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Research article

Does farmland inflow improve the green total factor productivity of farmers in China? An empirical analysis based on a propensity score matching method

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A R T I C L E I N F O

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A B S T R A C T

Promoting the "double security" of agricultural economy and ecology is the key to the agricultural modernization strategy, and the large-scale development of agriculture is an essential way for modern agriculture. Based on the micro-survey of 697 corn growers from August to September 2020 in China, the super-efficiency SBM model was used to calculate farmers' green total factor productivity. We further used the propensity score matching method to identify the impact of farmland inflow on farmers' green total factor productivity and dissect the internal mechanism. The study found that: firstly, compared with the non-inflowed households, the green total factor productivity of the inflowed households increased by 14.66%; secondly, farmland inflow can significantly improve farmers' green total factor productivity through the marginal output leveling effect, transaction benefit effect, and technology adoption effect; thirdly, the influence of farmland inflow on the green total factor productivity of farmers has heterogeneity in age, identity, and geographical location. Therefore, governments should establish a differentiated farmland inflow mechanism according to local conditions, enhance factor mobility and soil fertility monitoring capabilities, and drive a "win-win" between economic development and ecological protection.

1. Introduction

Agricultural modernization requires constructing a high-yield, high-quality, low-consumption agricultural production system and an agricultural ecosystem with reasonable resource allocation, timely environmental protection, and high conversion efficiency [1–3]. With the steady and rapid development of agriculture, the gross agricultural product has continued to rise in recent years. However, after the Lewis turning point, the successful practice of increasing farmers' income did not change the traditional development mode and improve the efficiency of agricultural production [4]. Such a vicious circle has become one of the obstacles to the development of agricultural modernization. At present, China's agricultural development has entered a new stage. Promoting green and high-quality development is the ultimate goal of agricultural ecological transformation. This puts forward new requirements for the high-quality development of agriculture and the environment. As an important part of realizing agricultural ecology, farmland inflow aims to improve green production efficiency in the process of agricultural transformation through large-scale and intensive management, thereby promoting agricultural modernization and ecological transformation [5,6]. Agricultural modernization and high-quality

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development need to improve the enthusiasm of farmland inflow, boost green total factor productivity with large-scale operation, and realize the "double security" of the agricultural economy and ecology [7]. Therefore, it is of great theoretical and practical significance to investigate the impact of farmland inflow on farmers' green total factor productivity.

Agricultural green total factor productivity is a crucial index to measure the "double security" of agricultural economy and ecology [8–10]. The maximum output efficiency reduces the pollution emissions of agricultural products as much as possible while achieving the maximum output of agricultural production given the input factors of agricultural production [11,12]. Academic circles have intensely discussed agricultural green total factor productivity throughout the existing literature. One is the measurement of agricultural green total factor productivity. Measurement methods are generally divided into parametric methods, such as the Cobb-Douglas production function method, transcend logarithmic production function method, and non-parametric methods, such as the non-radial SBM model and GML index [10,13–16]. Many studies use non-parametric methods to measure agricultural green total factor productivity. Second, the spatial and temporal differences and dynamic evolution of agricultural green total factor productivity. Based on the agricultural green total factor productivity measurement, existing studies have focused on temporal and spatial differences and dynamic evolution. The research found that agricultural green total factor productivity is consistent with the changing trend of agricultural Gross Domestic Product, with temporal differences and spatial agglomeration lag [10,17,18]. They strengthen regional linkage and promote regional green agriculture coordination and high-quality development [19]. Third, the influencing factors of agricultural green total factor productivity. Existing research and future directions are devoted to exploring the influencing factors of agricultural green total factor productivity and, based on this, exploring feasible strategies for improving quality and efficiency. The study found that crop insurance, technological progress, and environmental regulation positively stimulate agricultural green total factor productivity [20–22]. Climate factors such as air pollution and extreme weather have a negative impact on agricultural green total factor productivity, so it is urgent to deal with climate risks [20,23]. But there is no consensus on the impact of rural finance and carbon trading on agricultural green total factor productivity [24–28]. Therefore, the literature on measuring agricultural green total factor productivity and exploring spatial and temporal differences have been relatively complete. And subsequent research needs to focus on the influencing factors to explore the driving factors for improving agricultural green total factor productivity.

Farmland inflow is related to the scale, intensification, and modernization of agriculture, which is conducive to promoting the transformation of farmland resources from low-efficiency and low-value to high-efficiency and high-value, and effectively improving agricultural green total factor productivity. However, with the continuous improvement of the scale of farmland transfer and the increasingly diverse objects of farmland inflow, China's farmland inflow is facing a big problem. For example, the trading market is not sound, the risk protection system is not perfect, the supervision is not up to standard, the people's enthusiasm is not high, and the behavior is not standardized. The problem has greatly affected the orderly implementation of China's rural land transfer work. Therefore, to realize the development of agricultural modernization, solve the problem of low agricultural green total factor productivity, and promote the unified coordination of agricultural production efficiency and ecological protection, the focus is on building and improving the farmland inflow system. On the one hand, farmland inflow optimizes the allocation of agricultural factors and improves agricultural production efficiency through large-scale operations. Also, establishing a proper contract form can effectively solve the problems of farmland inflow barriers, contract instability, and high transaction costs, and improve agricultural production efficiency [29,30]. The view that farmland inflow promotes agricultural production efficiency is recognized by the academic community. On the other hand, based on the reallocation of agricultural production factors, most experts pointed out that farmland inflow has a significant role in promoting the agricultural ecological environment [31–33]. A few experts pointed out that the impact of farmland inflow on agricultural ecological environment is not significant [34].

Combing the literature, we can see that the academic research on farmland inflow and agricultural green total factor productivity provides a solid theoretical basis and empirical reference for this paper. However, it is still necessary to explore the impact on agricultural green total factor productivity from the perspective of farmland inflow. Therefore, the marginal contribution of this paper has three aspects. Firstly, in terms of research subjects, we measure agricultural green total factor productivity from the perspective of farmers. Farmers' agricultural green total factor productivity is an essential part of agricultural green total factor productivity. The research on agricultural green total factor productivity at the farmer level is relatively insufficient. Secondly, from the perspective of research, we bring the economic and ecological effects of farmland inflow into the comprehensive analysis framework to enrich the effectiveness and detailed verification of farmland inflow policies. The existing research focuses on the economic effect of farmland inflow or the ecological impact of farmland inflow, which is not included in the analysis framework simultaneously. Thirdly, in terms of research methods, based on the propensity score matching method, we built a model of the impact of farmland inflow on farmers' green total factor productivity to solve the sample selection bias. The research on the effects of farmland inflow on farmers' green total factor productivity ignores the selection bias and endogenous problems in the decision-making of farmland inflow.

