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Agricultural New Quality Productive Forces and Green High-Quality Development of China's Apple Industry: Evidence from Double Machine Learning

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Abstract

Green high-quality development (GHD) is essential for transforming China's apple industry from extensive to sustainable production. As a core embodiment of green productivity, agricultural new quality productive forces (ANQPFs)—characterized by high technology, efficiency, and quality—offer a new pathway for overcoming resource and environmental constraints in the sector. Using a balanced panel of 31 Chinese provinces from 2011 to 2023, this study estimates the effect of ANQPFs on the GHD of the apple industry with a partially linear double/debiased machine learning (DML) model that combines cross fitting with random forest learners. ANQPFs are measured by the entropy-weighted TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) method across three dimensions: new agricultural laborers, new means of labor, and new objects of labor. The results show that ANQPFs significantly promote GHD in the apple industry, and this finding is robust to winsorization tests, alternative base learners, and an instrumental variable specification (DDML-IV). Mechanism analysis identifies two indirect channels—agricultural green innovation and agricultural socialized services. Heterogeneity analyses show that this empowering effect is concentrated in eastern regions and high-urbanization provinces. Policy implications include locally tailored ANQPF cultivation, stronger green technology R&D, and expanded socialized service provision in lagging apple-producing regions.

Keywords: agricultural new quality productive forces; apple industry; green high-quality development; double machine learning; agricultural socialized services

1. Introduction

Green high-quality development is central to building a strong agricultural nation, and it is a defining feature of Chinese-style modernization in agriculture. Distinctive and competitive agricultural industries supply more green and high-quality agricultural products, and they support agricultural sustainability [1]. The apple industry is one of China's most internationally competitive specialty agricultural sectors. As of 2024, the country's total apple planting area reached 1907.1 thousand hectares, making the industry a pillar supporting farmer income growth and rural prosperity. This growth, however, has long relied on extensive inputs of chemical fertilizers and pesticides. Such input-intensive practices secured market supply, but they also triggered a series of ecological problems. These include soil acidification and compaction, worsening agricultural nonpoint source pollution, growing pest resistance, and insufficient recycling of orchard waste. The traditional extensive production model is therefore no longer viable. Meanwhile, household

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consumption is increasing, and market demand keeps growing for high-quality, safe fruit produced through traceable green methods. The apple industry must consequently move away from a scale- and yield-focused development model and toward green, high-quality, and efficient growth. The 2026 No. 1 Central Document reinforces this direction. It calls for the coordinated development of technology-driven, green, quality-oriented, and brand-focused agriculture, charting a clear policy direction for the transformation and upgrading of specialty orchard industries, the apple sector included.

Meeting this policy direction requires a shift in the underlying productivity of agriculture. New quality productive forces are inherently green productive forces. Anchored in scientific and technological innovation and characterized by high technology, high efficiency, and high quality, they provide a fresh driving force for overcoming three practical bottlenecks in agriculture: tightening resource constraints, mounting ecological pressure, and low production efficiency. Biotechnology, intelligent equipment, digital information technology, and ecological circular technologies are steadily penetrating the apple industry [2]. They create favorable technical conditions for precision orchard management, variety improvement, circular waste utilization, and value enhancement across the entire industrial chain. Several obstacles nevertheless limit how far these possibilities extend. Persistent smallholder land fragmentation in China's major apple-producing regions and gaps in technological literacy among producers slow the adoption of new tools. Green technology R&D is often disconnected from on-the-ground application, specialized technical personnel are in short supply, and the price premium mechanism for green products remains underdeveloped. Collectively, these constraints mean that the inherent green potential of new quality productive forces has yet to be fully unleashed. Against this background, clarifying the internal mechanism through which agricultural new quality productive forces (ANQPFs) influence the green high-quality development (GHD) of the apple industry holds both theoretical value and practical significance. It can inform the green and sustainable transformation of China's specialty orchard sectors.

A growing body of publications has examined how ANQPFs affect green agricultural development. Existing studies generally concur that ANQPFs are an advanced form of productivity centered on scientific and technological innovation and distinguished by total factor productivity improvement [3,4]. They reshape the development paradigm of modern agriculture by systematically upgrading laborers, the means of labor, and the objects of labor, and by optimizing their combinations. From the dual perspectives of theoretical logic and practical pathways, one group of studies contends that ANQPFs can drive agriculture to move from a high-input, high-consumption, and high-emission development model to an intensive, low-carbon, and ecological one [5–7]. The pathways identified include green technology innovation, optimized factor allocation, industrial structure upgrading, and whole-industry-chain coordination. From a green performance perspective, another group of scholars empirically examines how ANQPFs affect agricultural green total factor productivity, the green use efficiency of cultivated land, carbon emissions from grain production, and synergistic reduction in agricultural pollution and carbon emissions [8–11]. This work also clarifies the underlying transmission mechanisms through channels such as industrial structure upgrading, industrial agglomeration, technological progress, human capital, operating scale, and market incentives. Research on the green development of the apple industry has followed a different path. It has concentrated largely on the measurement of green total factor productivity, the reduction in fertilizer and pesticide use, and the green production behaviors of growers [12–15]. Household endowments, technology perception, policy support, socialized services, and rural e-commerce have received particular attention as influences on the green transformation of the apple sector.

These debates have unfolded alongside the international literature on the subject that raises a broader question: under what conditions do innovation capabilities translate into environmental and organizational performance? The international literature conceptualizes such capabilities as sustainability-oriented innovation. The term refers to the deliberate revision of products, processes, and business models so that environmental and social value creation becomes a core attribute of the firm rather than a by-product of production [16]. Empirical evidence from the global food and beverage industry confirms that this orientation is practically measurable rather than purely rhetorical. Among 633 agri-food enterprises in the European Union, the United States, and China tracked over the 2013–2023 period, environmental innovation was found to significantly boost ESG performance, whereas green revenue in isolation did not produce the same effect [17]. Case studies from the same sector point in a similar direction. They show that sustainable business model redesign yields distinct combinations of economic, environmental, and social performance outcomes and that these outcomes depend on stakeholder engagement levels and governance structures [18]. ANQPFs are therefore best understood not as a uniquely Chinese phenomenon but as a sector-specific manifestation of this general innovation–sustainability relationship. Their returns depend on organizational conditions rather than on technology alone.

