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Resilience in Farm Technical Efficiency and Enabling Factors: Insights from Panel Farm Enterprise Surveys in Kazakhstan and Uzbekistan

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Notices

Abstract

Economic resilience within the agrifood system is becoming increasingly crucial for assuring sustainable development. This is particularly so in regions with volatile and fragile environments, including Central Asia. Evidence remains scarce regarding what factors can enhance the economic resilience of agents within the agrifood system, including the resilience of productivity and technical efficiency. We partly fill this knowledge gap using the unique panel datasets of farm enterprises in Uzbekistan and southern Kazakhstan, collected in 2019 and 2022, during which these enterprises experienced significant economic shocks in input prices. Using novel methods that combine Inverse Probability Weighting and panel stochastic frontier analyses models, we show that farmers who received more agricultural training and who had been granted greater autonomy in their production decisions in 2018 experienced greater resilience in technical efficiency despite the need to reduce the use of chemical fertilizer and oil/diesel in response to their price surges. Our findings suggest that providing critical public goods like information (related to training) and enabling environment (related to decision-making autonomy) can potentially enhance the resilience in the technical efficiency of farm enterprises. Furthermore, with chemical fertilizer and oil/diesel being potentially environmentally harmful inputs, these farmers also indirectly demonstrated resilience toward environmental sustainability.

Keywords: Resilience, technical efficiency, training and autonomy, inverse probability weighting method, panel stochastic frontier analyses, Uzbekistan and Kazakhstan

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1 Background

Resilience against fragility has been considered an increasingly important feature of the agrifood systems in developing countries (e.g., World Bank 2007; Briguglio et al. 2009; OECD 2020; Barrett et al. 2021; Baliki et al. 2022). This is particularly so in the face of growing uncertainty due to the emergence of climate, environmental, and geopolitical/socioeconomic shocks, including recent responses to the COVID-19 pandemic and the Russia-Ukrainian conflict (e.g., IFPRI 2020; Glauber & Laborde 2023).

Despite such importance, the knowledge gap remains regarding what factors can potentially enhance the resilience of agrifood systems actors. Evidence is particularly scarce regarding the factors that can mitigate the fluctuation in technical efficiency against various shocks. Improving and sustaining high technical efficiency has been considered increasingly critical for not only growing food supply and agrifood incomes but also for achieving sustainable growth through resource conservations, environmental sustainability (Khatri-Chhetri et al. 2023), and reducing loss/waste (Smith & Landry 2021). Achieving resilience in technical efficiency is vital as the agrifood system in not only developed but also in developing countries has increasingly relied on growing energy inputs derived from fossil fuels and other nonrenewable resources (machinery, fuel, and fertilizers) (Pellegrini & Fernández 2018).

This study aims to narrow this knowledge gap by providing evidence based on unique panel datasets of farm enterprises collected in 2018 and 2021 in irrigated cotton producing areas of the Central Asian region that straddles across borders between Kazakhstan (South region) and Uzbekistan. The study periods correspond to before and after the significant socioeconomic shocks, encompassing the COVID-19 pandemic and the escalating uncertainty preceding the breakout of the Russo-Ukrainian war. Precisely, we assess how the provisions of vital public goods, including information/knowledge through training and enabling environment through granting more autonomy in production decision-making to farm enterprises, mitigated the declines in technical efficiency in the face of rising costs of oil/diesel and fertilizer.

We do so by employing novel econometric approaches that combine recently developed panel stochastic frontier analysis methods and methods that address potential endogeneity in multiple dimensions (i.e., endogeneity in the training receipt or autonomy in production decision, and the use of oil/diesel and fertilizer) based on the Inverse Probability Weighting (IPW) methods. Such multiple sources of endogeneity arise in analyses like ours, partly because the outcome of our interest, technical efficiency, is a variable that also needs to be estimated through methods that address endogeneity in input use decisions. As is described below, we use IPW to address the endogeneity associated with the training receipt or autonomy and combine it with the Karkaplan & Kutlu (2017) method that addresses the endogeneity of input use in stochastic frontier estimation.