Therefore, based on the micro-investigation data of 697 corn farmers in China in 2020, we use the super-efficiency SBM model to calculate the green total factor productivity of farmers. Then we further use the propensity score matching method to identify the impact of farmland inflow on farmers' green total factor productivity, and propose corresponding strategies for economic-ecological coordination and win-win.

2. Theoretical analysis

Based on the theory of the optimal allocation of resources, farmers realize the rational allocation of factor resources through the inflow of farmland in the allocation market of agricultural production factors. To reallocate the derived resources of other agricultural production factors and guide labor empowerment, capital empowerment, and technology empowerment. To be specific, the liberalization and improvement of farmland inflowed to market can promote the rational flow of farmland resources among operators and rationally allocate agricultural production factors through the marginal output flattening effect, the transaction benefit effect, and the technology adoption effect [35]. It will help improve the agricultural factor allocation market, bring into play the economic and ecological dual effects of agricultural production efficiency and ecological protection, and improve agricultural green total factor productivity from the farmers' perspective.

First, farmland inflow improves farmers' green total factor productivity through the marginal output flattening effect. The marginal product leveling effect refers to renting farmland resources from those with lower marginal products to those with higher marginal products so that the marginal products are equal. By leveling marginal output, farmland inflow promotes the transfer of labor force so that the cultivation experts with high planting management technology, agricultural production efficiency, and profitability continue to expand the scale, forming the farmland scale operation effect [36]. Thus, producing new agricultural production and management main body, realize farmer's production efficiency to improve steadily. Under the institutional environment, the government departments will incline agricultural subsidies and training to new agricultural production and operation entities. It enables farmers with funds and professional knowledge to continuously improve the inefficient, traditional farming mode, improve the way of farmland use, strengthen green modern agricultural management, improve agricultural productivity and sustainability, and improve farmers' green total factor productivity based on improving agricultural production efficiency.

Second, farmland inflow improves farmers' green total factor productivity through the transaction benefit effect. The free inflow of farmland has improved the income of investment transactions and indirectly stimulated farmers' enthusiasm for land investment, which can be called the "transaction benefit effect". In short, the transaction benefit effect is the incentive of the farmland market for farmers' farmland investment [37]. Therefore, as the participation in the farmland inflow market continues to increase, farmers have more information, and the transaction costs of farmland inflow search, negotiation, and contract performance are reduced, breaking the transaction barriers between the lessor and the lessee [38]. It is easier for farmers to obtain better-quality farmland, better soil fertility and more sustainability. The farmland transaction cost saved by farmers can be used to improve farmland production efficiency, invest in green agriculture, help increase agricultural output, and reduce production risks. Further, it can enhance the quality of the agricultural ecological environment and improve farmers' green total factor productivity.

Third, farmland inflow improves farmers' green total factor productivity through the technology adoption effect. According to the theory of induced technological change, farmland inflow will lead to large-scale operation, reduce the average cost of technology adoption by farmers, and improve the initiative of technology adoption [7]. In this regard, farmers who have inflowed their farmland can receive full support from the government, agricultural enterprises and other departments for agricultural subsidies, business demonstrations, and advanced technology training. The total penetration of social services, such as agricultural subsidies and training, has also reduced the technical barriers brought about by farmers' purchasing power constraints. And it ensured that farmers could adopt advanced technologies such as conservation farming technology and green production technology. In addition, large-scale farmers face higher requirements of government supervision and market supervision, encouraging farmers to seek green technologies and participate in promotion and demonstration actively. Implementing the sustainable concept of science and technology to feedback agricultural economic and ecological development will help farmers improve quality and efficiency in agricultural production and operation and improve farmers' green total factor productivity. Fig. 1 shows the impact mechanism.

Accordingly, the research hypothesis is put forward

H1 Farmland inflow will increase the green total factor productivity of farmers.
H2 Farmland inflow promotes farmers' green total factor productivity through the marginal output flattening effect, transaction benefit effect, and the effect of technology adoption.

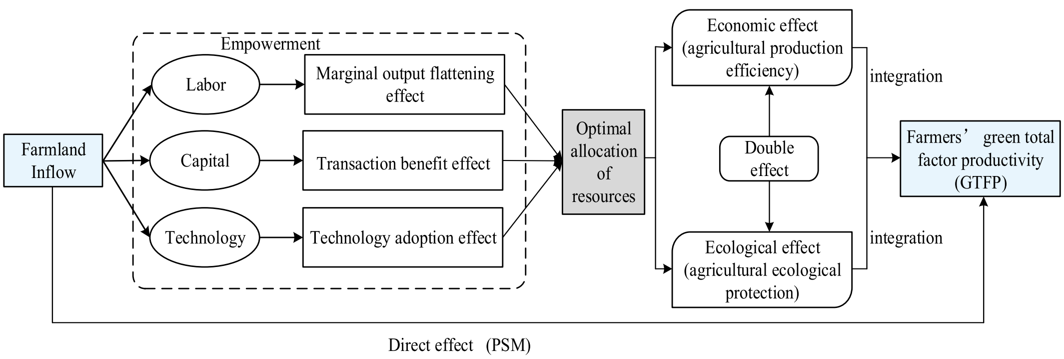

Fig. 1. Impact mechanism.

3. Materials and methods

3.1. Data sources

The data are from the rural special public survey carried out by the research group of Northwest A&F University on "Ecological Protection of the Yellow River Basin and High-Quality Development of Agriculture and Rural Areas" in China from August to September 2020. To ensure the representativeness of the survey sample, this paper adopts the method of combining random sampling and stratified sampling. According to the distribution along the Yellow River Basin, 2–5 sample townships are firstly selected from the sample counties, and then 2–5 sample villages are randomly selected in the sample townships, and 10–25 sample villages are randomly selected for each village. In this survey, a total of 718 questionnaires for corn farmers were distributed. Invalid questionnaires, such as information contradictions and missing data, were excluded, and 697 questionnaires were collected from farmers, with an effective rate of 97.08%. The farmer household questionnaire survey involves basic information on farmer households, household assets, production and operation conditions, income and expenditure in 2019, and ecological livability. The village questionnaire mainly includes the essential characteristics of the village and the development of rural industries, ecological livability, etc. It adopts the form of household interviews with investigators, focusing on interviews with village cadres, heads of professional cooperatives, etc.