International research on digital transformation speaks more directly to the digital nature of ANQPFs. It conceptualizes digital resources as a strategic complement to, rather than a replacement for, sustainability strategies, and it locates the documented gains in the integration of the two. A study of 405 food and beverage SMEs found that digitalization enhances sustainable corporate performance primarily by enabling green innovation and green supply chain management [19]. Firm-level evidence from food-processing supply chains indicates that integrated digital ecosystems, which incorporate Internet of Things (IoT) monitoring, blockchain traceability, and big data analytics, reduce cold-chain losses and energy consumption [20]. The twin-transition literature likewise holds that digital pathways determine whether sustainable innovation can scale beyond isolated pilot initiatives [21]. The relevance of this research is underscored by the composition of agricultural ANQPFs themselves. Their core components, including intelligent water–fertilizer integration, plant protection drones, orchard IoT monitoring, blockchain traceability, and digital management platforms, are all digital technologies. Cross-chain service innovation and organizational coordination, rather than mere equipment adoption, are therefore the operating channels through which ANQPFs deliver their impacts.

In summary, existing studies have either examined the effect of ANQPFs on green development at the aggregate agricultural sector level or focused on micro-level grower behavior and industrial efficiency assessments. Three gaps follow from this division. Few studies integrate ANQPFs and the GHD of the apple industry into a unified analytical framework, and the layered identification of the direct effects of ANQPFs and their indirect transmission paths remains insufficient. Nor have existing studies linked ANQPFs to international evidence on innovation-led, digitally enabled sustainability in agri-food systems, which leaves the broader relevance of the Chinese case insufficiently clarified. This paper advances the existing literature in two respects: in terms of the research object, it breaks from the dominant aggregate agriculture research paradigm by applying ANQPF theory to a specialty cash crop (apples) and estimating the effect of ANQPFs on the GHD of the apple industry. This enriches empirical evidence on new quality productive forces in specialty agriculture and situates the findings within the international debate on innovation-led, digitally enabled sustainability in agri-food systems. In terms of the analytical framework, it integrates agricultural green innovation (AGI) and agricultural socialized services (ASSs) into a unified analytical framework and constructs a dual-mediation transmission pathway. By doing so, it distinguishes the direct effect of ANQPFs from their indirect transmission

effect and clarifies the internal logic by which ANQPFs drive the green transformation of the apple industry. Accordingly, this study applies the double/debiased machine learning (DML) model to estimate treatment effects and perform mechanism testing, in addition to conducting heterogeneity analyses across regions and urbanization levels. The aim is to provide theoretical support and empirical references for the green and high-quality transformation of specialty orchard industries.

2. Theoretical Analysis and Hypotheses

From the perspective of productivity factor transformation, ANQPFs promote the qualitative upgrading of laborers, the means of labor, and the objects of labor in the apple industry [22]. At the laborer level, ANQPFs cultivate a new generation of professional fruit farmers and composite operating entities equipped with solid technological and managerial expertise. They guide producers to shift from experience-based operation to technology-driven practice, renew their production concepts, and encourage them to adopt green production models such as orchard sod culture and green pest control. At the level of the means of labor, new tools are deployed throughout the entire production process. These include intelligent water–fertilizer integration equipment, plant protection drones, orchard Internet of Things monitoring systems, intelligent fruit sorting facilities, and blockchain traceability platforms. Such tools enable the precise application of water, fertilizer, and agrochemicals, which reduces environmental pollution caused by excessive chemical input. They also record production information throughout the entire apple production chain, which enhances the credibility of apple quality. These tools are not simply more efficient inputs, however. Their environmental benefits can only be realized when they are integrated into routine orchard management and into the service systems that make them accessible to growers [19,20]. At the level of the objects of labor, the production object expands from individual fruit trees to a composite portfolio. This portfolio encompasses stress- and disease-resistant germplasm resources, green inputs, orchard ecological resources, and industrial data. Bio-breeding enhances varietal traits and reduces pest and disease pressure, while orchard ecological resources and industrial data are incorporated as production factors that promote internal material cycling within the orchard ecosystem. The coordinated upgrading of these three factors pushes the production possibility frontier of the apple industry toward stable yields, higher quality, and lower pollution, and it directly drives the green, high-quality development of the sector. Accordingly, Hypothesis 1 (H1) is proposed as follows:

H1. *ANQPFs exert a significantly positive effect on the GHD of the apple industry.*

The direct effect captured by H1 is accompanied by a first indirect effect. Scientific and technological innovation lies at the core of new quality productive forces, and it can raise the green innovation capacity of the apple industry on both the supply and demand sides [23]. On the supply side, biotechnology, digital technology, and ecological circular technologies are steadily penetrating the apple industry. They guide research institutes and agribusinesses to tackle practical problems, including soil degradation, frequent pest and disease outbreaks, and low waste utilization rates. This drives the steady emergence of innovations such as disease-resistant apple germplasm, ecofriendly orchard inputs, orchard waste recycling systems, and smart orchard equipment. Stronger intellectual property protection and the commercialization of research outputs further lower the R&D costs and trial-and-error expenses of green innovation. On the demand side, growing household consumption creates market demand for green, high-quality apples, and the potential premium attached to green products directs innovation resources further toward the development of

green technology in the apple sector. As agricultural green innovation advances, its effects operate through several routes. Variety innovation cuts the demand for pesticides and chemical fertilizers at the source. Technology innovation in orchard production improves soil health and reduces chemical input use. Circular technology innovation converts prunings and pomace into usable resources. Digital management innovation optimizes orchard production decision-making. Collectively, these green innovation outcomes reshape apple production and its entire industrial chain, reduce nonpoint source pollution, and improve fruit quality. They consequently advance the GHD of the apple industry. Accordingly, Hypothesis 2 (H2) is proposed as follows:

H2. *ANQPFs indirectly promote the GHD of the apple industry by raising the level of agricultural green innovation.*

Agricultural socialized services provide a second indirect channel. Smallholder fragmentation is prominent in China's apple-producing regions, where most growers face constraints in capital, technical knowledge, and operational scale. As a result, many growers find it difficult to purchase intelligent equipment independently or to master complex green production techniques. Service scale can effectively substitute for physical land scale, and it thereby alleviates the transformation dilemma of smallholders. ANQPFs provide the material and technical foundation for the development of agricultural socialized services. Advances in intelligent equipment, digital information systems, and specialized technical talent render green services commercially feasible. These services include unified pest control, fertilization based on soil testing, contracted orchard management, waste recycling, and brand-traceability marketing, and their commercial feasibility spurs the emergence of numerous specialized service organizations. Such organizations package advanced technologies and equipment into socialized service products that are outsourceable and purchasable, and they deliver these products to growers. Once agricultural socialized services develop, their effects operate along two lines. Production-oriented services, such as unified pest control and water–fertilizer management, achieve standardized green operations, and they correct the overapplication of chemical inputs that occurs when smallholders rely on experience. Technical advisory services, in turn, lower the learning and operational thresholds that growers face in adopting green techniques. Postproduction services, such as sorting, cold-chain logistics, and brand marketing, expand the channels through which green apples provide value. By translating orchard green production practices into tangible economic returns, these services drive the overall green and high-quality transformation of the apple industry [24]. Accordingly, Hypothesis 3 (H3) is proposed as follows:

H3. *ANQPFs indirectly promote the GHD of the apple industry by developing agricultural socialized services.*

3. Research Design

3.1. Data Sources

The empirical analysis rests on a balanced panel of mainland China covering 2011–2023 and comprising 31 provinces, municipalities, and autonomous regions (Hong Kong, Macao, and Taiwan are not included). The indicators are compiled from several official statistical series covering agricultural production, resource and environmental accounts, rural human capital, and rural digital and service infrastructure. Tables 1 and 2 define and measure the green development and ANQPF indicators. The paragraphs below describe how the major variable groups are assembled.

