0.043	0.112	0.011*
Lev	486	0.095	0.106	2,089	0.102	0.345	−0.007
Tagr	486	0.171	0.612	2,089	0.183	0.618	−0.012
Ten	486	0.456	0.210	2,089	0.467	0.200	−0.011
Cash	486	0.234	0.146	2,089	0.217	0.169	0.017*
HHI	486	0.301	0.118	2,089	0.310	0.137	−0.009

Notes: This table reports summary statistics by recall status for the sample period 2007 to 2023. The sample comprises 38 recalling firms with 486 firm-year observations and 227 non-recalling firms with 2,089 firm-year observations. AI_patents is the number of product-quality-related AI patent applications. Pcd through Inv are mechanism variables measuring quality control across suppliers, production, and marketing (see Table A.7 for detailed definitions). The Difference column reports mean differences from two-sample t-tests. AI patent data are from CNRDS and firms' annual reports; all other variables are from CSMAR. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

safety landscape. The representativeness of these recall incidents depends on the market power of recalling firms. If firms with substantial market power reduce recalls, this signals an improvement in sectoral product quality. We measure market power using the Lerner index, defined as the difference between main business revenue and the sum of main business cost, sales expenses, and management expenses, divided by main business revenue (Lerner et al., 2024). Higher values indicate greater market power. Figure 2a presents the average Lerner index for agri-food firms from 2007 to 2023. The index for recalling firms increases rapidly in 2015 and remains consistently higher than that for non-recalling firms, indicating that recalling firms possess greater market power. This suggests that these firms hold larger market shares, and their recalls are representative of food safety conditions in the agri-food sector.



(a) Lerner index

(b) AI patents by recall status

Figure 2: Trends in Market Power and AI Innovation among Chinese Agri-food Firms

Notes: Panel (a) plots the average annual Lerner index, where higher values indicate greater market power and price-cost margins. Panel (b) compares the average number of product-quality-related AI patent applications for firms with and without food recalls. Data are aggregated at the firm-year level.

Figure 2b illustrates the distribution of product-quality-related AI patent applications by recall status from 2007 to 2023. Recalling firms experienced higher growth in AI patent applications than non-recalling firms beginning in 2013, suggesting that AI innovation may reduce food recall risk. Although jointly developed patents grew faster between 2021 and 2023, independently developed patents remained above 50% of total patents among agri-food listed firms (see Appendix Figure A.2). Differences in mechanism variables show that non-recalling firms exhibit lower procurement concentration (Diff. $= 0.083$), fewer administrative penalties on suppliers (Diff. $= 1.133$), lower monitoring costs (Diff. $= 0.059$), and lower customer concentration (Diff. $= 0.101$) compared with recalling firms. They also demonstrate higher productivity (Diff. $= -0.555$) and inventory turnover (Diff. $= -1.319$). The distribution of mechanism variables across groups indicates that enhanced full-process quality control enabled by AI innovation may reduce food recall risk.

Figure 3 illustrates the distribution of product-quality-related AI patent applications across agri-food industries. Quality-oriented AI innovation has had a wide-ranging impact across China's agri-food industry chain. The average number of product-quality-related AI patent applications is 1.002 units in primary agriculture, 2.261 units in agri-sideline

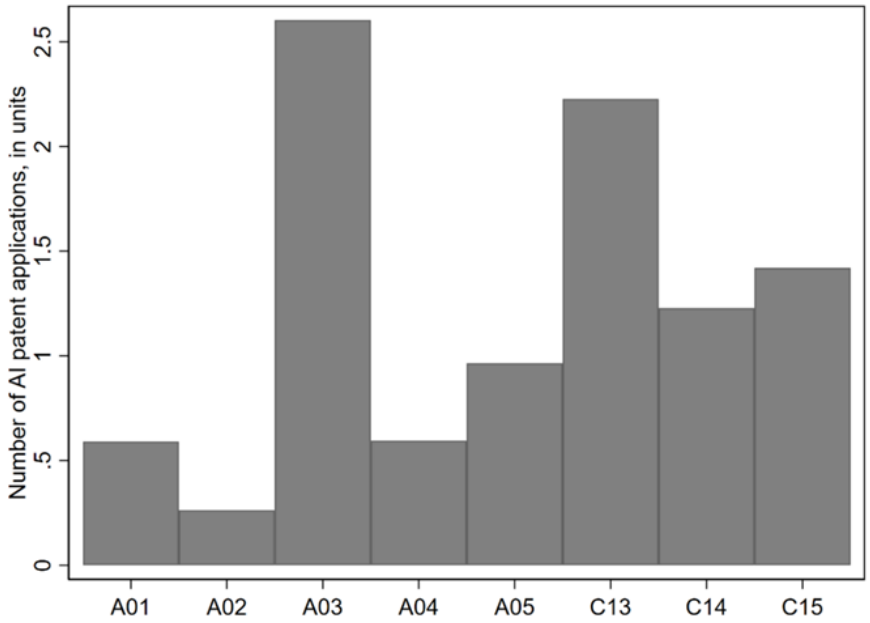


Figure 3: Industry-Level Heterogeneity in Product-Quality-Related AI Innovation

Notes: This figure illustrates the distribution of average product-quality-related AI patent applications across specific agri-food industries. Industry averages are calculated as the mean of firm-level patent counts over the 2007–2023 sample period.

production, and 2.638 units in food manufacturing. Within primary agriculture, the Animal Husbandry sector leads with an average of 2.603 units, representing 51.37% of total product-quality-related AI patents. Within food manufacturing, firms in the Alcohol, Beverages, and Refined Tea Manufacturing sector exhibit higher reliance on quality-oriented AI technology.

4 Empirical Strategy

This section outlines our empirical strategy to estimate the effect of AI innovation on food recalls among Chinese agri-food firms. Identification exploits three sources of variation: (i) within-firm changes in AI patenting over time, using lagged measures to mitigate reverse causality, (ii) cross-sectional differences in firms' exposure to AI innovation driven by heterogeneous innovation capacity, and (iii) geographic and sectoral variation in regulatory intensity and supply chain structure. We first estimate the baseline discrete choice model and examine mechanisms through a structural mediation framework that decomposes direct

and indirect effects. Then we explore heterogeneity and spillovers across ownership types, supply chain positions, recall categories, and competitive networks.

4.1 The Effects of AI Innovation on Food Recalls

To examine the relationship between AI innovation and food recalls, we first estimate a discrete choice model. The baseline specification is as follows:

$$\Pr\left(Recall_{i,t} = 1 \mid \mathbf{X}_{i,t}\right) = \alpha AI_patents_{i,t} + \phi \mathbf{X}_{i,t} + \delta_{j,t} + \varepsilon_{i,j,t}, \tag{1}$$

where i, j, and t denote the firm, industry, and year, respectively. The dependent variable is firms' food recall behavior, $Recall_{i,t}$, which equals 1 if firm i conducts a food recall in year t and 0 otherwise. The primary independent variable, $AI_patents_{i,t}$, is measured as the logarithm of one plus the number of product-quality-related AI patent applications filed by firm i in year t. $\mathbf{X}_{i,t}$ denotes a vector of control variables. Given that firms' food recalls may be simultaneously affected by common time trends, time-invariant firm characteristics, and industry-level shocks that vary over time, we include year fixed effects (λ_t), and industry fixed effects (φ_j). We cluster standard errors at the industry-year level to account for potential heteroskedasticity and serial correlation within industry. In Equation (1), the coefficient α is the parameter of interest. A negative coefficient indicates that AI innovation reduces the probability of food recalls.

4.2 Mechanisms: Full-Process Quality Control

To investigate how AI innovation reduces food recalls, we examine the underlying mechanisms using a two-stage empirical approach. We decompose the impact into quality improvements across three stages: supplier quality control, production quality control, and marketing quality control. Our identification strategy leverages the structure of the production process to isolate these distinct channels.

In the first stage, we estimate the effect of AI innovation on each quality control dimension:

$$Quality_{i,t} = \beta AI_patents_{i,t} + \phi \mathbf{X}_{i,t} + \delta_{j,t} + \varepsilon_{i,j,t}, \tag{2}$$

where $Quality_{i,t}$ represents a vector of mechanism variables capturing quality control at each stage. In the second stage, we estimate the effect of AI innovation on food recalls, controlling for the quality measures:

$$\Pr(Recall_{i,t} = 1 \mid \mathbf{X}_{i,t}) = \alpha_1 AI_patents_{i,t} + \alpha_2 Quality_{i,t} + \phi \mathbf{X}_{i,t} + \delta_{j,t} + \varepsilon_{i,j,t}. \tag{3}$$

The coefficient β in Equation (2) captures the direct impact of AI innovation on quality control, while α_1 in Equation (3) measures the direct effect of AI on recalls. The coefficient α_2 captures the extent to which improvements in quality control reduce recall risk. The indirect effect, given by the product $\beta \times \alpha_2$, quantifies the portion of AI's impact on product quality that operates through enhanced quality control mechanisms. We assess the statistical significance of this indirect effect using the Sobel test. Control variables and fixed effects are specified consistently with the baseline model. This two-stage framework enables us to distinguish the direct effect of AI on product quality from the effect mediated through organizational improvements in quality control.

4.3 The Moderating Effect of Corporate Social Responsibility

CSR has been characterized as a form of *"risk insurance"* that protects firm value when facing adverse events (Godfrey et al., 2009). We posit that CSR plays a similar role in shaping the relationship between AI innovation and product quality. Firms with stronger CSR commitments face higher reputational costs from quality failures and therefore have stronger incentives to deploy AI technologies for quality control across their supply chains,

production processes, and marketing activities. Consistent with prior evidence on CSR and product quality, we expect that the quality-enhancing effects of AI innovation are amplified among firms with higher CSR engagement (Kong, 2012).

To test this hypothesis, we extend the mechanism model in Equation (2) to include CSR and its interaction with AI innovation:

$$\begin{aligned} Quality_{i,t} = \beta_1 AI_patents_{i,t} + \beta_2 CSR_{i,t-1} + \beta_3 (AI_patents_{i,t} \times CSR_{i,t-1}) \\ + \phi \mathbf{X}_{i,t} + \delta_{j,t} + \varepsilon_{i,j,t}, \end{aligned} \tag{4}$$

where $CSR_{i,t-1}$ is the lagged CSR index for firm i, which mitigates concerns about reverse causality. The coefficient of interest is β_3, which captures how CSR amplifies the effect of AI innovation on quality control. A positive estimate of β_3 would indicate that CSR strengthens firms' incentives to invest in AI-driven quality improvements.

5 Main Results

We estimate the baseline relationship between AI innovation and food recalls using a discrete choice framework. Our primary specification is a probit model, with logit and linear probability models as robustness checks. We then examine the mechanisms and assess whether corporate social responsibility moderates the effect of AI innovation on product quality.