3.2. Model building

3.2.1. Decision-making equation

U_{1i} and U_{0i} represent the utility of the farmer *i* inflowed and not inflowed, and the difference between the two is $R_i^* = U_{1i} - U_{0i}$. The farmers will inflow into farmland, that is $R_i^* = 1$; On the contrary, it means that farmers will not inflow into farmland.

This paper assumes that the equation for farmers' participation in farmland inflow is:

$$R_i^* = \psi(x) + \varepsilon \tag{1}$$

In Eq. (1), R_i^* indicates whether the farmer has inflowed into farmland; x represents the factors that affect the farmer's participation in the decision-making of farmland inflow; ε is the random error term.

To measure the effect of farmland inflow on the green total factor productivity of farmers, this paper sets the green total factor productivity equation of farmers as follows:

$$Y_i^* = \varphi(Z) + \lambda R_i + \delta \tag{2}$$

In Eq. (2), Y_i^* is the green total factor productivity of farmers; Z is the exogenous explanatory variable that affects the green total factor productivity of farmers, R_i is the variable that farmer *i* inflows into farmland, and δ is the random disturbance term.

It should be noted that because some farmers have good initial conditions, even if they do not inflow into farmland, their green total factor productivity may be higher than that of the farmland inflow farmers. Therefore, differences in initial conditions largely contribute to sample selection bias. Thus, this paper uses the propensity score matching method to overcome the problem of sample selection bias caused by traditional estimation methods.

3.2.2. Propensity score matching method

Propensity score matching (PSM) method is a commonly used method to deal with the problem of sample selection bias. Its basic idea is to make the two households tend to be balanced and comparable by matching the farmland inflow households and the not farmland inflow households, and then compare their green total factor productivity differences. The specific steps are as follows. First, choose the covariate X_i. Concerning relevant literature, the factors affecting farmers' green total factor productivity and participation in farmland inflow are incorporated into the model to ensure that the assumption of negligence is satisfied. Secondly, the Logit model calculates the propensity score value of farmer *i* inflowing into farmland. Thirdly, this article uses K-nearest neighbor matching (K = 1, 4), caliper matching (cal = 0.01), and kernel matching (bandwidth = 0.06) for matching to solve the estimation deviation between the matching methods, which proves the reliability of the research conclusion. After matching, the mean and median deviation were further used to test the balance between the treatment and control groups and investigate the data balance of the two distributions. Finally, focusing on the changes in green total factor productivity of farmers who inflowed into farmland, the average treatment effect (ATT) was calculated as:

$$ATT = \frac{1}{N_1}\sum_{i:D_i=1}(y_i - \widehat{y}_{0i}) \tag{3}$$

In Eq. (3), N_1 indicates the number of farmer households in the treatment group and the number of farmer households transferred. $\sum_{i:D_i=1}$ means that only the sum is transferred to the account. y_i is the green total factor productivity of farmer *i*. $\widehat{y}_{oi}$ indicates the estimated value of green total factor productivity if the inflowed households have not inflowed into farmland.

3.3. Variable definition

3.3.1. Green total factor productivity

The explained variable is farmers' green total factor productivity (GTFP) of maize growers. Stochastic frontier analysis (SFA) and data envelopment analysis (DEA) are common methods to measure agricultural green total factor productivity. The SFA method requires setting the probability distribution from random error terms, and the frontier production function is susceptible to the influence of individual regions. However, although the DEA method does not need to set a specific production function, it does not include slack variables or ignores some inputs or outputs when using DEA for measurement, resulting in inaccurate measurement results. This paper accurately measures farmers' green total factor productivity based on the super-efficiency SBM model with modified slack variables [39–42]. There are two reasons. Firstly, input factors such as chemical fertilizers and pesticides in the agricultural production process will damage the ecological environment, so when measuring agricultural output, attention should be paid not only to the agricultural output value but also to the impact of agricultural production on the ecological environment. Secondly, the ordinary SBM model takes a value of 1 for DMUs with an efficiency of more than 1 and DMUs with an efficiency of just 1, which makes it impossible to distinguish between DMUs with an efficiency of more than 1 and DMUs with an efficiency of just 1. The super-efficiency SBM model with unexpected output directly incorporates relaxation variables into the objective function, which can effectively solve the above problems. Based on this, combining data availability and caliber consistency, aiming at the factor input, output and ecological factors in the agricultural production process, the agricultural input index, expected output index and undesired output index were selected to construct an evaluation system. And we use the super-efficiency SBM model to calculate the sample farmers' green total factor productivity and serve it as data support [43,44].

Three aspects of factor input and output indicators measure farmers' green total factor productivity. See Table 1 for details. The first is agricultural input indicators, including land, labor, mechanical operation, irrigation, seedlings, agricultural film, pesticide, chemical fertilizer, organic fertilizer, etc. It is taken as the input factor of farmers' agricultural production. The second is the expected output index, measured by the total agricultural output value, where the total agricultural output value is equal to the product price multiplied by the output. Finally, there is the undesired output indicator, measured by two types of agricultural non-point source pollution emissions and agricultural carbon emissions. On the one hand, agricultural non-point source pollution emissions mainly come from the excessive use of pesticides, agricultural film and chemical fertilizers, so three indicators are selected: pesticide residues, agricultural film residues and fertilizer loss. On the other hand, referring to the carbon emission models and calculation coefficients of existing research, the total amount of agricultural carbon emissions is measured by adding up the emissions of six carbon sources. See Appendix A1 for specific calculation formulas.

3.3.2. Farmland inflow

The core explanatory variable is farmland inflow (FI). Based on the counterfactual hypothesis, this paper examines the average processing effect of farmland inflow on farmers' green total factor productivity. It, therefore, characterizes farmland inflow as a dummy variable. Therefore, if the sample farmer chooses to inflow into farmland, it will be assigned as "1"; otherwise, it will be assigned as "0".