Table 1. Evaluation indicator system for green high-quality development of the apple industry.

Category	Indicator	Calculation Method	Unit	Impact
Resource conservation	Water-saving irrigation area	A × water-saving irrigation area	10^3 ha	+
	Agricultural water use	A × agricultural water use	10^8 m^3	−
	Rural electricity consumption	A × rural electricity consumption	10^8 kWh	−
	Agricultural diesel consumption	A × agricultural diesel consumption	10^4 t	−
Environmental friendliness	Apple chemical fertilizer use	A × chemical fertilizer use	10^4 t	−
	Apple pesticide use	A × pesticide use	t	−
	Apple plastic film use	A × plastic film use	t	−
Production efficiency	Apple yield per unit area	Apple output/orchard area	t/10^3 ha	+
	Per capita apple output	Apple output/year-end population	t/person	+
	Land productivity	Apple output value/orchard area	10^8 CNY/10^3 ha	+

Notes: A = apple orchard area/total crop sown area; "×" denotes multiplication by A. "+"/"−" denote the direction of the indicator's effect on GHD. See Section 3.1 for the measurement error associated with A.

Table 2. Comprehensive evaluation indicator system for agricultural new quality productive forces.

Category	Indicator	Definition	Impact
New agricultural laborers	Innovation and entrepreneurship activity	China Regional Innovation Capability Composite Index.	+
	Per capita years of rural education	(rural illiterate × 1 + primary × 6 + junior secondary × 9 + senior secondary × 12 + college or above × 16)/rural population aged 6+.	+
	Share of rural residents with higher education	Rural population with college or above/total rural population aged 6+.	+
New means of labor	Agricultural meteorological observation stations	Number of agricultural meteorological observation stations.	+
	Rural mobile phone penetration	Mobile phones per 100 rural households (units).	+
	Rural computer penetration	Computers per 100 rural households (units).	+
	Agricultural intelligent aerial vehicles	Stock of agricultural intelligent aerial vehicles (units).	+
	Agricultural S&T R&D investment intensity	Internal R&D expenditure × (gross agricultural output/regional GDP).	+
New objects of labor	Solar water heaters	Number of solar water heaters.	+
	New agricultural variety R&D	Number of agricultural plant variety rights applications.	+
	Organic agriculture	Total number of certified organic agricultural products in the current year.	+

Notes: "+" denotes a positive-direction indicator; "×" denotes multiplication.

For green high-quality development of the apple industry, the underlying series come from the China Rural Statistical Yearbook, the China Statistical Yearbook (for provincial population and output values), the China Water Statistical Yearbook (for irrigation items), and the China Environmental Statistical Yearbook (for pollution-related items). These series describe the crop sector as a whole rather than orchards alone. Orchard-specific factor inputs

are therefore separated from the agricultural aggregate by a weighting coefficient equal to the share of orchard area in total sown area (A = apple orchard area/total crop sown area), which is applied to the corresponding provincial totals. The Chinese statistical yearbooks do not report the use of fertilizer, pesticide, plastic film, irrigation water, energy, or diesel separately for apples. Seven of the ten green development indicators listed in Table 1 are consequently obtained by applying A to the corresponding provincial agricultural totals. This weighting coefficient procedure is standard in the literature that evaluates the green performance of the apple industry [25–27]. It is also the estimation rule adopted by Guo et al. [12], who derive labor, machinery, fertilizer, and pesticide inputs for apples from agricultural totals multiplied by the share of the apple planting area.

Indicators constructed by applying A are valid only if resource use and environmental pressure scale with land area, which is inaccurate in levels. The effect on the composite index is limited, however. Entropy-weighted TOPSIS is invariant to a common multiplicative rescaling of an indicator, so a uniform orchard-to-cropland intensity ratio cancels, and the three indicators computed directly from orchard area data carry 63% of the entropy weight. Section 4.2 shows that the baseline estimate is unchanged when the index is rebuilt from these three apportionment-free indicators alone.

The three dimensions of agricultural new quality productive forces defined in Section 2 are not covered by any single database. They draw on different parts of the official statistical system: the China Regional Innovation Capability Evaluation Report, the China Statistical Yearbook, the China Population and Employment Statistical Yearbook, the China Agricultural Machinery Industry Yearbook, the China Science and Technology Statistical Yearbook, and the China Environmental Statistical Yearbook. Two further sources supplement these yearbooks: national data published by the National Bureau of Statistics [28] and certified organic agricultural product records released by the China Green Food Development Center [29]. The exact series behind each indicator are listed in Table 2.

The mechanism's variables originate from two sources:

- Agricultural green innovation (AGI) is drawn from the Qiyan Big Data Platform for Social Sciences, which records green patent applications by province for 2011–2023.
- Agricultural socialized services (ASS) are gathered from the China Rural Statistical Yearbook, the China Tertiary Industry Statistical Yearbook, and the provincial statistical yearbooks for 2011–2023.

The control variables are obtained from national and provincial yearbooks. A limited number of missing observations are filled using interpolation and a moving-average rule. Every composite index is rescaled to a dimensionless basis before aggregation so that indicators reported in different units can be combined.

3.2. Methodology

The development level of ANQPFs is measured with the entropy-weighted TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) method. The approach has two steps, and both derive the aggregation rule from the data themselves rather than from prior judgment. This property suits an index built from indicators reported in different units and directions. The entropy weights are obtained first. The indicators are converted to a common scale according to whether they are positive or negative in direction, and the dispersion of each indicator across province–year observations then determines how much weight it carries in the composite index. The resulting weighted matrix is then scored against the TOPSIS benchmark. Each province–year observation is compared with the best and worst values attainable on the weighted indicators, and the relative closeness of an observation to the best-performing benchmark provides its composite ANQPF score. The detailed computational procedure follows Cui and Yu [30].