Kazakhstan and Uzbekistan offer particularly relevant contexts. Some Central Asia region countries like Kazakhstan have emerged as major exporters of essential agrifood commodities, including wheat (e.g., Araujo-Enciso & Fellmann 2020) and remain their critical global suppliers as their competitors like Ukraine face growing production challenges due to geopolitical uncertainty. Similarly, Central Asian countries like Uzbekistan and Turkmenistan remain among the largest exporters of fiber crops like cotton (Khan et al. 2020). Meanwhile, both Kazakhstan and Uzbekistan have seen significant intensification in their agrifood production over the years, characterized by the use of modern inputs like chemical fertilizer and energy inputs like oils/diesel used for operating agricultural equipment and infrastructure (e.g., irrigation), compared to some other developing countries that still rely on more traditional systems.[1] Relying on crop production technologies of intensive agriculture, Kazakhstan and Uzbekistan have reached stages with fairly sophisticated production systems, where efficiency tends to vary more widely, and greater scope exists for raising productivity through efficiency-enhancing production approaches and interventions (e.g., Fuwa et al. 2007).

We also focus on two types of public goods: information/knowledge provided to farmers through training and enabling environment indirectly provided through granting farm enterprises more autonomy in production decision-making. These are particularly relevant for the environment characterized by greater fragility. Information/knowledge has been considered particularly important in disequilibria that are more common in more sophisticated production systems facing growing external shocks (e.g., Foster & Rosenzweig 1995). Similarly, economic freedom, including the autonomy in production decision-making, has been considered an increasingly important component of resilience against shocks (e.g., Briguglio et al. 2009; Sondermann 2018; Callais & Pavlik 2022), including in former Socialist-bloc regions (Swinnen et al. 2010) like Kazakhstan and Uzbekistan.

This study contributes to various strands of literature. First, the study contributes to the literature on the roles of the public sector in enhancing economic resilience against fragility in agrifood systems in developing countries, including Barrett et al. (2021) and Baliki et al. (2022), among others that provide a conceptual framework, and Takeshima et al. (2022) which assesses the roles of public expenditures on economic flexibility, by providing evidence on the effects of public goods provision (information and knowledge, and economic freedom). By providing evidence on resilience against reduced use of nonrenewable resources (oil/diesel and chemical fertilizer), the study contributes to the literature on resource conservation and environmental sustainability (e.g., Cullen 2017; Laborde et al. 2020). The study also contributes to the literature on agrifood systems in Central Asia (Kienzler et al. 2011; Takeshima et al. 2020a) by providing recent micro-evidence of farm behaviors and productivity outcomes from Kazakhstan and Uzbekistan. Lastly, the study contributes to the literature on production economics and impact evaluation by integrating the methodologies on panel stochastic frontier analyses (e.g., Karakaplan & Kutlu 2017; Paul & Shankar 2020) and inverse-probability weighting method (e.g., Imbens & Wooldridge 2009). In doing so, the study builds on similar studies that assessed the effects of external factors on production technology characteristics in developing countries (Cavatassi et al. 2011; Takeshima 2017; Takeshima et al. 2018, 2020b; Salam et al. 2023).

The paper is structured as follows. Section 2 briefly discusses the study contexts. Section 3 presents the empirical approach. Section 4 describes data and descriptive statistics. Section 5 discusses the results. Lastly, section 6 concludes.

2 Agricultural training and farmers' decision-making autonomy in irrigated areas of Uzbekistan and Kazakhstan

The provision of public goods like knowledge/information and economic freedom have been important features of agricultural production, including major crops like cotton and wheat in Uzbekistan and South Kazakhstan. The nature of such provision, however, has varied

[1]For example, total agricultural energy use per agricultural population in 2021 (for which oil/diesel accounts for a substantial share) was about 30 and 19 billion joules (per capita per year) in Kazakhstan and Uzbekistan, compared to 7 and 2 billion joules in the entire Asia and Africa regions (FAO 2023). Similarly, fertilizer use in Kazakhstan and Uzbekistan was 285 kg per capita per year in NPK nutrients, compared to 183 and 34 in Asia and Africa (FAO 2023).

considerably across borders separating the Uzbek side and the Kazakhstan side, despite similar agroecological conditions within the region.