5.1 Baseline Evidence on AI and Food Recalls

Table 2 presents baseline estimates of the relationship between AI innovation and food recall probability. Column (1) reports results from a Probit model without fixed effects, serving as a benchmark specification. Column (2) introduces industry-year fixed effects to absorb time-varying industry-specific shocks, such as sector-specific regulatory enforcement, supply chain disruptions, or technology diffusion patterns, that could confound the relationship between AI innovation and product quality failures. Column (3) employs a one-year lag of AI patents

to partially address concerns about reverse causality and ensure that AI investment precedes recall outcomes temporally.

The coefficient on AI patents is negative and statistically significant at the 1% level across all Probit specifications, with point estimates ranging from -0.255 to -0.282. The stability of these estimates across specifications with progressively more demanding fixed effects structures suggests the relationship is not driven by unobserved heterogeneity at the industry-year level. To verify that results are not artifacts of the Probit functional form, Columns (4)-(6) replicate the analysis using Logit models, while Column (7) estimates a linear probability model (LPM) with firm and year fixed effects. The firm fixed effects specification exploits within-firm variation over time, identifying the effect from changes in a firm's AI innovation intensity rather than cross-sectional differences between firms. The negative coefficient persists across all model specifications, with comparable marginal effects, indicating robustness to functional form assumptions.

The marginal effects reported at the bottom of Table 2 offer a more interpretable economic magnitude: a one-standard-deviation increase in log AI patents corresponds to an approximately 5.5 percentage point reduction in recall probability. Given the baseline recall rate in our sample, this represents an effect size that is both statistically precise and economically meaningful. However, caution is warranted in causal interpretation. While the lagged specification and demanding fixed-effects structure mitigate some endogeneity concerns, the possibility remains that unobserved time-varying firm characteristics, such as management quality or shifts in organizational culture, drive both AI investment and quality improvements simultaneously.

Figure 4 illustrates the average marginal effects across the distribution of AI innovation intensity, revealing notable non-linearity. The protective effect is most pronounced at lower levels of AI innovation and exhibits diminishing returns at higher levels, consistent with standard production function properties where marginal productivity declines as factor inputs increase. This pattern suggests that initial AI investments targeting critical qual-

Table 2: Impact of AI Innovation on Food Recalls: Baseline Results

	Probit model			Logit model			LPM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variable	Recall	Recall	Recall	Recall	Recall	Recall	Recall
AI_patents	−0.282***	−0.255***		−0.514***	−0.437***		−0.048**
	(0.051)	(0.053)		(0.094)	(0.097)		(0.020)
AI_patents (lag)			−0.257***			−0.440***	
			(0.058)			(0.106)	
Size	0.463***	0.512***	0.505***	0.817***	0.888***	0.873***	0.093***
	(0.035)	(0.037)	(0.039)	(0.064)	(0.068)	(0.071)	(0.008)
Age	−0.628***	−0.353**	−0.436***	−1.134***	−0.630**	−0.780***	−0.075**
	(0.114)	(0.143)	(0.159)	(0.207)	(0.266)	(0.295)	(0.030)
Roa	−0.611**	−0.739**	−0.510*	−1.008**	−1.244**	−0.865	−0.144**
	(0.283)	(0.297)	(0.310)	(0.498)	(0.508)	(0.526)	(0.063)
Lev	−0.105	−0.076	−0.073	−0.162	−0.117	−0.113	−0.021
	(0.086)	(0.081)	(0.079)	(0.129)	(0.122)	(0.117)	(0.027)
Tagr	−0.075	−0.057	−0.405***	−0.157	−0.105	−0.681***	−0.014
	(0.099)	(0.076)	(0.146)	(0.272)	(0.174)	(0.259)	(0.011)
Ten	−0.389**	−0.457**	−0.443**	−0.748**	−0.893***	−0.852**	−0.098**
	(0.172)	(0.182)	(0.191)	(0.329)	(0.333)	(0.349)	(0.040)
Cash	0.316	0.061	0.032	0.546	0.241	0.203	0.078*
	(0.203)	(0.215)	(0.232)	(0.376)	(0.400)	(0.428)	(0.043)
HHI	−0.345	−0.902	0.573	−0.695	−1.203	1.045	0.091
	(0.264)	(8.840)	(1.347)	(0.490)	(15.517)	(2.408)	(0.210)
Firm FE	No	No	No	No	No	No	Yes
Industry–Year FE	No	Yes	Yes	No	Yes	Yes	Yes
Obs.	2,575	2,575	2,045	2,575	2,575	2,045	2,575
R^2	0.101	0.136	0.137	0.098	0.133	0.134	0.074
Marginal effects	−0.059***	−0.055***	−0.057***	−0.060***	−0.053***	−0.055***	−0.048**
p-value	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.019]

Notes: This table reports the baseline impacts of AI innovation on the probability of food recalls. Columns (1)–(3) use Probit models, (4)–(6) use Logit models, and (7) uses a Linear Probability Model (LPM) with firm fixed effects. AI_patents is the number of product-quality-related AI patent applications. Marginal effects (dy/dx) are reported for the non-linear models. p-values are in square brackets. Robust standard errors clustered at the industry-year level are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

ity control bottlenecks yield the largest safety gains, while subsequent investments generate progressively smaller incremental benefits. Taken together, these results provide preliminary support for Hypothesis 1, though we explore potential mechanisms and alternative explanations in subsequent analyses.

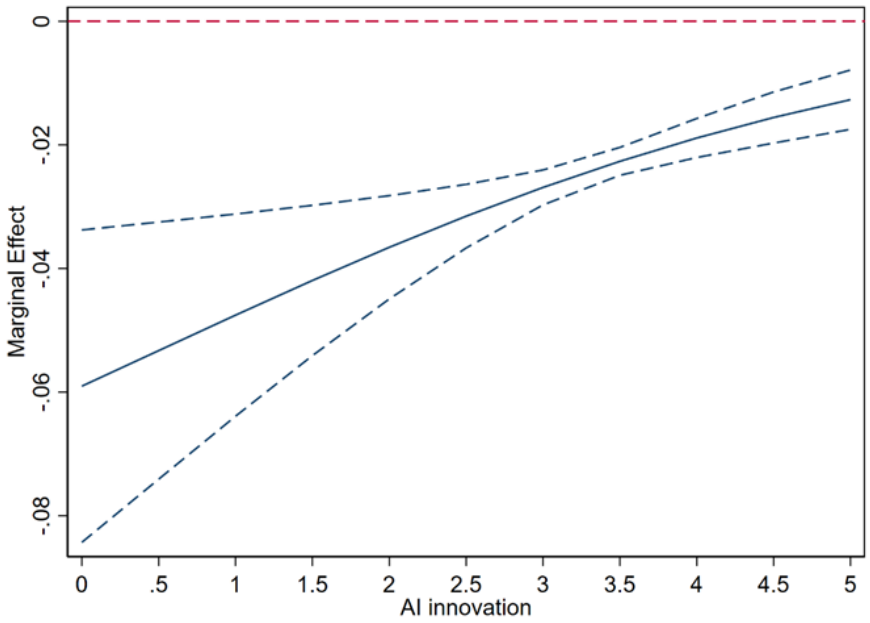


Figure 4: Average Marginal Effects of AI Innovation on Food Recall Probability

Notes: This figure presents the estimated marginal effects of product-quality-related AI patent applications on the probability of food recalls. Marginal effects (dy/dx) are calculated based on the Probit specification in Column (2) of Table 2, with other covariates held at their sample means. Error bars represent 95% confidence intervals.

5.2 Mechanisms Analysis

Table 3 examines the mechanisms through which AI innovation affects food recall probability. We employ a two-stage mediation framework to decompose AI's total effect into direct and indirect pathways operating through specific quality control dimensions.

Panel A reports first-stage regressions estimating how AI innovation affects six operational measures spanning the supply chain and production process. AI investment significantly reduces procurement concentration, with a coefficient of -0.067 at the 1% significance level, and lowers administrative penalties levied against suppliers by -0.362 at the 10% level. These results suggest improved supplier quality and diversity. During production, AI reduces monitoring costs by -0.008 while raising total factor productivity by 0.449 and inventory turnover by 0.368, both significant at conventional levels. AI also reduces customer concentration by -0.018 at the 1% level, potentially reflecting enhanced market reach or product diversification. The high R^2 values, particularly for TFP at 0.910 and monitoring costs at

0.871, indicate that AI innovation strongly predicts these operational outcomes. However, this also raises concerns about whether our control variables fully capture the underlying drivers of both AI investment and operational improvements.

Panel B presents second-stage regressions where recall probability is regressed on both AI patents and each mediating variable individually. The coefficient on AI patents remains negative and significant across all six specifications, ranging from -0.250 to -0.274, though notably smaller in magnitude than the baseline estimate in Table 2. This attenuation is consistent with partial mediation: the included mechanism variables absorb some, but not all, of AI's protective effect. The mediators exhibit theoretically consistent signs. Procurement concentration, supplier penalties, monitoring costs, and customer concentration all positively predict recalls, while productivity and inventory turnover negatively predict recalls. All Sobel test statistics are statistically significant, formally confirming mediation. However, the test assumes sequential ignorability, a strong assumption unlikely to hold if unobserved factors simultaneously drive AI innovation, operational choices, and recall risk.

The magnitudes of the Sobel statistics suggest productivity improvements constitute the dominant channel, with a test statistic of -0.318. This finding aligns with theoretical models emphasizing AI's role in standardizing production processes and reducing human error. Nonetheless, the statistical significance of all six mechanisms indicates AI operates through multiple complementary pathways. Supplier-side improvements, including diversification and penalty reduction, address input quality. Production-side enhancements, such as lower monitoring costs and higher productivity, improve process control. Demand-side changes, including reduced customer concentration and faster inventory turnover, enable quicker identification and containment of quality issues.

We note several caveats. First, the mediation framework assumes AI affects quality control measures, which in turn affect recalls. This temporal ordering is difficult to verify definitively with annual data. Quarterly or higher-frequency data would strengthen causal claims. Second, we cannot rule out that omitted variables, such as management attention

Table 3: Impact of AI Innovation on Full-Process Quality Control and Product Recalls

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Impacts on Full-Process Quality Control						
	Pcd	Aps	TFP	Cost	Ccd	Inv
AI_patents	−0.067***	−0.362*	0.449***	−0.008*	−0.018***	0.368**
	(0.020)	(0.217)	(0.082)	(0.004)	(0.005)	(0.157)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	2,575	2,575	2,575	2,575	2,575	2,575
R^2	0.650	0.429	0.910	0.871	0.770	0.834
Panel B: Impacts on Food Recalls						
	Recall	Recall	Recall	Recall	Recall	Recall
AI_patents	−0.274***	−0.255***	−0.264***	−0.250***	−0.261***	−0.266***
	(0.054)	(0.053)	(0.058)	(0.053)	(0.054)	(0.053)
Pcd	1.301***					
	(0.225)					
Aps		0.021***				
		(0.005)				
TFP			−0.710***			
			(0.072)			
Cost				0.415*		
				(0.244)		
Ccd					0.918***	
					(0.284)	
Inv						−0.109***
						(0.034)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	2,575	2,575	2,575	2,575	2,575	2,575
R^2	0.152	0.136	0.182	0.137	0.161	0.139
Sobel test statistic	−0.087***	−0.008***	−0.318***	−0.003***	−0.016***	−0.040***
p-value	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

Notes: The Sobel test statistic assesses mediation effects. Control variables include firm size, firm age, return on assets, leverage ratio, asset growth, equity concentration, cash flows, and industry concentration. p-values are reported in square brackets, and robust standard errors clustered at the industry-year level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

to quality or organizational culture, simultaneously drive AI investment and all six mediating variables, inducing spurious mediation. Third, the mechanisms examined here are not exhaustive. AI may also improve recall outcomes through channels not captured by our measures, such as enhanced traceability systems or predictive quality analytics. Despite these limitations, the consistency of the mediation patterns across diverse quality control di-

mensions provides suggestive evidence that AI's protective effect operates through tangible operational improvements rather than unobserved confounders alone. These findings provide suggestive support for Hypothesis 2.