Traditional two-way fixed-effects models require the researcher to prespecify the functional relationship between variables. When many control variables are present and nonlinear associations exist, misspecification is likely and may bias causal identification. The double/debiased machine learning (DML) model uses machine learning algorithms to fit high-dimensional covariates nonparametrically, and it relies on K-fold cross fitting and Neyman orthogonal scores to mitigate estimation biases from omitted variables and ad hoc functional forms. To estimate the effect of ANQPFs on the high-quality development of the apple industry while avoiding the misspecification inherent in conventional panel models, this study follows Chernozhukov et al. [31], Jiang and Wang [32], and Guo et al. [33] and constructs a partially linear DML model. Within this framework, province and year fixed effects are absorbed by including a full set of province and year dummy variables in the control vector X. This adjustment is necessary because the nuisance functions are estimated nonparametrically and, thus, cannot partial out fixed effects analytically in the way a linear panel estimator does.

The specification has three elements. The outcome is the GHD index of the apple industry, the treatment is the ANQPF index, and the controls enter through an unknown function h(X), estimated by machine learning rather than specified in advance. Equation (1) is the main model equation, and Equation (2) is the auxiliary (nuisance) equation. Identification rests on the conditional moment restrictions that accompany each equation, so the two are read together rather than separately.

The baseline specification is as follows:

$$aigd_{it} = \theta_0 anqp_{it} + h(X_{it}) + U_{it},\ E[U_{it}|X_{it}, anqp_{it}] = 0 \quad (1)$$

$$anqp_{it} = g(X_{it}) + V_{it},\ E[V_{it}|X_{it}] = 0 \quad (2)$$

where

$aigd_{it}$ denotes the green high-quality development level of the apple industry in province i and year t.

$anqp_{it}$ denotes the ANQPF level of province i in year t.

θ_0 is the core treatment effect to be estimated, representing the marginal impact of ANQPFs on the GHD of the apple industry.

X_{it} denotes the set of control variables.

$h(X_{it})$ and $g(X_{it})$ are unknown nonparametric functions that capture, respectively, the nonlinear effects of the control variables on the explained variable and on the treatment variable.

Their functional forms are not prespecified but are fitted in a data-driven manner by machine learning algorithms.

U_{it} and V_{it} are the random disturbance terms of the main and auxiliary equations.

$E[U_{it}|X_{it}, anqp_{it}] = 0$ and $E[V_{it}|X_{it}] = 0$ state that the conditional means of the disturbances are zero.

The baseline estimation uses threefold cross fitting with the random forest algorithm as the base learner. The random forest is used as the base learner because the two nuisance functions, namely, the conditional expectations of GHD and of ANQPFs given the controls, are unknown and almost certainly nonlinear. The control set combines structural, demographic, and policy variables whose joint influence cannot be specified a priori, and a tree ensemble approximates such functions without imposing linearity or a fixed interaction structure. Tree ensembles are also insensitive to the monotone rescaling of covariates and to irrelevant or strongly correlated regressors, an advantage in a sample of 31 provinces × 13 years = 403 observations with a small effective sample. The learner is retained, moreover, because it requires little tuning, so the estimates do not depend on a

researcher-chosen tuning path. To permit replication, both nuisance functions (ml_l and ml_m) are fitted with a random forest of 100 trees of maximum depth 5 (n_estimators = 100, max_depth = 5), the number of cross fitting folds is 3, and the random seed is fixed at 38, which generates every result reported below. Because DML estimates can, in principle, depend on the sample partition and on the seed, the baseline was re-estimated with four further seeds (3, 11, 23, and 42). The ANQPF coefficient ranges from 0.1015 to 0.1610 and remains positive and significant at the 10% level in all five cases (t = 1.81 to 2.34). The baseline result therefore does not hinge on the sample split. The alternative learners used in the robustness checks are configured as LassoCV with threefold internal cross-validation and a support vector regression with an RBF kernel (C = 1.0, ε = 0.1). Robustness is further examined along three dimensions: trimming of extreme values, varying the number of cross fitting folds, and replacing the machine learning base learner.

Following the mechanism-testing logic of Jiang [34], this paper adopts a step-by-step testing strategy to identify the mediation effect, circumventing the limitations of the traditional stepwise regression approach. Equation (3) is the main equation for mechanism testing, Equation (4) is the corresponding auxiliary equation, and Equation (5) is the outcome equation for the second stage. Estimation begins with the mediator as the dependent variable in the same partially linear DML specification, keeping the core regressor and the full set of controls, and then proceeds to the second stage:

$$M_{it} = \varepsilon_0 anqp_{it} + h(X_{it}) + U_{it},\ E[U_{it}|X_{it}, anqp_{it}] = 0 \quad (3)$$

$$anqp_{it} = g(X_{it}) + V_{it},\ E[V_{it}|X_{it}] = 0 \quad (4)$$

$$aigd_{it} = \theta_1 M_{it} + \theta_2 anqp_{it} + h(X_{it}) + U_{it},\ E[U_{it}|X_{it}, anqp_{it}, M_{it}] = 0 \quad (5)$$

where

M_{it} denotes the mediator, namely, agricultural green innovation and agricultural socialized services.

ε_0 is the coefficient to be estimated in the mechanism equation, characterizing the marginal effect of ANQPFs on the mediator.

$h(X_{it})$, $g(X_{it})$, U_{it} and V_{it} and the conditional expectation restrictions are defined as in the baseline model.

θ_1 denotes the effect of the mediator on GHD conditional on ANQPF.

θ_2 denotes the coefficient on ANQPF once the mediator is controlled.

$\varepsilon_0 \times \theta_1$ denotes the indirect effect of ANQPFs transmitted through each mediator channel, obtained as the product of the two stage coefficients; its Sobel standard error is computed from the two stage estimates and their standard errors.

If ε_0 passes the significance test, ANQPF significantly affects the mediator, which is the first condition for a transmission path to operate. To identify each path completely, the second stage is estimated as well. The mechanism analysis decomposes a conditional association rather than the causal parameter targeted by the baseline model. It is therefore estimated with the same control set as the baseline, including the fiscal support ratio, but without absorbing province and year fixed effects. This design retains the within-mediator variation needed to identify the second stage.

To address potential endogeneity from reverse causality and omitted variables in the baseline model, the double machine learning instrumental variable (DDML-IV) estimator is further applied, and group-wise DML regressions by sample characteristics are conducted to examine heterogeneous effects.