3.3.3. Match variables

Referring to relevant literature, we selected 15 control variables [31,32,34]. It includes age (A), education level (EL), health status (HS), new professional (NP) farmer, farmland endowment (FE), farmland fragmentation (FF), femonstration plot (FP), plot distance (PD), annual household income per capita (AI), family farming labor (FL), household productive assets (PA), cooperative organization (CO), agricultural products insurance (PI), credit support (CS) and location dummy variables. Among them, PA represents the number of productive assets in the farm households[1]; CS is obtained through factor analysis on the two questions of "credit policy communication" and "credit difficulty". Referring to the research of Ostrom [45], Fig. 2 shows the logical relationship between variables. See Appendix A2 for details.

3.4. Descriptive statistics

This paper makes a descriptive statistical analysis of the above variables. It can be seen from Table 2 that the average green total factor productivity of farmers is 0.454, which is at a low level. It is necessary to improve farmers' awareness of green production and ensure the advantages of agricultural green production. At the same time, the average inflow of agricultural land is only 0.336, which indicates that the proportion of farmers who flow into agricultural land is relatively small. Therefore, farmers should increase their enthusiasm for the inflow of agricultural land and give full play to the advantages of scale management.

4. Results and discussion

4.1. Benchmark regression results

This paper first establishes a super-efficiency SBM model to measure farmers' green total factor productivity. The green total factor productivity of the inflowed farmers, to examine whether the agricultural production efficiency and ecological protection caused by farmland inflow are unified.

[1] The productive assets mainly include: tractors, tricycles, agricultural trucks, seeders, rotary tillers, fertilization trenchers, sprayers, water cellars, etc.

Table 1
Input and output indicators.

Factor input and output		Unit	Factor input and output		Unit
Agricultural inputs	Land	hm^2	Agricultural Inputs	Fertilizer	kg (folded pure)
	Labor force	Person		Organic Fertilizer	kg (folded pure)
	Mechanical work	RMB	Expected output	Gross agricultural output	RMB
	Irrigation	RMB	Unexpected output	Pesticide Residues	kg
	Seedlings	RMB		Agricultural film residues	kg
	Agricultural film	kg		Fertilizer loss	kg
	Pesticide	kg		Agricultural carbon emissions	kg

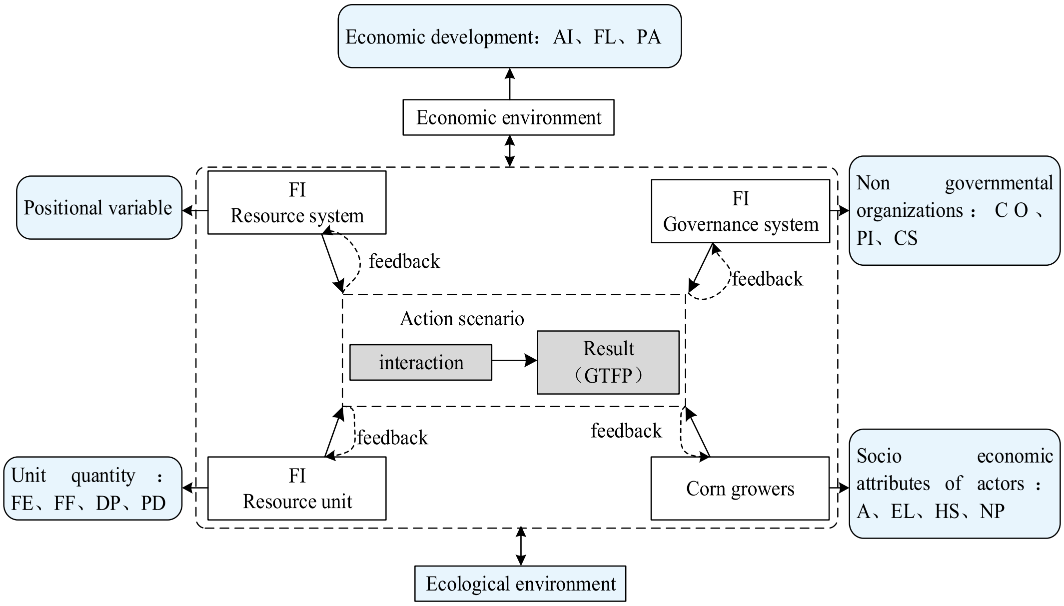

Fig. 2. The logical relationship between variables.

Table 2
Variable definitions and descriptive statistics.

Variable	Variable name	Mean	Std	Min	Max
GTFP	Farmers' green total factor productivity	0.454	0.335	0.029	5.829
FI	Farmland inflow	0.336	0.473	0	1
A	Age	57.111	10.784	26	85
EL	Education level	6.654	3.694	0	16
HS	Health status	2.617	0.683	1	3
NP	New professional farmer	0.057	0.273	0	2
FE	Farmland endowment	1.059	1.205	0	10.666
FF	Farmland fragmentation	4.506	14.831	0.03	206.667
DP	Demonstration plot	0.019	0.135	0	1
PD	Plot distance	962.940	918.885	0	9500
AI	Annual household income per capita	17616.71	30733.65	0	590666.7
FL	Family farming labor	1.720	0.841	0	5
PA	Household productive assets	1.956	2.621	0	50
CO	Cooperative organization	0.159	0.366	0	1
PI	Agricultural products insurance	0.813	0.390	0	1
CS	Credit support	0.059	0.998	−1.474	2.469
Province 1	Ningxia	0.403	0.491	0	1
Province 2	Inner Mongolia	0.323	0.468	0	1

4.1.1. Influential factors of farmland inflow

To match the inflow and non-inflow samples, it is necessary to carry out maximum likelihood estimation on the fitting value of the conditional probability of farmers' farmland transfer. Table 3 shows that the characteristics of actors, agricultural land resource units, economic environment, and governance system have a significant impact on the possibility of maize growers flowing into agricultural

Table 3
Estimation results of influencing factors of farmland inflow.