5.3 Moderating effect of Corporate Social Responsibility

Table 4 examines whether corporate social responsibility moderates the relationship between AI innovation and quality control mechanisms. We augment the first-stage regressions from Table 3 by including lagged CSR scores and their interaction with AI patents. The main effects of AI patents remain negative for procurement concentration, supplier penalties, monitoring costs, and customer concentration, and positive for productivity and inventory turnover, with magnitudes broadly consistent with Panel A of Table 3.

The CSR index itself exhibits statistically significant associations with several quality control dimensions. Higher CSR scores correlate with increased supplier penalties, with a coefficient of 0.731 at the 1% level, and with elevated productivity at 0.105, also significant at the 1% level. CSR also correlates negatively with monitoring costs at -0.001, significant at the 1% level. These patterns suggest that firms with stronger CSR commitments maintain more rigorous supplier oversight and invest in production process improvements, though the causal direction remains ambiguous.

The interaction term $AI_patents_{i,t} \times CSR_{i,t-1}$ provides the key test of moderation. The interaction is positive for productivity at 0.031 and negative for monitoring costs at -0.014, both significant at the 10% level. These coefficients indicate that CSR amplifies AI's effects specifically in the production stage: at higher CSR levels, AI investments generate larger productivity gains and steeper reductions in monitoring costs. By contrast, the interaction terms for supplier-side measures (procurement concentration and penalties) and demand-side measures (customer concentration and inventory turnover) are statistically insignificant and close to zero.

This asymmetric pattern warrants interpretation. Production processes constitute a

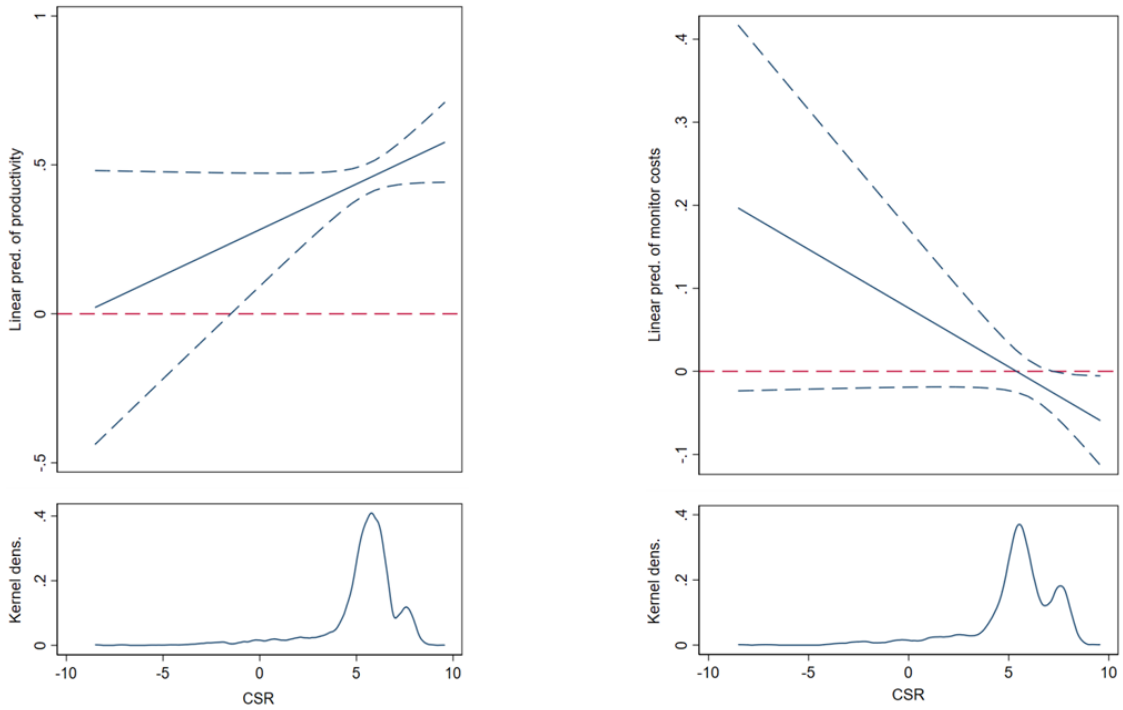
Table 4: The Moderating Role of CSR in AI-Enabled Quality Control Mechanisms

	(1) Pcd	(2) Aps	(3) TFP	(4) Cost	(5) Ccd	(6) Inv
AI_patents	−0.024**	−0.276***	0.282***	0.076	−0.022**	0.228*
	(0.010)	(0.096)	(0.097)	(0.049)	(0.011)	(0.121)
CSR (lag)	0.004	0.731***	0.105***	−0.001***	0.003	−0.028
	(0.003)	(0.113)	(0.011)	(0.000)	(0.002)	(0.020)
AI_patents × CSR (lag)	−0.001	0.026	0.031*	−0.014*	−0.003	0.021
	(0.003)	(0.153)	(0.016)	(0.008)	(0.004)	(0.017)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	2,045	2,045	2,045	2,045	2,045	2,045
R^2	0.643	0.529	0.863	0.873	0.769	0.832

Notes: This table reports the moderating effect of Corporate Social Responsibility (CSR). Dependent variables include procurement concentration (Pcd), administrative penalties on suppliers (Aps), total factor productivity (TFP), monitoring costs (Cost), customer concentration (Ccd), and inventory turnover (Inv). Robust standard errors clustered at the industry–year level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

domain of direct managerial control, where CSR-oriented governance structures, employee training programs, and quality-focused organizational cultures can reinforce AI-driven improvements. In contrast, supplier and customer relationships involve independent external parties whose behavior firms can influence but not fully control. Contractual frictions, information asymmetries, and divergent incentives between firms and their supply chain partners may limit the extent to which internal CSR commitments translate into enhanced coordination around AI-enabled quality improvements. Alternatively, the null findings for supplier and customer channels may reflect measurement limitations: our CSR index may inadequately capture supply chain-specific CSR practices such as supplier audits or fair trade certifications.

Figure 5 visualizes the moderating effect by plotting the conditional marginal effect of AI innovation on productivity (left panel) and monitoring costs (right panel) across the distribution of CSR scores. Both panels show that AI's impact strengthens monotonically with CSR engagement, with confidence intervals narrowing at higher CSR levels due to greater data density.



(a) Left panel (b) Right panel

Figure 5: Conditional marginal effects of AI innovation across CSR levels

Notes: This figure illustrates how the marginal effects of AI innovation on firm mechanisms vary with CSR scores. Panel (a) and Panel (b) show the interaction effects on productivity and monitoring costs, respectively. The horizontal axis represents CSR scores from the SNAI ranking. The solid lines indicate estimated marginal effects, and the dashed lines represent 95% confidence intervals.

5.4 Robustness Checks

We subject our main findings to several robustness tests addressing measurement, selection, and endogeneity concerns. First, we examine sensitivity to alternative AI innovation measures, including textual disclosures, granted patents, and innovation growth rates. Second, we distinguish between internally developed and externally acquired AI capabilities to isolate genuine innovation capacity. Third, we employ Heckman selection models and instrumental variables estimation to address potential sample selection bias and reverse causality. The negative relationship between AI innovation and recall probability persists across all specifications, though magnitudes vary in economically interpretable ways. Figure 6 summarizes these robustness results visually, and Table A.1 presents the corresponding estimation results.

5.4.1 Alternative Measures of AI Innovation

Our baseline specification uses AI patent applications to measure innovation intensity. While widely employed in the innovation literature, patent counts have well-known limitations. They capture inventive inputs rather than implemented technologies, treat all patents as equal despite heterogeneous quality, and omit non-patentable AI investments such as data infrastructure and algorithm development. We therefore examine whether our findings hold under alternative measures.

AI-related keywords in disclosure documents. We construct a text-based measure by identifying AI-related keywords in the management discussion and analysis (MD&A) sections of annual reports.[7] This approach captures managerial attention to AI initiatives and may include investments not reflected in patent filings, such as purchased software or organizational AI innovation. Column (1) of Figure 6 shows the coefficient on $AI_words_{i,t}$ is -0.282, significant at the 1% level. However, this measure introduces new concerns: firms may strategically emphasize AI in disclosures for signaling purposes unrelated to actual implementation, and keyword frequency may reflect disclosure style rather than substantive AI activity. The significant coefficient is nonetheless consistent with our main findings.

Granted patents and innovation growth. We examine two timing-based variants: granted AI patents, which indicate completed examination and approval ($AI_authors_{i,t}$), and the year-over-year growth rate of granted patents ($AI_growth_{i,t}$), which captures innovation momentum. Columns (2) and (3) of Figure 6 show coefficients of -0.203 and -0.047, respectively, both significant at conventional levels. The granted patents specification addresses the concern that our baseline results reflect filing activity rather than substantive innovation, since granted patents have survived regulatory scrutiny. The smaller coefficient on growth rates suggests that the level of AI capability matters more than the rate of change,

[7] We calculate the frequency of AI-related keywords in the MD&A section and normalize by total word count in that section. This yields a measure of the intensity of AI-related disclosure. The AI dictionary is provided in Table A.8.

consistent with models where quality control improvements depend on accumulated technological stock rather than marginal investment flows. The consistency across these measures strengthens confidence that we are capturing genuine technological change rather than measurement artifacts.

Internally developed versus acquired AI capabilities. A critical limitation of aggregate patent counts is that they conflate internally developed innovations with externally acquired technologies. Firms may purchase or license AI patents to signal technological sophistication without developing implementation capabilities. If acquired patents contribute less to quality control than internally developed innovations, our baseline estimates may understate AI's true effect.

We identify in-house AI patents using two complementary approaches. First, we conduct text analysis of annual reports using keywords such as "technology transfer agreements," "AI service procurement," "equipment leasing," and "patent acquisition" to identify firms that explicitly acquire AI capabilities from external providers. We then exclude these firms from subsequent analysis to isolate internally developed patents. Second, we cross-reference the China Patent Transfer Database (sourced from CNRDS), which contains over 50 million patent transaction records since 1998. We identify AI patents that were transferred into agri-food firms using IPC codes and assignee information, then exclude these from the firm's patent count. The resulting measure captures only internally developed AI patents that genuinely reflect each firm's innovation capacity.