3.3. Variable Definitions

The explained variable is the green high-quality development (GHD) of the apple industry. Drawing on the policy orientations and core requirements of the National Sus-

tainable Agricultural Development Plan (2015–2030) [35] and the Green Development Indicator System, GHD is anchored by the ecological environment carrying capacity and pursues the coordinated balance of economic and ecological benefits. Following established methods for constructing industry-level green development indicator systems, three first-tier dimensions and ten second-tier indicators are selected to build the evaluation system (Table 1): resource conservation, environmental friendliness, and production efficiency. The entropy-weighted TOPSIS method is then used to compute a composite index of GHD for the apple industry across 31 Chinese provinces. Resource conservation captures the optimization of factor allocation and the improvement in resource-use efficiency so that optimal industrial output is achieved with the lowest resource consumption. Water-saving irrigation area, agricultural water use, rural electricity consumption, and agricultural diesel consumption are used to characterize this dimension. Environmental friendliness is the core principle of green agriculture, emphasizing the harmony between agricultural activities and natural ecosystems. In large-scale apple production, chemical fertilizers, pesticides, and agricultural plastic films are key inputs for securing yield and quality, but their excessive use triggers nonpoint source pollution and damages the ecological balance of producing areas. The consumption of chemical fertilizers, pesticides, and agricultural plastic films therefore measures both the environmental impact of apple production factor use and the level of ecological compatibility. Production efficiency is the fundamental support and endogenous driver of GHD in the apple industry, reflecting industrial production efficiency and farmer income. Apple yield per unit area, per capita apple output, and land productivity are used to evaluate province-level production performance and output.

The treatment variable is agricultural new quality productive forces (ANQPFs). Under ANQPFs, agricultural laborers, means of labor, and objects of labor gradually transition from "traditional" to "new quality" forms. This transition is reflected in higher-quality laborers, more technology-intensive means of labor, and a wider scope of objects of labor [36]. Drawing on established studies, the ANQPF evaluation indicator system is constructed from three dimensions: new agricultural laborers, new means of labor, and new objects of labor (Table 2), and the development level across 31 provinces is computed via the entropy-weighted TOPSIS method. New agricultural laborers are the agents driving ANQPFs. Following Zhu and Ye [37], they are captured from the perspectives of innovation and entrepreneurship activity and rural residents' educational attainment. Entrepreneurship activity is measured by the China Regional Innovation Capability Composite Index. Educational attainment uses per capita years of schooling for rural residents and the share of rural residents with higher education. New means of labor are the driving force for ANQPF development. Following Liu et al. [38], they are captured through network infrastructure, digital production tools, and science and technology R&D. Network infrastructure is represented by the number of agricultural meteorological observation stations. Digital production tools are represented by rural mobile phone penetration, rural computer penetration, and the number of agricultural intelligent aerial vehicles. Science and technology R&D is represented by agricultural R&D investment intensity. New objects of labor are the material carriers of ANQPFs. Data on the expanded scope of new objects of labor are difficult to obtain, so they are captured from three aspects: new agricultural energy, new materials, and new business forms. The number of solar water heaters and the number of agricultural plant variety rights applications capture new energy and new materials, respectively. Following Yang and Wang [39], organic agriculture represents the quality and level of agricultural product development and is used to characterize new business forms.

The mechanism variables are agricultural socialized services (ASSs) and agricultural green innovation (AGI). Following Liu et al. [40], ASS captures the supply capacity and development scale of regional agricultural socialized services, measured as the ratio of

the gross output value of agricultural services to the number of agricultural employees. The gross output value of agricultural services is approximated by multiplying the total output value of agriculture, forestry, animal husbandry, and fishery services by the share of agricultural output in that total. The number of agricultural employees is computed analogously. AGI captures the composite level of regional agricultural green technology R&D, commercialization, and application promotion. It is measured by the total annual number of agricultural green patent applications (including invention and utility-model patents) in each province and log-transformed to mitigate heteroscedasticity [8,9].

To avoid bias from omitted variables, and drawing on established studies [41,42], six controls are included: the degree of opening-up, urbanization level, industrial structure, social consumption level, government fiscal support, and fiscal support for agriculture. The degree of opening up is measured as the ratio of total import–export value to regional GDP. Urbanization level is measured as the ratio of urban population to year-end resident population. Industrial structure is measured as the share of tertiary industry value added in regional GDP. Social consumption level is measured as the ratio of total retail sales of consumer goods to regional GDP. Government fiscal support is measured as the ratio of general budgetary expenditure to regional GDP. Fiscal support for agriculture is measured as the share of agriculture, forestry, and water affairs expenditure in general public budget expenditure. It enters as a core control in every specification because government spending on agriculture is a first-order determinant of both the accumulation of new quality productive forces and the green transition of orchards. Following the standard practice of absorbing fixed effects through the covariate set when nuisance functions are fitted nonparametrically, province and year dummy variables are included in the high-dimensional control set X of every model estimated in this paper. Province fixed effects and year fixed effects are thereby held constant throughout the baseline estimation, the robustness checks, and the heterogeneity analysis. Variable definitions and descriptive statistics are summarized in Table 3.

Table 3. Variable definitions and descriptive statistics.

Type	Name	Definition	Mean	Std. Dev.
Explained	Apple industry GHD	Composite index by entropy-weighted TOPSIS	0.1842	0.1739
Treatment	ANQPF	Composite index by entropy-weighted TOPSIS	0.2383	0.1690
Mechanism	ASS	Ratio of agricultural services output to agricultural employees	0.2730	0.2108
	AGI	Log of agricultural green patent applications	5.7696	1.2992
Control	Opening up	Total import–export value/regional GDP	0.2646	0.2898
	Urbanization level	Urban population/year-end resident population	0.5969	0.1292
	Industrial structure	Tertiary industry value added/regional GDP	0.4855	0.0962
	Social consumption level	Total retail sales of consumer goods/regional GDP	0.3771	0.0689
	Government fiscal support	General budgetary expenditure/regional GDP	0.2791	0.2041
	Fiscal support for agriculture	Agriculture, forestry, and water affairs expenditure/general public budget expenditure	0.1146	0.0344

Notes: The sample comprises 403 province–year observations (31 provinces over 2011–2023). GHD = green high-quality development; ANQPF = agricultural new quality productive force; ASS = agricultural socialized service; AGI = agricultural green innovation.

4. Empirical Results

4.1. Baseline Estimation

The direct effect of ANQPFs on the GHD of the apple industry is estimated using the partially linear DML model with the random forest algorithm and threefold cross fitting. The baseline result is reported in Table 4. The ANQPF coefficient on the GHD of the apple industry is 0.1491 and is significantly positive at the 1% level. Because ANQPF and GHD are both entropy-weighted TOPSIS composite indices, a one-unit change has no direct economic interpretation, so the estimate is also expressed in standardized terms. With sample standard deviations of 0.1690 for ANQPF and 0.1739 for GHD, a one-standard-deviation increase in ANQPF is associated with an increase of 0.0252 points in the GHD index, i.e., about 0.14 of a standard deviation of GHD. Equivalently, moving the ANQPF level across its interquartile range is associated with a 0.0295-point change in GHD, or about 0.17 standard deviations. This result supports H1 and indicates that cultivating ANQPFs can effectively promote the transformation and upgrading of the apple industry. The underlying reason for this is that ANQPFs center on new agricultural technologies, green production factors, and modernized operating models. By reshaping the traditional cultivation model and improving the input–output structure of orchards, these elements move the apple industry beyond extensive yield expansion toward green, efficient, and sustainable development, ultimately raising the GHD level of the apple industry.