Variable	Coefficient	Std	Z value
A	−0.020**	0.009	−2.18
EL	−0.026	0.025	−1.01
HS	0.188	0.140	1.35
NP	0.545*	0.303	1.80
FE	−0.008	0.005	−1.47
FF	0.017**	0.008	2.10
DP	0.779	0.631	1.23
PD	0.001**	0.001	2.28
AI	0.007	0.004	1.55
FL	0.124	0.109	0.253
PA	0.133***	0.300	−4.90
CO	−0.294	0.253	−1.16
PI	1.261***	0.308	4.09
CS	−0.647	0.094	−0.69
Ningxia	−1.474***	0.301	−4.90
Province 1	−1.347***	0.305	−4.42
Province 2	−0.671	0.786	−0.85
LR value	85.54		
Pseudo R^2	0.096		
Sample size	697		

Note: ***, **, and * represent the significance levels of 1%, 5%, and 10%, respectively, the same as below.

land. In terms of actor characteristics, A has a significant negative impact on farmland inflow, which is consistent with existing research. The reason is that the older the farmers are, the less time and energy they have in crop cultivation, and the less likely they are to flow into the farmland. NP has a significant positive impact on farmland inflow. This shows that the healthier the farmers are, the stronger their ability to cultivate crops is, and the more willing they are to flow into the farmland. In terms of the farmland resource unit, FF and PD have a positive and significant impact on farmland inflow. The main reason is that it is difficult to form large-scale operations under the conditions of farmland fragmentation and long distance between plots, and it is necessary to carry out farmland inflow to promote large-scale operations. In terms of the economic environment, PA has a significant positive impact on farmland inflow. This shows that the increase in productive household assets has increased the funds invested by farmers in intensive management. To maximize the capital benefits, households will increase the scale of planting and promote the inflow of agricultural land. In terms of the governance system, PI has a significant positive impact on farmland inflow. If farmers have agricultural product insurance as a guarantee, it can effectively reduce the risk of agricultural land inflow, and the possibility of agricultural land inflow will be higher [46].

4.1.2. Common support domain test

To ensure the rationality and validity of the matching, the common support domain test under the three matching types is also required. Table 4 shows that most observed values are within the common support domain under the three matching methods. It indicates that in examining the effect of farmland inflow on farmers' green total factor productivity, only a few samples are in the propensity score matching process. There has been a loss. Therefore, using the propensity score matching method to estimate farmland-inflowed farmers' green total factor productivity is appropriate.

In addition, to directly reflect the testing effect of the common support domain, after matching the treatment group of the inflowed households with the control group not inflowed into the households, this article further investigates the changing trend of the probability density map before and after matching (Figs. 3 and 4). It can be seen that before the matching, the distribution of the treatment and control groups is very different, and the probability density is significantly different (Fig. 3). After matching, the probability distributions of the remaining two groups of sample households are obviously convergent (Fig. 4), indicating that the farmers in the treatment group and the farmers in the control group are similar in all aspects, and the sample selection bias is basically eliminated.

4.1.3. Balance test

Three matching methods were selected for the balance test to ensure the quality of the estimation results. As shown in Table A1, after matching, the P–R^2 value dropped from 0.096 before matching to 0.003–0.019 after matching, the LR value dropped significantly from 85.33 before matching to 1.90–12.00 after matching, and the mean deviation of explanatory variables dropped from 13.9% before matching to 2.7%–6.5% after matching. The median deviation decreased from 14.7% before matching to 1.8%–5.6% after matching. It can be seen that after matching, the mean deviation and median deviation between the treatment group and the control group were significantly reduced. Through the balance test, the matching results were reliable. The data characteristics of the treatment and control groups tended to be consistent and comparable. To sum up, the matching effect between the treatment and control groups is relatively satisfactory.

Table 4
Common support domain test.

Matching method	K-nearest neighbor match (K = 1, K = 4)			Caliper match (caliper = 0.01)			Kernel match (bandwidth = 0.06)		
	Control	Treat	Total	Control	Treat	Total	Control	Treat	Total
Out-of-domain	9	454	463	9	454	463	9	454	463
In-domain	8	226	234	20	214	234	8	226	234
Total	17	680	697	29	668	697	17	680	697

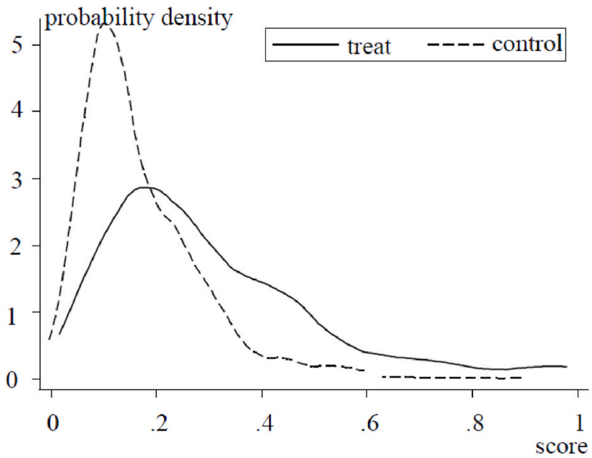

Fig. 3. Before.

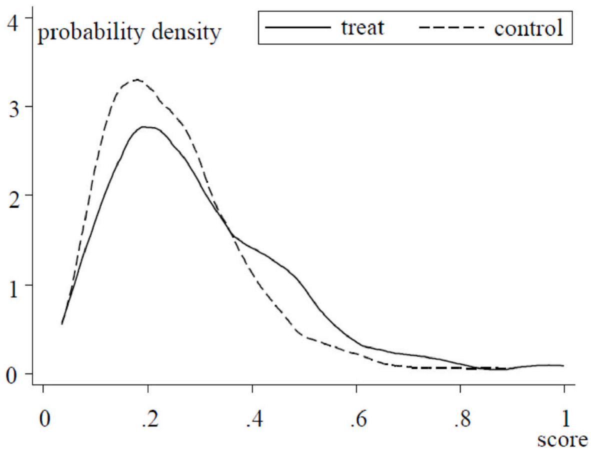

Fig. 4. After.

4.1.4. Average treatment effect

To ensure the robustness of the estimation results, this paper uses four matching methods to estimate the average treatment effect of farmland inflow and farmer green total factor productivity, as shown in Table 5. The estimation results show that the estimation results of the four matching methods are consistent, the average treatment effect has passed the significance test, and the direction and extent of the impact of farmland inflow on the green total factor productivity of farmers are basically the same, indicating that the estimation results are robust. It can be seen from Table 5 that farmland inflow has a positive average treatment effect on the green total factor productivity of farmers, and it has passed the significance test. It shows that the green total factor productivity of the inflowed households increased by 14.7% compared with the non-inflowed households, and the growth rate was 35.8%[2]. The average green total factor productivity of farmers increased from 0.454 to 0.616. Although the increase in statistical significance is slight, in practical

[2] The calculation formula of growth rate is: growth rate = ATT/mean value of control group × 100%.