Columns (4) and (5) of Figure 6 report results using in-house AI innovation measures. The estimated coefficients remain significantly negative and are substantially larger in magnitude than the baseline estimates. This is a notable finding: it demonstrates that internally developed AI innovation has stronger protective effects than the baseline specification suggests, implying that the full sample results may be attenuated by inclusion of firms with weaker or acquired AI capabilities. These results reinforce confidence in the causal interpre-

tation of our main findings.

5.4.2 Addressing Selection Bias and Reverse Causality

Two endogeneity concerns threaten causal interpretation. First, firms with superior quality management may self-select into AI investment, generating spurious correlation. Second, reverse causality could arise if recalls trigger defensive AI innovation or if firms anticipating quality failures reduce discretionary innovation spending.

We address selection bias using a Heckman two-stage procedure. The first stage estimates the probability that a firm engages in AI innovation using a probit specification that includes all baseline controls plus one additional instrument: lagged provincial optical fiber density ($Density_{p,t-1}$). This variable proxies for local digital infrastructure availability and plausibly affects AI innovation costs. The exclusion restriction requires that historical infrastructure investments do not directly affect contemporaneous recall outcomes except through their effect on AI innovation. This assumption is more credible for food recalls, which arise from idiosyncratic production failures, than for outcomes like productivity that may directly benefit from digital infrastructure. Nonetheless, the assumption remains untestable and could be violated if infrastructure correlates with unobserved regional characteristics such as regulatory enforcement intensity or supply chain modernization.

Column (6) of Figure 6 reports Heckman results. The inverse Mills ratio is -3.140 with a p-value below 0.001, indicating significant selection into AI innovation. The coefficient on AI patents in the second stage remains negative at -0.201 and significant at the 1% level. Compared to the baseline estimate of approximately -0.255, the Heckman-corrected coefficient is somewhat smaller in magnitude, suggesting that positive selection into AI innovation (firms with better quality management adopt AI) partially inflates the naive OLS estimates. However, the effect remains economically and statistically significant, indicating our main findings are not entirely driven by selection bias. This conclusion depends entirely on the validity of the exclusion restriction.

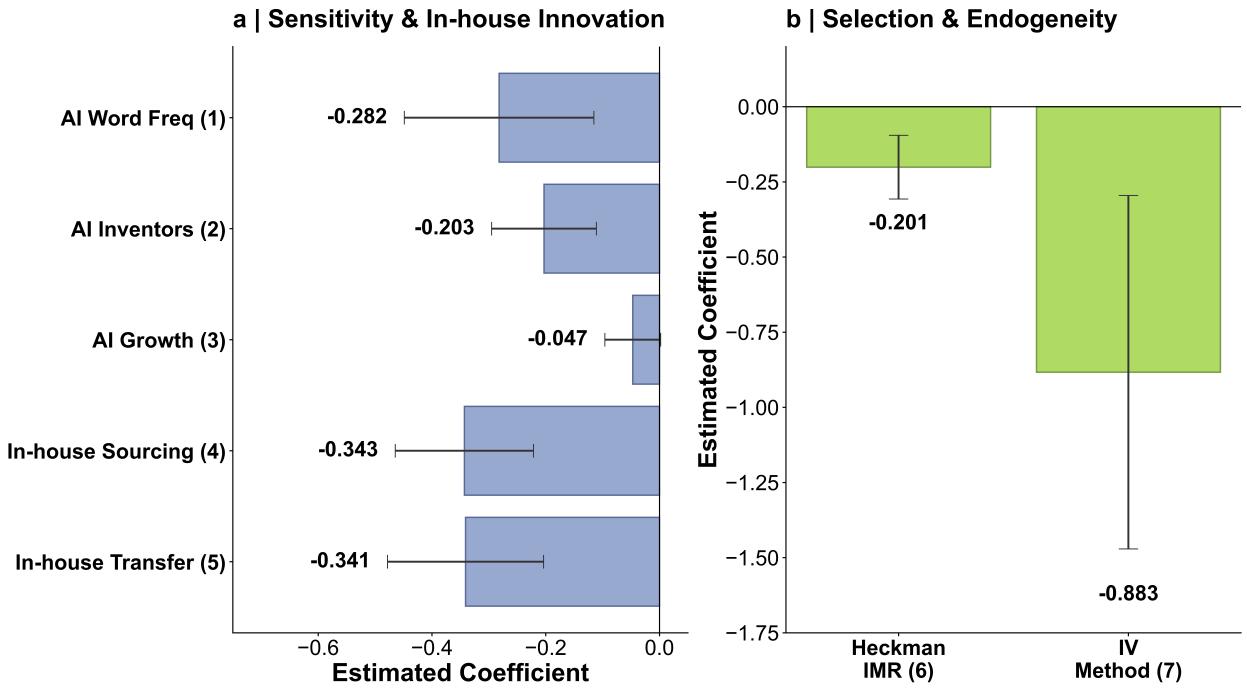


Figure 6: Robustness Checks: Alternative AI Measures and Identification Strategies

Notes: Panel A presents sensitivity tests using alternative AI measures, including keyword-based disclosure measures, granted patents, growth rates, and internally developed patents (Columns 1 to 5). Panel B presents results from Heckman selection correction and instrumental variables estimation using provincial optical fiber density as an instrument (Columns 6 to 7). Error bars represent 95% confidence intervals. All coefficients are negative and statistically significant, consistent with baseline estimates. Table A.1 shows more estimation results.

We also implement two-stage least squares (2SLS) estimation using provincial optical fiber density as an instrument for AI innovation. This addresses reverse causality by isolating variation in AI investment driven by exogenous infrastructure availability rather than endogenous firm responses to recall risk. Column (7) of Figure 6 presents 2SLS results. The Wald test statistic is 4.110 with a p-value of 0.042, rejecting the null hypothesis of exogeneity at the 5% level and confirming that instrumentation is warranted. The coefficient is -0.883, substantially larger in magnitude than OLS estimates. This pattern could reflect either measurement error attenuation in OLS (classical errors-in-variables bias toward zero) or violations of the monotonicity assumption in the IV framework. The IV estimate should be interpreted as a local average treatment effect (LATE) for firms induced to adopt AI by infrastructure availability, which may differ from the average effect across all firms. The

large standard error of 0.300 also indicates limited precision, with the 95% confidence interval ranging from approximately -1.47 to -0.30, cautioning against over-interpreting the point estimate.

5.5 Heterogeneity

We examine how the protective effect of AI innovation varies across firm and sector characteristics. These analyses provide insights into the conditions under which AI-driven quality improvements are most effective. Figure 7 presents the heterogeneous effects across three dimensions: ownership structure, supply chain position, and recall type.

5.5.1 Heterogeneity by Ownership Structure

We first investigate whether AI innovation's impact on product quality differs between state-owned enterprises (SOEs) and non-state-owned enterprises (non-SOEs). Results presented in Panel A of Figure 7, and Table A.2, Columns (1) and (2), show that AI innovation significantly reduces recall risk in both categories, though the magnitude differs substantially. The coefficient for non-SOEs is -0.391 compared with -0.167 for SOEs, suggesting AI innovation generates larger safety gains in the private sector.

Several factors explain this disparity. First, SOEs face stringent government regulation that may reduce managerial autonomy in technology investment decisions. Second, state ownership typically attenuates profit incentives, leading firms to prioritize risk avoidance and media management over proactive investment in innovation. Prior research documents that Chinese SOEs adopt new technologies more slowly and with less intensity than private firms (Lin et al., 2011; Zhai and Liu, 2023). Consequently, while SOEs benefit from AI innovation when it is adopted, they invest less aggressively in quality-focused AI applications than their non-SOE counterparts. This pattern reflects broader organizational constraints rather than inherent technological limitations.

5.5.2 Heterogeneity by Supply Chain Position

We next examine whether AI's quality-enhancing effects vary with a firm's position in the agri-food supply chain. Following the China Securities Regulatory Commission classification system, we partition firms into three categories: primary agriculture (raw material production), agri-sideline manufacturing (intermediate goods), and food manufacturing (finished products). Each stage faces distinct production technologies and quality control challenges.

Results in Panel B of Figure 7, and Table A.2, Columns (3) through (5), reveal significant negative coefficients across all three sectors, confirming that AI reduces recall risk throughout the supply chain. However, the magnitude exhibits a clear declining pattern moving downstream. Primary agriculture shows the largest coefficient at -0.511, followed by agri-sideline manufacturing at -0.328, and food manufacturing at -0.156.

This pattern aligns with the technological characteristics of production at each stage. Raw material production involves substantial environmental variability and natural contamination risks that are particularly amenable to AI monitoring and detection. As production moves downstream and becomes increasingly controlled through standardized manufacturing processes, the marginal contribution of AI-driven monitoring diminishes. Additionally, downstream firms can mitigate inherited quality problems through further processing and quality screening, reducing dependence on upstream AI innovations. An alternative interpretation is that downstream firms face more complex quality control challenges spanning multiple dimensions beyond those AI currently addresses effectively, such as sensory attributes or packaging integrity.

5.5.3 Heterogeneity by Recall Type

Finally, we distinguish between mandatory recalls initiated under regulatory or public pressure and voluntary recalls initiated by firms themselves. These two categories reflect fundamentally different signals about underlying product quality: mandatory recalls indicate that quality failures escaped internal detection systems, while voluntary recalls may reflect either

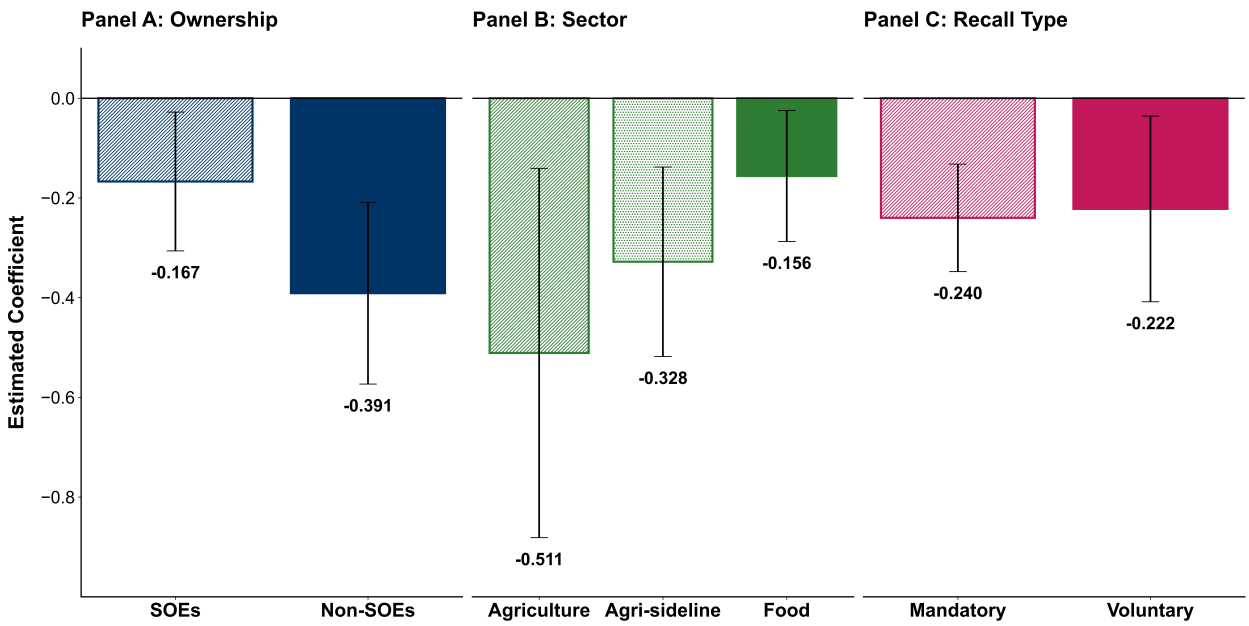


Figure 7: Heterogeneity Analysis of AI Innovation on Product Quality

Notes: This figure presents heterogeneous effects of AI innovation on food recall probability across three dimensions: firm ownership (Panel A), supply chain position (Panel B), and recall type (Panel C). The vertical axis reports estimated probit coefficients, and numerical values below error bars indicate point estimates for each subgroup. Error bars represent 95% confidence intervals. In Panel B, diagonal hatching denotes primary agriculture, solid fill denotes agri-sideline production, and dotted stippling denotes food manufacturing. All specifications include firm-level controls (size, age, ROA, leverage, asset growth, equity concentration, cash flow, and industry concentration) and industry-year fixed effects. Standard errors are clustered at the industry-year level.

superior internal monitoring or lower liability concerns.