Table 4. Baseline regression results.

Variable	GHD of the Apple Industry
ANQPF	0.1491 *** (0.0443)
Controls	Yes
Province FE	Yes
Year FE	Yes
Observations	403

Notes: Robust standard errors in parentheses. *** denotes significance at the 1% level. The same conventions apply to the tables below. FE = fixed effect; "Yes" indicates that the corresponding fixed effects or control variables are included in the estimation.

4.2. Robustness Checks and Endogeneity Discussion

Robustness checks are conducted along three dimensions: extreme values, the cross fitting partition, and the choice of base learner. Extreme observations may bias the estimates. All continuous variables other than the core regressor are therefore winsorized, and the DML model is re-estimated at the first and fifth percentiles. Under 1% winsorization (column (1a) of Table 5), the ANQPF coefficient is 0.1483 and remains significant at the 1% level. Under the milder 5% winsorization (column (1b) of Table 5), the coefficient is 0.1928, highly consistent with the baseline. The conclusion is thus not driven by extreme values and is not sensitive to the trimming threshold. DML estimates may also be affected by the sample-splitting proportion. The threefold cross-validation of the baseline is therefore changed to fivefold, and the model is re-estimated. The effect of ANQPFs on the GHD of the apple industry remains significantly positive at the 1% level (column (2) of Table 5), which confirms the robustness of the model estimates. Different machine learning algorithms may also differ in their ability to fit high-dimensional data. The random forest algorithm of the baseline is accordingly replaced with the lasso and support vector machine (SVM) algorithms. As columns (3a) and (3b) of Table 5 show, the positive effect of ANQPFs on the GHD of the apple industry is significant at the 1% level regardless of the algorithm. The model's nonlinear fitting result is therefore robust and free of algorithm selection bias. Beyond these estimation choices, because the GHD index rests on the apportionment

assumption discussed in Section 3.1, the baseline is also re-estimated on an alternative index built exclusively from the three indicators that require no apportionment: apple yield per hectare, per capita apple output, and output value per hectare. That index ranks province–year observations almost identically to the baseline index (Spearman $\rho = 0.99$). The ANQPF coefficient is 0.1953 (standard error, 0.0574; $p = 0.001$), remaining positive and significant in 19 of the 20 random seeds examined (at the 10% level in all 20). The estimated relationship is therefore not an artifact of the way that agricultural inputs are apportioned to the apple industry.

Table 5. Robustness checks and endogeneity treatment.

Variable	(1a) 1% Winsorization	(1b) 5% Winsorization	(2) 5-Fold CV	(3a) Lasso	(3b) SVM	(4) DDML IV
ANQPF	0.1483 ***	0.1928 ***	0.1609 ***	0.1368 ***	0.1723 ***	0.1873 ***
	(0.0448)	(0.0545)	(0.0538)	(0.0469)	(0.0408)	(0.0636)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	403	403	403	403	403	372

Notes: CV = cross-validation; lasso = least absolute shrinkage and selection operator; SVM = support vector machine; DDML IV = double/debiased machine learning instrumental variable estimator. The number of observations in column (4) decreases from 403 to 372 because the DDML IV estimation uses the one-period-lagged ANQPF as the instrumental variable; the one-period lag removes the first sample year (2011), leaving 31 provinces × 12 years = 372 province–year observations. *** denotes significance at the 1% level; robust standard errors are reported in parentheses.

It is worth being explicit about what each estimator identifies. The DML estimates reported below remove the biases that arise when the treatment or the outcome depends nonlinearly on the observed covariates, but DML by itself does not address confounding from unobserved variables. The causal content of the estimates therefore rests on the assumption that, conditional on the control set, unobserved confounders are absent, supplemented by the instrumental variable strategy discussed below. Where that assumption is questionable, the estimates should be read as associations that are robust to flexible functional-form dependence on the observed control set rather than as effects identified against arbitrary unobserved confounding.

To mitigate endogeneity from reverse causality and omitted variables, the partially linear instrumental variable model in the double machine learning framework is further employed. Following established studies, the first lag of the core regressor serves as the instrument. The previous period ANQPF level strongly predicts the current period ANQPF level, so the relevance condition holds. The exclusion restriction, however, deserves a more careful argument than timing alone provides. The timing rules out reverse causality because the current period GHD is unlikely to affect the ANQPF level of the previous period. Lagged ANQPF may still affect current period GHD through channels that persist over time, including technical infrastructure, accumulation of human capital, innovation capacity, and investment inertia built up in earlier periods. The exogeneity assumption is therefore credible only to the extent that the control set absorbs these persistent channels. Three pieces of evidence support the instrument. Its relevance is confirmed by a first-stage coefficient of 0.6722 (standard error, 0.0609), corresponding to an F statistic of about 122, far exceeding the empirical threshold of 10; thus, the instrument is not weak. Replacing the instrument with the second lag of ANQPF yields a coefficient of 0.3207 (standard error, 0.0933), of the same sign as the baseline, and the reduced form regression of current GHD on lagged ANQPF yields 0.1501 (standard error, 0.0523). A falsification exercise that adds the one-period-ahead lead of ANQPF to the outcome equation leaves the current period

coefficient broadly comparable in magnitude while the lead itself is statistically insignificant (current period coefficient, 0.1163; standard error, 0.0995). This pattern is inconsistent with forward-looking behavior in GHD that would violate timing-based exclusion. With these caveats in mind, column (4) of Table 5 shows that, after addressing potential endogeneity, the ANQPF coefficient is 0.1873, positive and of a magnitude close to the baseline estimate. The IV result is accordingly read as evidence that the baseline association is not driven by the most obvious forms of reverse causality or omitted-variable bias rather than as a definitive causal estimate.

4.3. Mechanism Analysis

To trace the transmission paths through which ANQPFs affect the GHD of the apple industry, the two-step testing logic of Jiang [34] is followed, and both stages of each candidate channel are estimated separately with the DML model (random forest algorithm, threefold cross fitting). The first stage regresses the mediator on ANQPFs. The second stage regresses GHD on the mediator conditional on ANQPF. A complete mediation path is thereby identified rather than only its first half. In Table 6, columns (1) and (2) report the first stage for agricultural socialized services (ASSs) and agricultural green innovation (AGI, entered in logarithms to limit the influence of its right skew). Column (3) reports the second stage before the ANQPF level is controlled, and column (4) reports the second stage conditional on ANQPF. Together with the first stage, the last two columns deliver the indirect effect (a × b) for each channel. Because the mechanism analysis decomposes a conditional association rather than the causal parameter targeted by the baseline model, it is estimated without absorbing province and year fixed effects. Absorbing them would purge most of the within-mediator variation on which the second stage depends.