The provision of information/knowledge, particularly on agricultural extension services, has been implemented primarily by the public sector in the framework of agricultural and rural development programs. However, it has been more organized and structured on the Uzbekistan side of the border where extension support has been provided through organizing various institutions, including Farm Union, Agricultural Service Center, Agro-firms, Water Users Associations, as well as academic and research institutes (Kazbekov & Qureshi 2011; Shtaltovna and Hornidge 2014), often through approaches including Training-and-Visit and Farmer Field Schools (Steinke et al. 2021). Lately, new “regional centers for agricultural services” that provide knowledge and training for individual farms have been promoted in Uzbekistan. Recent studies suggest that access to enhanced frequency of extension visits, improved irrigation technologies, cooperation status among farmers, and participatory extension methods strongly enhance the technical efficiency of wheat producers in Uzbekistan (e.g., Djuraeva et al. 2022). In contrast, on the Kazakhstan side of the border, extension has been provided in a less structured manner through a network of information and consultation centers (Shtaltovna & Hornidge 2014). In both country settings, farmers report about mandatory training they must attend regarding cotton, and in the case of Uzbekistan, also in wheat cultivation. While in Kazakhstan, mandatory training in cotton cultivation is requested by private gins as part of a contract farming agreement, in Uzbekistan, the government administration offers mandatory training to producers of cotton and wheat, two strategic crops.

Until recently, the Uzbek government implemented more restrictive farm production regulations, including the cotton delivery quota system (Djanibekov et al., 2020). This included the state control of input, credit, and extension sectors, with priority often given to cotton and wheat cultivators, and also significant restrictions on the choice of crops, land usage, land tenure security, and marketing rights of their outputs (Zorya et al., 2019; Asfaw 2021; Akhmadiyeva & Herzfeld 2021). On the Uzbek side of the border, cotton and wheat farmers are required to adhere to stringent agro-technical production norms that regulate a variety of cultivation activities, all the way up to and including harvesting process (Kurbanov et al. 2022). Second, on the Uzbekistan side, farmers were required to fulfill the production targets for cotton and wheat (Asfaw 2021). Neglecting to adhere to these production quotas results in the classification of unproductive land utilization and constitutes a breach of the contractual agreement between the farmer and the cotton gin. Following three consecutive years of such noncompliance, farmers risk losing their tenured farmland (Djanibekov et al., 2020). The constrained autonomy of farmers in choosing crop cultivation methods impedes their capacity to respond to exogenous events, such as socioeconomic shocks related to the COVID-19 pandemic and the Russo-Ukrainian war. In contrast, the Kazakh government has implemented relatively more liberal market-based agricultural reforms by distributing land of former collective farms to individuals for organizing small-scale commercial farming in its Southern region and limiting involvement in the production decision-making process (Petrick et al., 2017). On the Kazakhstan side of the border, farmers are provided with various elements of an enabling environment, including more substantial property rights on land and free and competitive markets for agricultural inputs and outputs.

These institutional variations across borders separating the Uzbekistan and Kazakhstan sides, combined with their additional intra-country variations in otherwise highly similar agroecological conditions within Central Asia, offer a useful setting to assess the effects of the provision of training and economic freedom on resilience against external shocks.