Table 5
Average treatment effect.

Matching method	Treatment group mean	Control group mean	ATT
K-nearest neighbor matching (K = 1)	0.557	0.404	0.153***
K-nearest neighbor matching (K = 4)	0.557	0.415	0.142***
Caliper match (caliper = 0.01)	0.557	0.398	0.159***
Kernel matching (bandwidth = 0.06)	0.557	0.424	0.133***
Average value	0.557	0.410	0.147***

terms, farmland inflow has an essential role in improving farmers' green total factor productivity. The main reason for increasing is that farmers who transfer farmland to scale can obtain government green production subsidies and effectively integrate existing resources. The main reason for the increase is that farmers who transfer farmland on a large scale can obtain green production subsidies from the government and effectively integrate existing resources. Under the condition of resource integration, farmers can effectively realize scale operation, improve supporting facilities and reduce agricultural production costs. Thus, it can improve the level of green production technology, improve agricultural production efficiency and green development level, and ultimately improve farmers' green total factor productivity.

In addition, this paper selects the representative quantiles of 0.10, 0.25, 0.50, 0.75, and 0.90, namely the low-efficiency group, the medium-low efficiency group, the medium-efficiency group, the medium-high-efficiency group, and the high-efficiency group, to analyze the effect of farmland inflow on different efficiency levels. The quantile regression results in Table 6 show that the quantile regression coefficients are unequal. The rest of the quantiles except the 0.10 quantile have passed the 1% significance test, indicating that farmland inflow has a differentiated impact on the farmers' green total factor productivity. Overall, the incentive effect of farmland inflow on farmers' green total factor productivity showed an inverted "U" shape that first increased and then decreased, reaching the maximum at the 0.75th percentile, then offering a downward trend. It shows that the incentive effect of farmland inflow on the green total factor productivity of low-efficiency farmers is smaller than that of high-efficiency farmers. It is because low-efficiency farmers are worse than high-efficiency farmers in terms of scale, capacity, capital, and technology, and their efficiency is high. The farmers will generate economies of scale after farmland inflow, promote the quality and efficiency of agricultural production and operation, stimulate and enhance farmers' green total factor productivity, and achieve the dual goals of economic development and ecological protection.

4.2. Heterogeneity analysis

4.2.1. Age heterogeneity

Combined with the existing literature, this paper takes 60 years old as the boundary. It divides the age of farmers into two situations: those below 60 years old and 60 years old and above, representing two groups of middle and young age and old age, respectively. The results in Table A2 show that farmland inflow significantly impacts farmers' green total factor productivity in different age groups. The green total factor productivity of rural land under 60 years old was 11.2% higher than that of non-migrant households, with a growth rate of 26.7%. For the inflow households under 60 years old, their green total factor productivity increased by 11.16% compared with the non-inflow households, with a growth rate of 26.74%. As for the inflow households aged 60 and above, their green total factor productivity increased by 16.46% compared with the non-inflow households, with a growth rate of 27.83%. It is worth noting that the green total factor productivity brought about by farmland inflow by farmers aged 60 and above is relatively high. The main reason is that China is about to enter a moderate age of aging, and the majority of the elderly population is in agricultural production and operation. Therefore, older farmers have more affection for farmland and richer agricultural production experience than middle and younger farmers.

4.2.2. Identity heterogeneity

In this paper, farmers are divided into two types: new-type farmers and ordinary farmers. The results in Table A3 show that farmland inflow significantly impacts the green total factor productivity of farmers with different identities. For ordinary farmers, the green total factor productivity of farmland inflow increased by 14.8%, with a growth rate of 35.7%. For new-type farmers, the green total factor productivity inflowed from farmland increased by 17.9% compared with that of non-inflowed farmers, with a growth rate of 51.0%. This shows that the green total factor productivity of new-type farmers' farmland is higher than that of ordinary farmers. The reason is that, compared with ordinary farmers, new farmers have advantages in production and operation ability, professional skills,

Table 6
Quantile regression results of farmers' GTFP.

Variable	QR_10	QR_25	QR_50	QR_75	QR_90
Farmland inflow	0.018 (0.011)	0.033*** (0.013)	0.093*** (0.023)	0.177*** (0.035)	0.161*** (0.051)
Control variable	Y	Y	Y	Y	Y
Constant term	0.306*** (0.046)	0.410*** (0.052)	0.524*** (0.092)	0.635*** (0.143)	0.749*** (0.208)
R^2	0.239	0.220	0.192	0.169	0.154

Note: Standard errors are in parentheses. The same is below.

information channels, economic income, ecological payment, etc. The stimulating effect of total factor productivity is higher than that of ordinary farmers.

4.2.3. Geographical heterogeneity

In this paper, the whole sample is divided into two parts: the middle Yellow River sample and the upper Yellow River sample. Table A4 shows the sub-sample regression results based on geographic location. The impact of farmland inflow has passed the 1% significance test in the middle and upper reaches of the Yellow River on farmers' green total factor productivity, and the coefficient sign is positive. But the growth rate of the upper reaches of the Yellow River (33.0%) is higher than that of the middle (30.7%). It indicates that farmland inflow has a more significant effect on improving the green total factor productivity of farmers in the upper reaches of the Yellow River. The possible explanation is that the upper reaches of the Yellow River with severe desertification have more space for ecological and economic development, compared with the agricultural engineering facilities, advanced technology and mature biological measures in the middle reaches of the Yellow River. Therefore, the development of farmland inflow will help to improve the problems such as serious ecological damage and desertification in the upper reaches of the Yellow River, improve the coverage of ecological regions in the upper reaches of the Yellow River, and vigorously develop advanced agricultural technology and infrastructure construction.

4.3. Mechanism analysis

According to the previous benchmark regression model analysis and robustness test results, it is empirically found that farmland inflow has a positive impact on the green total factor productivity of farmers. But how farmland inflow affects farmers' green total factor productivity remains to be further tested. The specific results are shown in Table 7.

4.3.1. Marginal output flattening effect

By balancing the marginal output, farmland inflow will engender new agricultural production and management entities, encouraging farmers to improve their planting capacity continuously, thereby improving their total green factor productivity. Therefore, the marginal output flattening effect is measured by farmers' planting and management ability, and uses a Likert five-level scale.