Results in Panel C of Figure 7, Table A.2, Columns (6) and (7), show statistically significant coefficients for both recall types. The coefficient for mandatory recalls is -0.240, while voluntary recalls exhibit a coefficient of -0.222. The reduction in mandatory recalls provides stronger evidence of genuine product quality improvements. Since regulatory agencies mandate these recalls based on detected failures, AI innovation that lowers mandatory recalls demonstrates that AI-driven quality control systems successfully prevent defective products from reaching consumers, thereby averting regulatory enforcement actions. In contrast, voluntary recalls may partially reflect strategic disclosure decisions unrelated to underlying quality improvements. Firms might use voluntary recalls to signal quality consciousness or preempt regulatory action, making the voluntary recall coefficient more difficult to interpret

causally.

6 Spillover Effects

Technology spillovers have long been recognized as a critical mechanism through which innovation generates economy-wide productivity gains and sustains long-run growth. (Aghion et al., 2015). Empirical evidence increasingly documents meaningful spillover effects across firms and industries (Hsu and Wang, 2023; Qiu and Wan, 2015; Wang et al., 2024). A fundamental distinction exists between the two spillover mechanisms. Horizontal spillovers operate within industries, allowing innovations by one firm to enhance the productivity and performance of competitors. Vertical spillovers operate along supply chains, whereby innovations by suppliers or customers affect downstream and upstream firms, respectively.

Our baseline analysis establishes that firm-level AI innovation meaningfully reduces food recall risk. A natural question follows: Do these safety improvements extend beyond the innovating firm through industry and supply chain networks? This section investigates both horizontal and vertical spillover effects of AI innovation on food recall risk.

6.1 Horizontal Spillovers

Horizontal spillovers arise from competitive dynamics within industries. Superstar firm theory provides the mechanism: when a leading firm achieves a significant breakthrough in AI-driven quality control, competitors face intensified pressure to undertake similar investments to maintain market position (Byun et al., 2021; Koenig, 2023; Li and Miao, 2024; Stiel and Schiersch, 2022). This competitive dynamic can generate industry-wide improvements in quality standards and product safety.

We measure horizontal spillovers using the average AI innovation effort of competitors within the same industry:

$$\text{AI_horizon}_{i,t} = \frac{\sum_{k \neq i}^{N} \text{AI_competitors}_{k,t}}{N-1}, \tag{5}$$

where i and k index firms within the same industry, t denotes the year, and $\text{AI_competitors}_{k,t}$ is the number of product-quality-related AI patent applications filed by competitor k in year t. This measure captures the intensity of competitive AI innovation independent of the firm's own innovation efforts.

6.2 Vertical Spillovers

Vertical spillovers operate through supply chain connections linking suppliers and customers. The agri-food sector provides an ideal setting to examine these linkages. Upstream suppliers provide raw materials and intermediate goods; downstream firms transform these inputs into final products. AI innovations at either end can generate quality improvements for connected participants.

Forward spillovers from suppliers. When upstream suppliers adopt AI-driven quality control systems, they deliver higher-quality materials and intermediates to downstream firms, reducing defect-related recalls. We measure this using the average AI innovation of a firm's top five suppliers:

$$\text{AI_upstream}_{i,t} = \frac{\sum_{k=1}^{5} \text{AI_suppliers}_{i,k,t}}{5}. \tag{6}$$

Backward spillovers from customers. When downstream firms implement AI-enabled traceability and monitoring systems, they can more precisely identify and trace defective products backward through supply chains, creating competitive pressure for upstream firms to strengthen quality controls. We measure this using the average AI innovation of a firm's top five customers:

$$\text{AI_downstream}_{i,t} = \frac{\sum_{k=1}^{5} \text{AI_customers}_{i,k,t}}{5}. \tag{7}$$

To estimate spillover effects, we extend the baseline specification to include measures of competitors', suppliers', and customers' AI innovation:

$$\begin{aligned}\Pr(\text{Recall}_{i,t} = 1 \mid \mathbf{X}_{i,t}) =& \alpha_1 \text{AI_patents}_{i,t} + \alpha_2 \text{AI_horizon}_{i,t} \\ &+ \alpha_3 \text{AI_upstream}_{i,t} + \alpha_4 \text{AI_downstream}_{i,t} \\ &+ \phi \mathbf{X}_{i,t} + \delta_{j,t} + \varepsilon_{i,j,t}.\end{aligned} \tag{8}$$

The coefficient α_1 captures the direct effect of own AI innovation, while α_2, α_3, and α_4 capture horizontal, forward, and backward spillover effects, respectively. All specifications include baseline controls and industry-year fixed effects.

Results are presented in Table A.3 and visualized in Figure 8. Across all columns, we observe significantly negative coefficients for own AI innovation and all spillover variables. First, the coefficient on $\text{AI_horizon}_{i,t}$ is negative and statistically significant, indicating that firms reduce recall risk when competitors increase AI innovation. This horizontal spillover likely reflects competitive pressure to match rivals' quality investments, though we cannot rule out common shocks affecting entire industries simultaneously. Second, both vertical spillover coefficients are economically substantial: upstream supplier AI innovation with a coefficient of -0.684 and downstream customer AI innovation with a coefficient of -0.529 both significantly reduce a firm's recall probability. The forward spillover from suppliers suggests that supplier quality improvements substantially reduce defect risk at downstream firms. The backward spillover from customers indicates that downstream quality monitoring systems create pressure for upstream improvements.

However, several caveats warrant emphasis. First, the spillover measures assume that relationships with the top five suppliers and customers adequately capture supply chain exposure, but firms may have more diffuse supply networks. Second, we cannot fully distinguish between genuine spillovers and unobserved common shocks affecting connected firms simultaneously. For instance, industry-wide regulatory changes or media scrutiny might induce correlated AI innovation and quality improvements. Third, the direction of causality

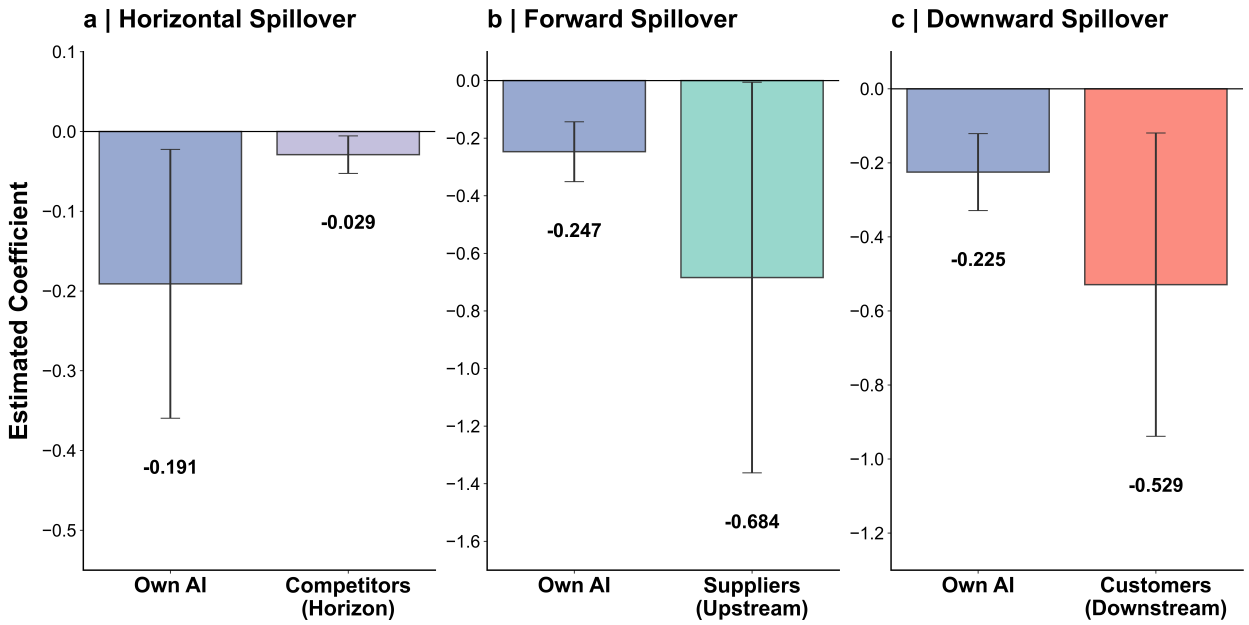


Figure 8: Direct and Spillover Effects of AI Innovation on Food Recalls

Notes: This figure displays point estimates and 95% confidence intervals for own-firm AI effects and spillover effects. Panel (a) shows horizontal spillovers from industry competitors. Panels (b) and (c) display vertical spillovers from suppliers and customers, respectively. All specifications include firm-level controls and industry, year, and industry-year fixed effects with standard errors clustered at the industry-year level.

remains ambiguous: firms may strategically select suppliers and customers based on their quality practices, generating spurious correlation between partners' AI innovation and their own recall risk. Despite these limitations, the consistency of spillover effects across horizontal and vertical dimensions provides suggestive evidence that AI-driven quality improvements propagate through production networks. The evidence supports a broader conclusion: AI functions not merely as a firm-level productivity enhancer but as an organizational technology that strengthens coordination and monitoring capabilities throughout supply chains. This implies that the full benefits of AI innovation extend well beyond individual adopters, though the magnitudes should be interpreted cautiously, given identification challenges.