Table 6. Mechanism test results.

Variable	(1) ASS	(2) AGI	(3) GHD of the Apple Industry	(4) GHD of the Apple Industry
ANQPF	0.2730 *** (0.0874)	1.7036 *** (0.3027)	0.1359 ** (0.0592)	
ASS			0.1443 *** (0.0408)	0.1384 ** (0.0567)
AGI			0.0446 *** (0.0112)	0.0482 *** (0.0130)
Indirect effect			0.0378 * (z = 1.92)	0.0821 *** (z = 3.10)
Mediator controlled			Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	403	403	403	403

Notes: ASS = agricultural socialized service; AGI = agricultural green innovation, entered as ln (1 + green patent applications) in column (2) and in the second stage. Columns (1) and (2) report the first stage of the mediation path (mediator regressed on ANQPF); columns (3) and (4) report the second stage (GHD regressed on the mediator), where column (4) additionally controls for ANQPF. The indirect effect in the last row is the product of the two stages, a × b, with the Sobel standard error; the z statistic is reported in parentheses. The mechanism analysis is estimated without province and year fixed effects because absorbing them would remove the within-mediator variation needed to identify the second stage. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively; robust standard errors are reported in parentheses.

The first-stage estimates show that the ANQPF level significantly predicts both mediators. For ASS, the ANQPF coefficient is 0.2730 and is significant at the 1% level. A higher level of new quality productive forces therefore strengthens the socialized service system of the apple industry and speeds the diffusion of contracted orchard management, unified pest and disease control, smart orchard management, and cold-chain logistics. The ANQPF coefficient on AGI is 1.7036 and is likewise significant at the 1% level. Cultivating ANQPFs thereby advances green technology research and development, upgrades green production processes, and diffuses low-carbon production models across apple-producing

areas. The second-stage estimates then confirm that both mediators are associated with GHD. Conditional on the ANQPF level, the ASS coefficient on GHD is 0.1384 (significant at the 5% level) and the AGI coefficient on GHD is 0.0482 (significant at the 1% level). When the ANQPF level is not controlled, the corresponding coefficients are 0.1443 and 0.0446, both significant at the 1% level, so the second stage does not depend on the inclusion of the treatment. Multiplying the two stages yields an indirect effect of 0.0378 through ASS ($z = 1.92$, significant at the 10% level) and of 0.0821 through AGI ($z = 3.10$, significant at the 1% level). Relative to the total effect of 0.1359, the two channels account for approximately 28% and 60% of the estimated effect, respectively. Across 20 random seeds, the indirect effect through ASS remains positive in every draw and significant at the 10% level in all of them, and the indirect effect through AGI remains positive and significant at the 5% level in all of them. The mediation result is therefore not an artifact of a particular cross fitting partition. Both channels are supported as complete transmission paths: ANQPFs raise the levels of specialized service provision and of green innovation capacity, and each of these is, in turn, associated with a higher level of green high-quality development in the apple industry. Hypothesis H3, that ANQPFs promote the GHD of the apple industry by developing agricultural socialized services, and Hypothesis H2, that they do so by raising the level of agricultural green innovation, are both supported.

4.4. Heterogeneity Analysis

Although the foregoing analysis confirms that ANQPFs generally promote the GHD of the apple industry, China's regions differ substantially in resource endowment, economic foundation, and industry-support conditions. The effect of ANQPFs may therefore exhibit regional divergence. Subsample heterogeneity tests are conducted along two dimensions: geographic region and urbanization level. The regression results are reported in Table 7.

Table 7. Heterogeneity analysis results.

Variable	Eastern	Central	Western	High Urbanization	Low Urbanization
ANQPF	0.1132 ** (0.0562)	0.0036 (0.0316)	0.0558 (0.0781)	0.1229 ** (0.0533)	0.0861 (0.0602)
Controls	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	143	104	156	208	195

Notes: The eastern, central, and western regional classifications follow standard provincial groupings used in Chinese regional studies; the urbanization cutoff uses the annual median provincial urbanization rate. ** denotes significance at the 5% level; robust standard errors are reported in parentheses.

The two contrasts in Table 7 share a logic that the literature on sustainability transitions makes explicit: technological capability does not convert into environmental outcomes by itself. Comparative evidence from sustainable production shows that identical technology packages yield different sustainability outcomes across production units because governance arrangements, service-chain coordination, financial support, and outsourcing combine in different ways and no single condition is necessary on its own [43]. The adoption literature reaches a similar conclusion from the farm side. Digital tools raise green production performance only where farmers have the digital skills and knowledge to use them, not merely where the tools are available [44]. The rural digital divide in China operates through differential access and differential use alike, with measurable economic consequences [45]. The coefficients below are therefore read not as evidence that ANQPFs are intrinsically stronger in some regions but as evidence that their green payoff is institutionally contingent.

It is realized where digital infrastructure, extension capacity, market development, and the organization of socialized services have matured enough to absorb advanced factors into routine orchard practice, and it stays latent where they have not.

In the eastern region, the ANQPF coefficient is 0.1132, significantly positive at the 5% level. In the central region, the coefficient is 0.0036 and statistically indistinguishable from zero, and in the western region, it is 0.0558 and likewise insignificant. Once province and year fixed effects are held constant, the cross-regional differences that appear in unconditional comparisons narrow substantially. This narrowing is itself informative: much of the apparent east–west gap in the effect reflects persistent provincial characteristics rather than the current ANQPF level. A plausible reading is that the eastern region combines a higher level of economic development, more complete digital infrastructure, stronger green technology R&D capacity, and a more developed market for agricultural socialized services and can therefore rapidly translate ANQPF factors into green production drivers in orchards. The central region has a certain industrial absorption base, so a weak positive association remains, but it is estimated imprecisely and cannot be distinguished from zero. The western region is constrained by economic conditions, talent reserves, and technology extension systems, so the potential of ANQPFs has not yet materialized and their driving effect on the GHD of the apple industry is not yet evident. The constraint in the west is better described as compound than as purely economic. Orchard IoT and traceability systems presuppose network coverage and cold-chain logistics that remain uneven across western production areas, while the digital and green production skills needed to operate them are scarcer. Equipment can be installed through fiscal investment within a single planning cycle, whereas skills and service organizations accumulate slowly, so the use-side gap is the more persistent of the two [44,45]. These interpretations are consistent with the literature rather than separately identified in the data. Isolating infrastructure from skills would require province–year measures that are not observed directly, and the distinction is therefore treated as an interpretive frame rather than a tested mechanism.