3 Empirical approach

3.1 Simpler reduced-form models

We first estimate a simple farm fixed-effects model

$$Y_{it} = \beta_y + \beta_k K_{it} + \beta_R R_{it} + \beta_X S_{it} + \beta_{RS} R_{it} S_{it} + \beta_d D_t + c_i + \varepsilon_{it} \quad (1)$$

in which Y_{it} denotes outcomes of our interests in natural log, i.e., production revenue per land, cost per land and profit per land by farm enterprise i in year $t \in \{2018, 2021\}$. K_{it} is a vector of variables of major production inputs per land, i.e., labor, agricultural equipment, and other expenditures (in natural log). R_{it} is an indicator of the level of training farm i received in t, or the level of autonomy farm i was granted in t. S_{it} is the price of oil/diesel, or chemical fertilizer that farm i faced in their locality in t. D_{it} is a year dummy variable. Notations β's are estimated parameters, c_i is unobserved time-invariant farm fixed-effects, and ε_{it} is an idiosyncratic error term.

Our parameter of interest is β_{RS} which measures the interaction effects of training or autonomy, and prices of oil/diesel or chemical fertilizer. Positive β_{RS} indicates that receiving more training and/or autonomy in production decision-making partly mitigate the negative effects of increased prices of oil/diesel or chemical fertilizer.

Our main analyses delve more into the effects on technical efficiency, as described in the subsequent section. However, the regression (1) is used to show that results in our main analyses are not due to the artefacts of complex model specifications. In turn, since results from (1) alone tell us little about possible pathways, we show in our main analyses described in subsequent section that effects through technical efficiency is one of the pathways that may drive patterns in (1).

3.2 Panel Stochastic Frontier Analysis (SFA) model with exogenous variables only

We first estimate panel SFA model by (Paul & Shankar 2020) (*SFPS* hereafter) that includes only exogenous variables. Specifically, this specification is applied to the case where we focus on the portion of agricultural training that is mandatory so that farmers are required to participate, and the prices of oil/diesel and chemical fertilizer that are more exogenous than the quantity of these inputs used. Following Paul & Shankar (2020), we estimate the following functional form:

$$\begin{gathered}
\widetilde{Y}_{it} = \beta_y + \beta_k \widetilde{K}_{it} + \beta_d \widetilde{D}_{it} + \ln\left\{\frac{\Phi\left(\gamma_y + \gamma_s S_{it} + \gamma_z R_{it}^{ex} + \gamma_{sz} S_{it} R_{it}^{ex}\right)}{\sqrt{\left[\Phi\left(A_{i,2018}\right) \cdot \Phi\left(A_{i,2021}\right)\right]}}\right\} + \tilde{v}_{it} \\
A_{i,2018} = \gamma_y + \gamma_s S_{i,2018} + \gamma_z R_{i,2018}^{ex} + \gamma_{sz} S_{i,2018} R_{i,2018}^{ex} \\
A_{i,2021} = \gamma_y + \gamma_s S_{i,2021} + \gamma_z R_{i,2021}^{ex} + \gamma_{sz} S_{i,2021} R_{i,2021}^{ex} \\
\text{Average technical efficiency} = E\left[\Phi\left(\gamma_y + \gamma_s S_{it} + \gamma_z R_{it}^{ex} + \gamma_{sz} S_{it} R_{it}^{ex}\right)\right]
\end{gathered} \quad (2)$$

in which $\widetilde{Y}_{it}$, $\widetilde{K}_{it}$, $\widetilde{D}_{it}$ are within-transformed versions of Y_{it}, K_{it} and D_{it}. Price variables S_{it} enter the equation *without* the within-transformation. R_{it}^{ex} is an exogenous subset of R_{it} and refers to the mandatory portions of the training received, which is exogenous and can enable consistent estimation of (2) (models for endogenous portions of R_{it} are discussed in subsequent subsections). Φ is the cumulative normal distribution function. $\tilde{v}_{it}$ is an idiosyncratic effect that is separate from unobserved time-invariant farm fixed effects, i.e., $\tilde{v}_{it} = v_{it} - \bar{v}_{it}$.