7 Conclusions

This paper provides the first systematic evidence that AI innovation meaningfully improves product quality. Using data from 265 Chinese agri-food firms from 2007 to 2023, we find that

doubling AI patent applications reduces recall risk by 5.5 percent, an economically substantial effect driven primarily by non-state-owned enterprises in agricultural sectors. We trace this improvement through a full-process quality control framework: AI enhances supplier vetting and material screening, automates safety-critical production processes through real-time monitoring and predictive maintenance, and improves traceability and responsive decision-making in marketing. Corporate social responsibility amplifies these gains, suggesting that governance and ethical orientation complement technological deployment. Importantly, AI benefits propagate through supply networks, as innovations by competitors, suppliers, and customers collectively reduce food safety risk across the industry.

Our findings suggest concrete policy priorities. Policymakers should actively support AI innovation among large firms, which set operational standards and demonstrate tangible safety benefits. However, because small and medium enterprises dominate China's fragmented food sector yet face substantial AI adoption barriers, governments should design tiered support mechanisms tailored to their capacity. Most critically, current AI policy evaluations emphasize profitability while overlooking public welfare gains. Future assessments should integrate economic indicators with social welfare metrics, particularly product quality and public health outcomes. This balanced approach ensures that public and private AI investments serve both commercial competitiveness and fundamental public health objectives.

References

Abramson, Josh, Jonas Adler, Jack Dunger, Richard Evans, Tim Green, Alexander Pritzel, Olaf Ronneberger, Lindsay Willmore, Andrew J Ballard, Joshua Bambrick, et al. 2024. "Accurate structure prediction of biomolecular interactions with AlphaFold 3." *Nature*, 630(8016): 493–500.

Abrardi, L., C. Cambini, and L. Rondi. 2022. "Artificial intelligence, firms and consumer behavior: A survey." *Journal of Economic Surveys*, 36(4): 969–991.

Acemoglu, D., and T. Lensman. 2024. "Regulating transformative technologies." *American Economic Review: Insights*, 6(3): 359–376.

Acemoglu, Daron. 2025. "The simple macroeconomics of AI." *Economic Policy*, 40(121): 13–58.

Achilleas, K., and S. Anastasios. 2008. "Marketing aspects of quality assurance systems: The organic food sector case." *British Food Journal*, 110(8): 829–839.

Aghion, Philippe, Benjamin F Jones, and Charles I Jones. 2017. "Artificial intelligence and economic growth." National Bureau of Economic Research.

Aghion, P., U. Akcigit, and P. Howitt. 2015. "Lessons from Schumpeterian growth theory." *American Economic Review*, 105(5): 94–99.

Alekseeva, L., M. Gine, S. Samila, and B. Taska. 2020. "AI Adoption and firm performance: Management versus IT." Available at SSRN 3677237.

Aobdia, D. 2020. "The economic consequences of audit firms' quality control system deficiencies." *Management Science*, 66(7): 2883–2905.

Back, Seoin, Alán Aspuru-Guzik, Michele Ceriotti, Ganna Gryn'ova, Bartosz Grzybowski, Geun Ho Gu, Jason Hein, Kedar Hippalgaonkar, Rodrigo Hor-

mázabal, Yousung Jung, et al. 2024. "Accelerated chemical science with AI." *Digital Discovery*, 3(1): 23–33.

Barbancho-Maya, G., and A. A. López-Toro. 2022. "Determinants of quality and food safety systems adoption in the agri-food sector." *British Food Journal*, 124(13): 219–236.

Bauer, A. M., D. Henderson, and D. P. Lynch. 2018. "Supplier internal control quality and the duration of customer-supplier relationships." *The Accounting Review*, 93(3): 59–82.

Ben Ayed, R., and M. Hanana. 2021. "Artificial intelligence to improve the food and agriculture sector." *Journal of Food Quality*, 2021(1): 5584754.

Byun, S. K., J. M. Oh, and H. Xia. 2021. "Incremental vs. breakthrough innovation: The role of technology spillovers." *Management Science*, 67(3): 1779–1802.

Chen, K., X. Chen, Z.-a. Wang, and R. Zvarych. 2024. "Does artificial intelligence promote common prosperity within enterprises?—Evidence from Chinese-listed companies in the service industry." *Technological Forecasting and Social Change*, 200: 123180.

Dalgic, T. 2013. *Customer-oriented marketing strategy: Theory and practice.* Business Expert Press.

Ferrier, P., and R. Lamb. 2007. "Government regulation and quality in the US beef market." *Food Policy*, 32(1): 84–97.

Godfrey, P. C., C. B. Merrill, and J. M. Hansen. 2009. "The relationship between corporate social responsibility and shareholder value: An empirical test of the risk management hypothesis." *Strategic Management Journal*, 30(4): 425–445.

Grace, D. 2023. "Burden of foodborne disease in low-income and middle-income countries and opportunities for scaling food safety interventions." *Food Security*, 15(6): 1475–1488.

Hsu, Y. J., and Y. Wang. 2023. "Technology spillover, corporate investment, and stock returns." *Journal of Empirical Finance*, 73: 238–250.

Javaid, M., A. Haleem, I. H. Khan, and R. Suman. 2023. "Understanding the potential applications of Artificial Intelligence in Agriculture Sector." *Advanced Agrochem*, 2(1): 15–30.

John, J., and N. R. Draper. 1980. "An alternative family of transformations." *Journal of the Royal Statistical Society Series C: Applied Statistics*, 29(2): 190–197.

Jones, Charles I. 2026. "AI and Our Economic Future." National Bureau of Economic Research.

Jumper, John, Richard Evans, Alexander Pritzel, Tim Green, Michael Figurnov, Olaf Ronneberger, Kathryn Tunyasuvunakool, Russ Bates, Augustin Žídek, Anna Potapenko, et al. 2021. "Highly accurate protein structure prediction with AlphaFold." *Nature*, 596(7873): 583–589.

Kaynak, H. 2003. "The relationship between total quality management practices and their effects on firm performance." *Journal of Operations Management*, 21(4): 405–435.

Koehler, M., and H. Sauermann. 2024. "Algorithmic management in scientific research." *Research Policy*, 53(4): 104985.

Koenig, F. 2023. "Technical change and superstar effects: Evidence from the rollout of television." *American Economic Review: Insights*, 5(2): 207–223.

Kong, D. 2012. "Does corporate social responsibility matter in the food industry? Evidence from a nature experiment in China." *Food Policy*, 37(3): 323–334.

Kong, D., L. Shi, and Z. Yang. 2019. "Product recalls, corporate social responsibility, and firm value: Evidence from the Chinese food industry." *Food Policy*, 83: 60–69.

Lai, K. H., and T. E. Cheng. 2005. "Effects of quality management and marketing on organizational performance." *Journal of Business Research*, 58(4): 446–456.

Lerner, J., J. Liu, J. Moscona, and D. Y. Yang. 2024. "Appropriate entrepreneurship? The rise of China and the developing world." NBER Working Paper 32193.

Levinsohn, J., and A. Petrin. 2003. "Estimating production functions using inputs to control for unobservables." *The Review of Economic Studies*, 70(2): 317–341.

Lin, C., Y. Ma, P. Malatesta, and Y. Xuan. 2011. "Ownership structure and the cost of corporate borrowing." *Journal of Financial Economics*, 100(1): 1–23.

Li, Y., and Z. Miao. 2024. "The rise of superstar firms in the United States: The role of global sourcing." *Journal of Comparative Economics*, 52(1): 113–144.

Mac Clay, P., R. Feeney, and J. Sellare. 2024. "Technology-driven transformations in agri-food global value chains: The role of incumbent firms from a corporate venture capital perspective." *Food Policy*, 127: 102684.

Naseem, S., and M. Rizwan. 2025. "The role of artificial intelligence in advancing food safety: A strategic path to zero contamination." *Food Control*, 111292.

Nucci, F., C. Puccioni, and O. Ricchi. 2023. "Digital technologies and productivity: A firm-level investigation." *Economic Modelling*, 128: 106524.

Pei, Xiaofang, Annuradha Tandon, Anton Alldrick, Liana Giorgi, Wei Huang, and Ruijia Yang. 2011. "The China melamine milk scandal and its implications for food safety regulation." *Food policy*, 36(3): 412–420.

Pouliot, S., and D. A. Sumner. 2013. "Traceability, recalls, industry reputation and product safety." *European Review of Agricultural Economics*, 40(1): 121–142.

Prentice, C., and M. Nguyen. 2020. "Engaging and retaining customers with AI and employee service." *Journal of Retailing and Consumer Services*, 56: 102186.

Psarommatis, Foivos, and Victor Azamfirei. 2024. "Zero Defect Manufacturing: A complete guide for advanced and sustainable quality management." *Journal of Manufacturing Systems*, 77: 764–779.

Qian, C., S. Murphy, R. Orsi, and M. Wiedmann. 2023. "How can AI help improve food safety?" *Annual Review of Food Science and Technology*, 14(1): 517–538.

Qiu, J., and C. Wan. 2015. "Technology spillovers and corporate cash holdings." *Journal of Financial Economics*, 115(3): 558–573.

Raisch, S., and S. Krakowski. 2021. "Artificial intelligence and management: The automation–augmentation paradox." *Academy of Management Review*, 46(1): 192–210.

Reitano, M., M. S. Segovia, and R. M. Nayga Jr. 2025. "A systematic review on the impact of Artificial Intelligence in the agri-food supply chain." *Food Policy*, 137: 102983.

Robinson, C. J., and M. K. Malhotra. 2005. "Defining the concept of supply chain quality management and its relevance to academic and industrial practice." *International Journal of Production Economics*, 96(3): 315–337.

Senoner, J., T. Netland, and S. Feuerriegel. 2022. "Using explainable artificial intelligence to improve process quality: evidence from semiconductor manufacturing." *Management Science*, 68(8): 5704–5723.

Song, Y., Z. Wang, C. Song, J. Wang, and R. Liu. 2024. "Impact of artificial intelligence on renewable energy supply chain vulnerability: Evidence from 61 countries." *Energy Economics*, 131: 107357.

Stiel, C., and A. Schiersch. 2022. "Testing the superstar firm hypothesis." *Journal of Applied Economics*, 25(1): 583–603.

Taneja, A., G. Nair, M. Joshi, S. Sharma, S. Sharma, A. R. Jambrak, E. Roselló-Soto, F. J. Barba, J. M. Castagnini, and N. Leksawasdi. 2023. "Artificial intelligence: Implications for the agri-food sector." *Agronomy*, 13(5): 1397.

Taylor, M., H. A. Klaiber, and F. Kuchler. 2016. "Changes in US consumer response to food safety recalls in the shadow of a BSE scare." *Food Policy*, 62: 56–64.

Thomsen, M. R., and A. M. McKenzie. 2001. "Market incentives for safe foods: an examination of shareholder losses from meat and poultry recalls." *American Journal of Agricultural Economics*, 83(3): 526–538.

Toorajipour, R., V. Sohrabpour, A. Nazarpour, P. Oghazi, and M. Fischl. 2021. "Artificial intelligence in supply chain management: A systematic literature review." *Journal of Business Research*, 122: 502–517.