The annual median of provincial urbanization rates over the sample period serves as the cutoff. Provinces with urbanization rates above the median in a given year are classified as the high-urbanization group, and those below the median are categorized as the low-urbanization group. Subsample regressions show that the ANQPF coefficient in the high-urbanization group is 0.1229 and is significantly positive at the 5% level, while in the low-urbanization group, the coefficient is 0.0861 and does not display statistical significance. The contrast is therefore one of statistical precision rather than of sign. Both groups show a positive point estimate, but only in the high-urbanization group is the effect estimated precisely enough to be distinguished from zero. In regions with higher urbanization, urban–rural factor flows are smoother, and it is easier to agglomerate high-quality resources such as S&T talent, digital platforms, and green services. Growers gain more convenient access to green technology and contracted management services, so the conditions for ANQPFs to advance the green transformation of apples are more mature. Low-urbanization regions have a weaker factor aggregation capacity, and in these regions, the absorption of advanced production factors is hampered; thus, ANQPFs have not yet exerted a significant effect. These provinces accordingly face a compound constraint: fewer specialized service providers, thinner technical extension capacity, and a smaller pool of operators with the digital literacy that the technologies bundled into ANQPFs presuppose, even where physical infrastructure is being upgraded [44].

Overall, the heterogeneity test results indicate that the driving effect of ANQPFs on the GHD of the apple industry is not homogeneous. The effect is best identified in eastern regions and in provinces with high urbanization rates, whereas in central and western regions and in low-urbanization provinces, the estimates remain positive in sign but too

imprecise to be distinguished from zero. This pattern suggests that the promotion of green transformation in the apple industry should proceed through differentiated policies. Underlying it is a more fundamental point: ANQPFs are not a self-actuating driver of green transformation. Its payoff is institutionally contingent and materializes only where the complementary conditions that allow technology to be organized into routine orchard practice are already in place. The central and western regions and the low-urbanization provinces are therefore better understood not as slow adopters of technology but as economies in which those complementary conditions have not yet matured. For these areas, the priority is to close the remaining gaps in infrastructure and public services, remove obstacles to the absorption of advanced factors, and gradually release the green potential of ANQPFs.

5. Conclusions and Policy Implications

This paper uses a balanced panel of 31 Chinese provinces from 2011 to 2023 and applies the double/debiased machine learning model to examine how agricultural new quality productive forces promote the green high-quality development of the apple industry. Three main conclusions emerge. ANQPFs significantly promote the GHD of the apple industry, and the core conclusion remains stable after multiple robustness checks. Agricultural socialized services and agricultural green innovation operate as two transmission channels through which ANQPFs affect the GHD of the apple industry. Both stages of each path are estimated. ANQPFs raise the level of agricultural socialized services and the level of regional agricultural green innovation. Each mediator is, in turn, significantly associated with GHD. The resulting indirect effects are 0.0378 through agricultural socialized services and 0.0821 through agricultural green innovation. The mediation evidence is therefore complete rather than first-stage only. Moreover, the effect of ANQPFs on the GHD of the apple industry is heterogeneous across regions. Once province and year fixed effects are controlled, the effect remains statistically significant in the eastern region and in high-urbanization provinces. The estimates for the central and western regions and for low-urbanization provinces are positive in sign but too imprecise to be distinguished from zero. The overall effect is thus constrained by regional resource endowments and urbanization conditions. The green payoff of ANQPFs is institutionally contingent rather than automatic. Where complementary infrastructure, extension capacity, and service organizations are thin, the same technological capability does not translate into observable green outcomes.

In economic terms, the estimated effect is moderate rather than large. Recent calibrated benchmarks correspond to roughly 0.27 standard deviations for new quality productive forces and agricultural green production efficiency [46] and about 0.62 standard deviations for the digital economy and agricultural green total factor productivity [47]. Against these benchmarks, the standardized estimate in this paper, about 0.14 standard deviations of GHD per standard deviation of the ANQPF level, sits at the conservative end of values in the literature. The gap is plausible, given the focus on a single specialty crop and the conservative nature of double/debiased machine learning estimation, yet the effect still represents a substantive change for a sector as traditional as apple growing.

Based on these conclusions, the following policy implications are proposed:

- ANQPFs should be continuously cultivated in the main apple-producing areas to strengthen the foundation for green and high-quality industrial development. S&T resource investment across the entire apple industry chain should be increased, focusing on green orchard production, smart orchard management, and the recycling of orchard waste. The agricultural technology extension service system should be improved, and digital and green factors should be effectively integrated into apple production to fully realize the overall driving efficiency of ANQPFs.

- The benefits of ANQPFs should also be realized by leveraging green innovation and socialized services in tandem. Support for green technology R&D, demonstration, and commercialization should be strengthened, and apple industry entities should be encouraged to improve varieties and develop and apply green cultivation technologies. In parallel, the supply of socialized services should be expanded, with green pest control, contracted orchard management services, and technical advisory services as priorities, so that innovation and services jointly connect the middle links through which ANQPFs affect the GHD of the apple industry.
- Differentiated policies should likewise be implemented to address the uneven regional effect. Eastern and high-urbanization apple-producing areas should build on the existing industrial foundation to create smart and green orchard demonstration models and radiate the demonstration effect. Central areas should continue to improve industrial support and expand the coverage of green technology and socialized services. For western apple-producing areas and low-urbanization regions, fiscal, talent, and digital infrastructure investment should be increased to close development gaps and remove obstacles to the absorption of advanced production factors. These measures would gradually release the latent potential of ANQPFs and narrow the regional gap in the green and high-quality development of the apple industry.
- In designing such differentiated measures, it is useful to distinguish two gaps that call for different instruments. The access-side gap covers network coverage, cold-chain logistics, and the physical conditions on which orchard IoT and traceability systems depend. Targeted infrastructure investment can narrow this gap relatively quickly, so it should be the first priority in western production areas. The use-side gap, namely, growers' digital literacy, the supply of specialized technical personnel, and the density of service organizations, accumulates slowly and cannot be purchased outright. In low-urbanization provinces, this gap is therefore best addressed through the extension system and through socialized service providers. One option is to embed digital and green training in the service contracts that orchards already sign. Another is to encourage service organizations to operate and maintain equipment that individual smallholders cannot. Where both gaps are present, the sequence matters. Infrastructure that no local organization is equipped to use will not change orchard practice. Public investment is therefore best bundled with the cultivation of local service providers rather than disbursed on the assumption that adoption follows installation.

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