It can be seen from Table 7 that the estimated results in column (1) show that farmland inflow has a significant positive effect on the green total factor productivity of farmers, and the estimated coefficient is 0.1624. The estimation result of column (2) shows that the farmland inflow can produce the marginal output flattening effect, which means that the farmland inflow can have the marginal output flattening effect through labor transfer so that those with high planting capacity can continue to operate agriculture. The two variables in column (3) have passed the significance test, indicating that after controlling the farmland inflow variables, the positive impact of intermediary variables on farmers' green total factor productivity is still significant. From the parameter estimates and their significance, it can be seen that there is a partial mediation effect of the marginal output flattening effect, which accounts for 0.089 of the total effect. It shows that about 8.9% of the impact of farmland inflow on farmers' green total factor productivity is achieved through the marginal output flattening effect. Farmland inflow affects farmers' green total factor productivity by improving the marginal output flattening effect. It verifies the existence of the marginal product leveling effect path to a certain extent.

4.3.2. Transaction benefit effect

Farmland inflow can significantly reduce the cost of information exchange, and the funds can be used for green agricultural production and operation, thereby improving farmers' green total factor productivity. Therefore, the transaction benefit effect is measured by the degree of agricultural capital surplus, and the Likert five-level scale is used.

The estimation results in column (4) show that the inflow of farmland can significantly improve the transaction benefit effect, which means that the transfer of farmland is conducive to reducing the barriers to farmers' access to information and reducing the

Table 7
Test results of intermediary mechanism.

	GTFP	Mechanism 1	GTFP	Mechanism 2	GTFP	Mechanism 3	GTFP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Farmland inflow	0.162*** (0.026)	0.254*** (0.072)	0.119*** (0.026)	0.201*** (0.061)	0.121*** (0.026)	0.143* (0.078)	0.124*** (0.026)
Mechanism 1			0.057*** (0.014)				
Mechanism 2					0.061*** (0.016)		
Mechanism 3							0.068*** (0.013)
Constant	0.399*** (0.015)	2.444*** (0.290)	0.304*** (0.111)	2.100*** (0.249)	0.315*** (0.112)	0.946*** (0.315)	0.380*** (0.041)
Control variable	Y	Y	Y	Y	Y	Y	Y
Sample size	697	697	697	697	697	697	697

transaction costs of the transfer of farmland. The two variables in column (5) have passed the significance test, indicating that after controlling the farmland inflow variables, the positive impact of intermediary variables on farmers' green total factor productivity is still significant. It can be seen from the parameter estimates and significance that the transaction benefit effect is a partial intermediary, accounting for 0.076 of the total effect. It shows that about 7.6% of the impact of farmland inflow on farmers' green total factor productivity is realized through the intermediary effect of the transaction benefit effect. That is, the inflow of farmland affects the green total factor productivity of farmers by changing the capital endowment of farmers, which to some extent verifies the existence of the path of transaction benefit effect.

4.3.3. Technology adoption effect

The scale effect derived from farmland inflow drives various government departments to provide financial, technical and training support, which increases the possibility of farmers adopting advanced technologies. Therefore, the technology adoption effect is measured by the number of advanced agricultural technologies adopted in agricultural production and operation, including water and fertilizer integration technology, biological carbon sequestration technology, mechanical farming technology, biological pesticide application technology, soil testing, formulation technology, etc. Therefore, the mediation effect test is used to investigate whether the influence mentioned above paths are established.

The estimation result of column (6) shows that the inflow of farmland can significantly improve the technology adoption effect. The two variables in column (7) have passed the significance test, indicating that after controlling the farmland inflow variables, the positive impact of intermediary variables on farmers' green total factor productivity is still significant. It can be seen from the parameter estimates and significance that the technology adoption effect is a partial mediator, accounting for 0.059% of the total effect. It shows that about 5.9% of the impact of farmland inflow on farmers' green total factor productivity is achieved through the intermediary effect of technology adoption. Farmland inflow affects farmers' green total factor productivity by improving technical level, which verifies the existence of technology adoption effect path to a certain extent.

5. Conclusion and recommendations

5.1. Conclusion

Farmland inflow is the key to realizing agricultural modernization and improving agricultural green total factor productivity. To this end, based on the micro survey data in 2020, the super efficiency SBM model is used to measure farmers' green total factor productivity. And we used PSM to identify the impact and mechanism of agricultural land transfer on farmers' green total factor productivity. The research conclusions are as follows: First, the green total factor productivity of the inflowed households increased by 14.66% compared with the non-inflowed households. Second, farmland inflow can significantly improve farmers' green total factor productivity through the marginal output leveling effect, transaction benefit effect, and technology adoption effect. Third, the heterogeneity shows that the positive effect of farmland inflow on the green TFP of farmer households is more significant in the samples of older household heads, new-type farmer households, and the upper reaches of the Yellow River.

5.2. Policy recommendations

In response to the above conclusions, to guide and motivate farmers to improve the green total factor productivity of farmland inflow and effectively achieve economic-ecological "dual security", the following three aspects should be focused on in policy. First, fully activate the farmland market and increase farmers' enthusiasm to transfer their farmland. The government should improve the reasonable, standardized, and efficient farmland transfer mechanism, and give play to the marginal output leveling effect, transaction benefit effect, and technology adoption effect. It is conducive to promoting the linkage between agricultural production efficiency and high-quality economic development, improving farmers' green total factor productivity, and realizing the "win-win" of driving economic growth and ecological protection. Second, establish and improve the farmland inflow system. On the one hand, the local government should strengthen the role of demonstration, training and incentive for large farmers, optimize the planting structure, and encourage the transfer of farmland among business entities. On the other hand, the village committee should form a professional and standardized farmland inflow, promote the transfer of rural land management rights to the new agricultural operation subject, and further promote agricultural modernization and high-quality development. Third, establish and improve the soil strength monitoring system. The government should improve the supervision mechanism, establish a digital land force monitoring system, and promote public participation in the digital supervision mechanism. It is conducive to reducing agricultural ecological loss, boosting the coordination of agricultural economic development and ecological protection, and ensuring the steady growth of high-quality agricultural land ecology. Fourth, formulate incentive environmental regulations. The government should give appropriate economic subsidies or environmental incentives to farmers' green agricultural production behavior, reduce farmers' green agricultural production costs, and improve farmers' enthusiasm for implementing green agricultural production behavior. Farmers who have implemented or continue to implement green production behavior should also be given certain economic and spiritual rewards to form a demonstration effect that can encourage other farmers to actively follow.