Wang, Hanchen, Tianfan Fu, Yuanqi Du, Wenhao Gao, Kexin Huang, Ziming Liu, Payal Chandak, Shengchao Liu, Peter Van Katwyk, Andreea Deac, et al. 2023. "Scientific discovery in the age of artificial intelligence." *Nature*, 620(7972): 47–60.

Wang, Z., T. Zhang, X. Ren, and Y. Shi. 2024. "AI adoption rate and corporate green innovation efficiency: evidence from Chinese energy companies." *Energy Economics*, 132: 107499.

Zhai, S., and Z. Liu. 2023. "Artificial intelligence technology innovation and firm productivity: Evidence from China." *Finance Research Letters*, 58: 104437.

Ziani, I., H. Bouakline, A. El Guerraf, A. El Bachiri, M.-L. Fauconnier, and F. Sher. 2025. "Integrating AI and advanced spectroscopic techniques for precision food safety and quality control." *Trends in Food Science & Technology*, 156: 104850.

Online Appendix for "Artificial Intelligence Innovation and Product Quality: Evidence from Food Recalls in China"

A Additional Figures and Tables

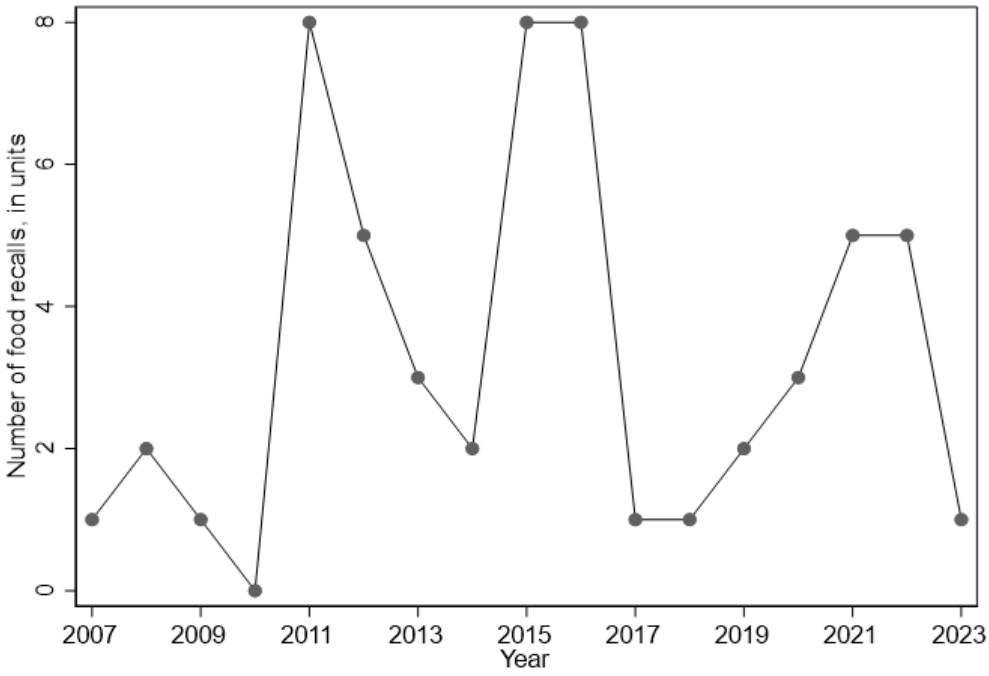


Figure A.1: Food recalls among Chinese agri-food listed firms during 2007-2023

Notes: Food recalls of agri-food listed firms are collected from recall announcements by the Shanghai and Shenzhen Stock Exchanges, as well as reports from authoritative media sources such as Xinhua News, China Food Safety News, and Sina News.

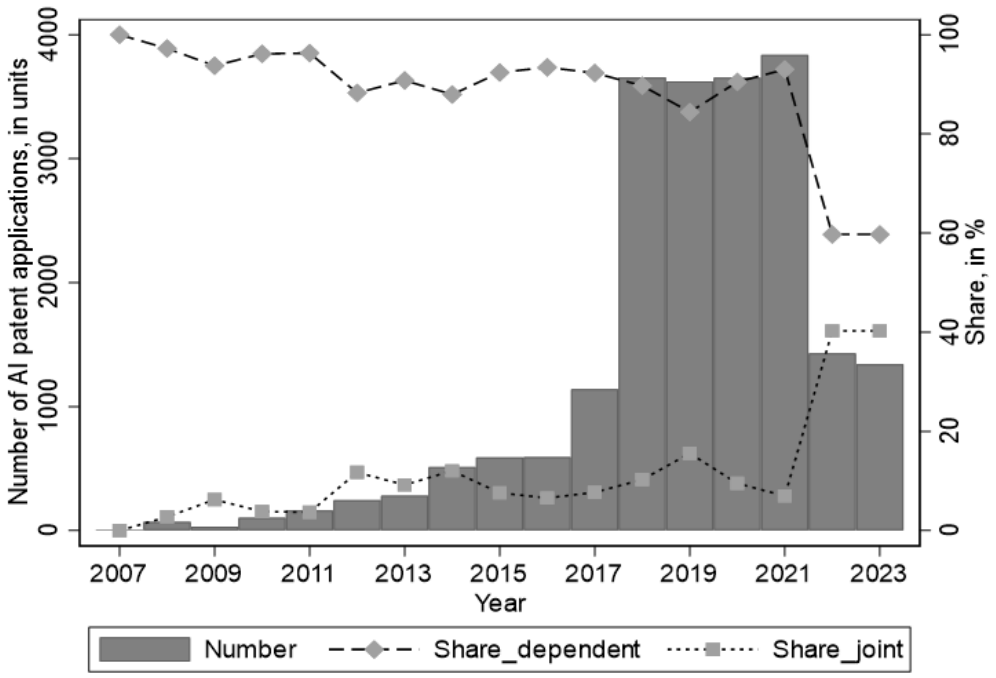


Figure A.2: Placebo test for the effects of AI innovation on food recalls

Notes: The figure reports estimates from placebo specifications in which AI innovation is assigned to pre-treatment periods. The absence of systematic effects supports the validity of the identification strategy.

Table A.1: Robustness Checks

	Sensitivity Tests on AI Innovation					Firm Selection Bias	
	(1) Recall	(2) Recall	(3) Recall	(4) Recall	(5) Recall	(6) Recall	(7) Recall
AI_words	-0.282^{***}						
	(0.085)						
AI_authors		-0.203^{***}					
		(0.047)					
AI_growth			-0.047^{*}				
			(0.025)				
AI_patents				-0.343^{***}	-0.341^{***}	-0.201^{***}	-0.883^{***}
				(0.062)	(0.070)	(0.054)	(0.300)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	2,575	2,575	2,488	1,709	2,575	2,045	2,045
R^2	0.130	0.134	0.220	0.154	0.137	0.148	—
Inverse Mills ratio	—	—	—	—	—	-3.140^{***}	
p-value	—	—	—	—	—	[0.000]	
Wald test statistic	—	—	—	—	—		4.110^{**}
p-value	—	—	—	—	—		[0.042]

Notes: Columns (1)–(4) report sensitivity tests using alternative measures of AI innovation. Columns (5)–(7) address potential firm selection bias. The Wald test evaluates the null hypothesis that the explanatory variables are exogenous in the Probit model. Control variables include firm size, firm age, return on assets, leverage ratio, asset growth, equity concentration, cash flows, and industry concentration. p-values are reported in square brackets, and robust standard errors clustered at the industry-year level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table A.2: Heterogeneity Analysis

	Ownership Types		Categories of Sectors			Types of Food Recalls	
	SOEs	Non-SOEs	Agriculture	Agri-sideline	Food	Mandatory	Voluntary
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Recall	Recall	Recall	Recall	Recall	Recall	Recall
AI_patents	−0.167**	−0.391***	−0.511***	−0.328***	−0.156**	−0.240***	−0.222**
	(0.071)	(0.093)	(0.189)	(0.097)	(0.067)	(0.055)	(0.095)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1,078	1,497	665	680	1,230	2,541	2,233
R^2	0.175	0.174	0.293	0.063	0.207	0.135	0.368

Notes: Control variables include firm size, firm age, return on assets, leverage ratio, asset growth, equity concentration, cash flows, and industry concentration. Robust standard errors clustered at the industry-year level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table A.3: Spillover Effects

	Horizontal spillover	Vertical spillovers	
	(1)	(2)	(3)
	Recall	Recall	Recall
		Forward spillover	Downward spillover
AI_patents	−0.191**	−0.247***	−0.225***
	(0.086)	(0.053)	(0.053)
AI_horizon	−0.029**		
	(0.012)		
AI_upstream		−0.684**	
		(0.346)	
AI_downstream			−0.529**
			(0.209)
Controls	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes
Obs.	2,575	2,575	2,575
R^2	0.157	0.138	0.141

Notes: Control variables include firm size, firm age, return on assets, leverage ratio, asset growth, equity concentration, cash flows, and industry concentration. Robust standard errors clustered at the industry-year level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table A.4: Agri-Food Industries and Distribution of Firms

Industry	Codes	Sectors	No. of Firms	Obs.	Proportion (%)
Agricultural	A01	Agriculture	27	273	10.602
	A02	Forestry	5	42	1.631
	A03	Animal Husbandry	20	189	7.340
	A04	Fishery	9	133	5.165
	A05	Agriculture, Forestry, Animal Husbandry, and Fishery	6	28	1.087
Agri-sideline	C13	Agricultural and Sideline Food Processing Industry	70	680	26.408
Food	C14	Food Manufacturing	80	628	24.388
	C15	Alcohol, Beverages, and Refined Tea Manufacturing	48	602	23.379
Total	—	—	265	2,575	100.000

Notes: Agri-food industries are classified according to the *Industrial Classification for National Economic Activities* (GB/T 4754–2017) and the China Securities Regulatory Commission (CSRC), fourth quarter of 2023.

Table A.5: Food recalls of agri-food listed firms in China from 2007 to 2023

#	Firm Name	Date	M/V	Product and Reason
1	Shanghai Meilin	12/10/2007	M	Luncheon meat (Nitrofuran metabolite detected; carcinogenic)
2	Yili Industrial	09/18/2008	M	Children's Milk Powder, Liquid Milk (Melamine detected by AQSIQ)
3	Bright Dairy & Food	09/18/2008	M	Infant Formula and Yogurt (Melamine detected by AQSIQ)
4	Tsingtao Brewery	10/13/2009	M	Beer (Overage/expired glass bottles)
5	Shuanghui Development	03/19/2011	M	Ham sausage (Leptin incident; voluntary recall following CCTV exposure)
6	Beijing Yanjing Brewery	04/29/2011	M	Beer (Redemption date earlier than production date)
7	Sanquan Foods	11/08/2011	M	Quick-frozen food (Microbial exceedance)
8	Sanquan Foods	11/22/2011	M	Quick-frozen food (Staphylococcus aureus detected)
9	Winall Hi-Tech Seed	11/30/2011	M	Seeds (Failed purity test by Ministry of Agriculture)
10	Shenlong Hi-Tech Seed	11/30/2011	M	Seeds (Failed germination rate)
11	Shandong Denghai Seeds	11/30/2011	M	Seeds (Failed purity test)
12	Gansu Dunhuang Seed	12/06/2011	M	Seeds (Failed purity test)
13	By-Health	02/19/2012	M	Spirulina (Excessive heavy metals)
14	Yili Industrial	06/18/2012	M	Infant formula (Abnormal mercury content)
15	Bright Dairy & Food	06/28/2012	V	Ubiquitous Milk (Lye adulteration found in self-inspection)
16	Fen Wine Factory	08/29/2012	V	Yellow Cap Fenjiu (Black floating material)
17	Bright Dairy & Food	09/10/2012	M	Fresh milk in sachet bottles (Rancid product)
18	By-Health	03/12/2012	M	Pueraria extract (Lack of production license)
19	Shunxin Agriculture	04/02/2013	M	Erguotou (Forged product quality rank)
20	Beingmate	05/02/2013	M	Infant food aid (Excessive mercury content)
21	Shandong Delisi Food	09/05/2014	M	Eight-treasure dumpling (Sodium saccharin/cyclamate failed standards)
22	Beijing Yanjing Brewery	12/12/2014	M	Bottled drinking water (Excessive bacterial counts)

Continued on next page

Table A.5 – continued from previous page

#	Firm Name	Date	M/V	Product and Reason
23	By-Health	06/19/2015	M	Fish oil capsules (Illegal Ginkgo biloba extract)
24	Tangrenshen Group	06/26/2015	M	Streaky bacon (Acid value exceeds standards)
25	Chuying Agro-Pastoral	07/28/2015	M	Pork (Forbidden chloramphenicol detected)
26	Hainan Yedao	08/02/2015	M	Deer and turtle wine (Sildenafil added illegally)
27	Yanghe Brewery	09/08/2015	M	Yanghe daqu wine (Alcohol content inconsistent with label)
28	King's Luck Brewery	09/08/2015	M	Gaogou wine (Alcohol content failed standards)
29	Longda Meat	12/01/2015	M	Lean meat ham (Excessive bacterial colonies and E. coli)
30	Nanfang Black Sesame	12/31/2015	M	Black sesame (Excessive E. coli)
31	VV Food Beverage	01/26/2016	M	Peanut oil (Benzopyrene content failed standards)
32	Yanghe Brewery	02/18/2016	M	Yanghe daqu wine (Ester and ethyl acetate levels failed)
33	Heilongjiang Agriculture	03/29/2016	M	Soybean oil (Excessive Benzopyrene)
34	Royal Group	04/06/2016	M	AD milk (Excessive E. coli)
35	Shuanghui Investment	09/14/2016	M	Sausage (Temperature control failure during production)
36	Shandong Delisi Food	09/24/2016	M	"Cowboy" sausage (Unknown white hairs detected)
37	Jinjian Cereals	09/27/2016	M	Student milk (Improper transportation; caused gastric discomfort)
38	Nanfang Black Sesame	10/05/2016	M	Black sesame (Excessive E. coli)
39	Sanquan Foods	05/26/2017	M	Rice dumplings (Bacterial and coliform counts failed standards)
40	Haitian Seasoned Foods	10/13/2018	M	Seasoning (Amino acid nitrogen content failed standards)
41	Sanquan Foods	02/21/2019	M	Dumplings (Suspected African swine fever virus nucleic acid)
42	Wens Foodstuff	04/16/2019	M	Various products (General failure of safety standards; $50k penalty)

Continued on next page

Table A.5 – continued from previous page

#	Firm Name	Date	M/V	Product and Reason
43	Xiangjia Husbandry	06/11/2020	M	Chicken (Sodium pentachloro phenate and carbazide detected)
44	Bright Dairy & Food	12/07/2020	M	"Cow Punch" milk (Excessive E. coli)
45	Panda Dairy	12/23/2020	M	Condensed milk (Failed in total number of colonies)
46	Beijing Yanjing Brewery	03/02/2021	M	Yanjing beer (Bottle explosion risk)
47	Lanzhou Manor Ranch	04/15/2021	M	Yogurt (Acidity test failed national standards)
48	Tianrun Dairy	05/06/2021	M	Cheese (Yeast and mold exceeded standards)
49	Homey Aquatic	11/01/2021	M	Jelly Fish Head (Excessive Aluminum residue)
50	Yanker Shop Food	11/10/2021	M	Black sugar plums (Excessive lead detected)
51	Keming Foods	01/07/2022	M	Wheat flour (Deoxynivalenol failed)
52	Wens Foodstuff	06/24/2022	M	Pure milk (Failed non-fat milk solids standard)
53	Maiquer	08/23/2022	M	Pure milk (Contains illegal propylene glycol)
54	Longda Meat	08/09/2022	M	Raw pork (Sodium pentachloro phenate detected)
55	Longda Meat	08/25/2022	M	Pork products (Excessive levels of enrofloxacin)
56	Wens Foodstuff	02/06/2023	M	Fresh milk (Failed total bacterial colonies)

Notes: This table reports major food recall events involving publicly listed agri-food firms in China. Column M V indicates whether the recall was mandatory or voluntary. Recall information is compiled from official announcements by regulatory authorities and firm disclosures.

Table A.6: IPC Codes for Product–Quality–Related AI Patents among Agri-Food Firms

IPC Code(s)	Keyword Overview
G05B15/02; G06K9/66; G07C9/00; G08B19/00; G08B25/10	Information system integration services for artificial intelligence systems, smart home systems, and other information systems in the production field.
G05D1/02; G05D1/08; G05D1/10; G05D1/12; G06F1/16	Manufacturing of wearable intelligent devices, intelligent unmanned aerial vehicles, and other intelligent consumer equipment, including digital home intelligent terminal equipment, intelligent sensing and control equipment, and financial electronic application products.
G06F3/01	Manufacturing of wearable intelligent devices and intelligent unmanned aerial vehicles; manufacturing of other intelligent consumer equipment such as digital home intelligent terminal equipment and intelligent perception and control equipment; information system integration services (e.g., artificial intelligence systems and smart home systems); artificial intelligence–optimized operating systems, middleware, function libraries, computer vision and auditory software, and biometric recognition software.
G06F9/44; G06F9/455; G06N3/00; G06N3/04; G06N3/06; G06N3/063; G06N3/067; G06N3/10; G06N3/12; G06N5/00; G06N5/02; G06N5/04	Artificial intelligence–optimized operating systems; artificial intelligence middleware and function libraries; computer vision and auditory software; biometric identification software; and other artificial intelligence application software development.
G06K9/00; G06K9/62; G06N3/02; G06N3/08	Artificial intelligence systems in the production field and smart home systems; information system integration services; artificial intelligence–optimized operating systems, middleware, function libraries; computer vision and auditory software; biometric identification software; and other application software development.
A61B5*; G16H	Keywords related to human brain structure and brain diseases, including amygdala- and epilepsy-related technologies.
G06F40*; A61B5/0476; A61B5/0478	None.

Notes: IPC codes for AI patent applications are based on the *Strategic Emerging Industries Classification and International Patent Classification Relationship Table (2021)* issued by the China National Intellectual Property Administration (CNIPA). Specifically, product-quality-related AI patent applications are classified in Section G and encompass subclasses such as G05B, G05D, G06N, and G06K, among others.

Table A.7: Definition and Measurement of Dependent and Independent Variables

Variable	Description
Recall	Indicator variable equal to 1 if the firm experiences a food recall in a given year and 0 otherwise.
AI_patents	Logarithm of one plus the number of AI patent applications filed by the firm.
Pcd	Supplier concentration, measured as the share of procurement expenditures accounted for by the top five suppliers.
Aps	Number of administrative penalties imposed on suppliers by the State Administration for Market Regulation (SAMR).
TFP	Total factor productivity calculated using the Levinsohn–Petrin (LP) method.
Cost	Monitoring cost, measured as the ratio of operating costs to operating revenue.
Ccd	Customer concentration, measured as the share of revenues accounted for by the top five customers.
Inv	Inventory intensity, measured by the inventory turnover ratio.
CSR	Corporate social responsibility index from independent CSR ratings (SNAIs), transformed using a log-modulus specification due to zero scores for firms without independent CSR reports.
Size	Firm size, measured as the logarithm of total assets.
Age	Firm age, measured as the logarithm of one plus the number of years since establishment.
Roa	Return on assets.
Lev	Leverage ratio, defined as total liabilities divided by total assets.
Tagr	Growth rate of total assets.
Ten	Equity concentration, measured as the share of equity held by the top ten largest shareholders.
Cash	Cash holdings, measured as (money funds plus trading financial assets) divided by total assets.
HHI	Industry concentration measured by the Herfindahl–Hirschman Index.

Note: This table shows the definitions and measurement methods for the dependent, independent, and control variables used in this paper.

Table A.8: AI Dictionary

#	Keyword	#	Keyword
1	Agent	40	Intelligent Search
2	AI Chip	41	Intelligent Supervision
3	AI Products	42	Intelligent Transportation
4	AI Ethics	43	Intelligent Voice
5	Algorithm	44	Internet of Things (IoT)
6	Artificial Intelligence (AI)	45	Knowledge Graph
7	Augmented Intelligence	46	Knowledge Representation
8	Augmented Reality (AR)	47	Long Short-Term Memory (LSTM)
9	Autonomous Driving	48	Machine Learning
10	Big Data	49	Machine Translation
11	Big Data Analysis	50	Natural Language Processing (NLP)
12	Big Data Management	51	Neural Network
13	Big Data Marketing	52	Pattern Recognition
14	Big Data Operations	53	Predictive Analytics
15	Big Data Platform	54	Question Answering System
16	Big Data Processing	55	Recurrent Neural Network (RNN)
17	Big Data Risk Control	56	Reinforcement Learning
18	Biometrics	57	Recommendation System
19	Business Intelligence (BI)	58	Robotic Process Automation (RPA)
20	Chatbot	59	Smart Agriculture
21	Cloud Computing	60	Smart Banking
22	Computer Vision	61	Smart Chip
23	Convolutional Neural Network (CNN)	62	Smart Elderly Care
24	Data Mining	63	Smart Environmental Protection
25	Deep Learning	64	Smart Finance
26	Deep Neural Network (DNN)	65	Smart Governance
27	Distributed Computing	66	Smart Healthcare
28	Edge Computing	67	Smart Home
29	Face Recognition	68	Smart Insurance
30	Feature Extraction	69	Smart Investment Advisory
31	Feature Recognition	70	Smart Retail
32	Human–Computer Dialogue	71	Smart Sensor
33	Human–Computer Interaction (HCI)	72	Smart Speaker
34	Human–Machine Collaboration	73	Speech Recognition
35	Image Recognition	74	Speech Synthesis
36	Intelligent Computing	75	Support Vector Machine (SVM)
37	Intelligent Customer Service	76	Unmanned Driving
38	Intelligent Education	77	Virtual Reality (VR)
39	Intelligent Robot		

Notes: AI-related keywords are compiled from the *Artificial Intelligence Index Report 2023* and the Juchao Information Network.