Of course, this paper also has some limitations. We only analyzed the impact of land inflow on farmers' green total factor productivity, and did not carefully examine the impact of different types of land inflow and the degree of land inflow. At the same time, due to the limitation of sample size, we did not analyze the impact of land outflow on farmers' green total factor productivity. Farmers with the intention of land outflow may have a negative impact on farmers' green total factor productivity through the slack effect.

Therefore, we will conduct a second survey on the existing situation to enrich the number of samples and discuss the above issues in future research.

Author contribution statement

Lin Li: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Wrote the paper.
Jiliang Han: Performed the experiments; Analyzed and interpreted the data.
Yuchun Zhu: Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data.

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Data availability statement

Data will be made available on request.

Declaration of interest's statement

The authors declare no competing interests.

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Appendix A

Appendix A1. The undesired output

The Undesired output includes agricultural non-point source pollution and agricultural carbon emissions.

On the one hand, agricultural non-point source pollution emissions mainly come from the excessive use of pesticides, agricultural film and chemical fertilizers, so three indicators are selected: pesticide residues, agricultural film residues and fertilizer loss. Among them, pesticide residue is equal to pesticide application amount multiplied by pesticide residue coefficient, and agricultural film residue is equal to agricultural film use multiplied by agricultural film residue coefficient. Combined with the "First National Pollution Census Bulletin", the pesticide residue coefficient is 50%, and the agricultural film residue coefficient is 10%. The fertilizer loss mainly includes nitrogen and phosphorus pollutants generated when applying nitrogen fertilizer, phosphorus fertilizer and compound fertilizer. Therefore, the calculation formula of fertilizer loss amount is the sum of nitrogen and phosphorus pollution emissions. Specifically, nitrogen pollution discharge = nitrogen pollution discharge coefficient × nitrogen fertilizer application amount, where nitrogen pollution discharge coefficient = nitrogen pollution production coefficient × fertilizer loss rate. Phosphorus emissions are the same. The nitrogen pollution production coefficients of nitrogen fertilizer, phosphorus fertilizer, and compound fertilizer (1:1:1 ratio of nitrogen, phosphorus, and potassium) were 1, 0, and 0.33, respectively, and the phosphorus pollution production coefficients were 0, 0.44, and 0.15, respectively. Combined with existing research, the loss rate of chemical fertilizer is 65% in each region. Nitrogen pollution discharge + phosphorus pollution discharge = fertilizer loss.

On the other hand, referring to the carbon emission models and calculation coefficients of existing research, the total amount of agricultural carbon emissions is measured by adding up the emissions of six carbon sources. The emission coefficients of the six types of carbon sources are 0.8956 kg/kg for chemical fertilizers, 4.9341 kg/kg for pesticides, 5.18 kg/kg for agricultural film, 0.5927 kg/kg for diesel, and 20.476 kg/hm^2 for agricultural irrigation. And agricultural plowing 3.126 kg/hm^2.

Appendix A2. The logical relationship between variables

To study the objectivity of the problem, based on the social ecosystem framework of Ostrom[45], this paper takes the factors contained in the resource unit, resource system, economic environment, actors, and governance system as matching variables into the analysis. Among them, actors refer to the characteristics of farmers. Economic environment refers to the level of economic development and external environmental factors. Resource units include unit quantity, mobility, and interactivity. The governance system mainly includes the property rights system and rule factors. The resource system mainly refers to the scale, scarcity, and location of the resource system.

Table A1
Balance test.

Matching method	P-R2	LR value	Mean deviation (%)	Median deviation (%)
Before match	0.096	85.33	13.9	14.7
K-nearest neighbor matching (K = 1)	0.019	12.00	6.5	5.6
K-nearest neighbor matching (K = 4)	0.015	9.59	5.8	4.5
Caliper match (caliper = 0.01)	0.017	10.22	5.8	4.9
Kernel matching (bandwidth = 0.06)	0.003	1.90	2.7	1.8

Table A2
Age heterogeneity regression results.

Matching method	Under 60 (lower-middle age)			60 years old and above (senior age)		
	Treat	Control	ATT	Treat	Control	ATT
K-nearest neighbor matching (K = 1)	0.529	0.407	0.122***	0.591	0.429	0.162***
K-nearest neighbor matching (K = 4)	0.529	0.436	0.093***	0.591	0.434	0.157***
Caliper match (caliper = 0.01)	0.529	0.408	0.121***	0.593	0.414	0.179***
Kernel matching (bandwidth = 0.06)	0.529	0.418	0.111***	0.591	0.431	0.160***
Average value	0.529	0.417	0.112***	0.591	0.427	0.165***
Sample size	393			304		

Table A3
Regression results of identity heterogeneity.

Matching method	Ordinary farmers			New-type farmers		
	Treat	Control	ATT	Treat	Control	ATT
K-nearest neighbor matching (K = 1)	0.561	0.396	0.165***	0.538	0.342	0.196***
K-nearest neighbor matching (K = 4)	0.561	0.429	0.133***	0.538	0.360	0.177***
Caliper match (caliper = 0.01)	0.564	0.398	0.166***	0.512	0.345	0.167***
Kernel matching (bandwidth = 0.06)	0.561	0.433	0.128***	0.538	0.360	0.178***
Average value	0.562	0.414	0.148***	0.531	0.352	0.179***
Sample size	557			140		

Table A4
Regression results of geographic heterogeneity.

Matching method	Upper Yellow River			Middle Yellow River		
	Treat	Control	ATT	Treat	Control	ATT
K-nearest neighbor matching (K = 1)	0.613	0.464	0.149***	0.526	0.404	0.122***
K-nearest neighbor matching (K = 4)	0.613	0.464	0.149***	0.526	0.404	0.122***
Caliper match (caliper = 0.01)	0.614	0.466	0.148***	0.530	0.403	0.127***
Kernel matching (bandwidth = 0.06)	0.613	0.450	0.163***	0.526	0.401	0.125***
Average value	0.613	0.461	0.152***	0.527	0.403	0.124***
Sample size	281			416		

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