The term $\ln\{\cdot\}$ corresponds to the time-varying technical efficiency of farm i in year t. A negative γ_s would suggest that a higher prices of chemical fertilizer or oil/diesel (S_{it}) is efficiency-reducing. In other words, farmer i's technical efficiency is less resilient against sudden price-increasing shocks in chemical fertilizer or oil/diesel. A statistically significantly positive γ_{sz} indicates that receiving mandatory training mitigates the negative effects of higher input prices on technical efficiency.

3.3 IPW-Stochastic Frontier Analysis (SFA) model for endogenous variables

To assess the effects of potentially more endogenous shocks and inputs use variables, we apply extensions of the class of Inverse-Probability-Weighted (IPW) Regression Adjustment models (Cavatassi et al. 2011; Takeshima 2017; Takeshima et al. 2018, 2020). Specifically, we estimate,

$$\text{Probability}\left(R^* = 1 | Z_{i,t=2018}\right) = \widehat{p_i} = \Phi(Z\theta) = \int_{-\infty}^{z\theta} \phi(v)dv. \tag{3}$$

where Z_{it} is the set of exogenous variables, $\hat{p}$ is the predicted propensity of farm households' exposures to shocks above certain thresholds, R^* is a binary variable indicating such exposure, and θ is a set of estimated parameters. Φ is the standard normal distribution function, while ϕ and v are the standard normal density function and its element.

We then estimate various models of the panel stochastic frontier function $f(\cdot)$ (described in more detail below) <u>separately</u> for farmers with $R^* = 1$ and $R^* = 0$,

$$Y_{it} = f(\cdot). \tag{4}$$

$$W_i = \begin{cases} 1/\widehat{p_i}, & \text{if } R^* = 1 \\ 1/(1-\widehat{p_i}), & \text{if } R^* = 0 \end{cases} \tag{5}$$

where W_i is individual specific weights applied to the estimation of (4).

We then compare qualitatively the parameters β, between two types of farmers ($R^* = 1$ and $R^* = 0$). The qualitative differences in β between these groups are then interpreted as evidence that the efficiency effects of variables of interest changes in response to R^*. This is because weights applied to each sample based on IPW lead to matching samples, so that any differences in parameters from two samples can be attributed to the difference in R^*. **Error! Reference source not found.** provides a simple illustration our empirical approach.

The IPW-SF model belongs to the class of "doubly-robust" models; the consistency of the model is assured if either of equation (3) or (4) is correctly specified, even if the other equation is not (Robins & Rotnitzky 1995). Similar weighted SFA models based on more general frameworks of weights have been used in the past literature, including Takeshima (2019), Kutlu (2022) and Salam et al. (2023) among others.

Since the IPW estimation approach involves IPW based on estimated probability $\hat{p}$, standard errors are estimated through paired bootstrap (Efron 1979). Similar bootstrap approaches have been used in past studies (e.g., Takeshima 2017).

3.3.1 IPW Paul & Shankar (2020) (IPW-SFPS model)

We estimate IPW-SFPS to address the potential endogeneity of training receipt and/or economic freedom, on the effects of exogenous shocks (prices of oil/diesel and chemical fertilizer). IPW-SFPS can be estimated by specifying $f(\cdot)$ in weighted stochastic frontier function (4) as:

$$\tilde{Y}_{it} = \beta_y + \beta_k \tilde{K}_{it} + \beta_d \tilde{D}_{it} + \ln \left\{ \frac{\Phi(\gamma_y + \gamma_s S_{it})}{\sqrt{[\Phi(\gamma_y + \gamma_s S_{i,2018}) \cdot \Phi(\gamma_y + \gamma_s S_{i,2021})]}} \right\} + \tilde{v}_{it} \quad (6)$$

for each group differentiated by R^*, and applying the weights as (5). We then obtain the marginal effects of S_{it} on average technical efficiency,

$$\frac{\partial \Phi(\gamma_y + \gamma_s S_{it})}{\partial S_{it}} = \gamma_s \cdot \phi(\gamma_y + \gamma_s S_{it})$$

in which ϕ is the standard normal density function. If the marginal effect is statistically significant for $R^* = 0$ but insignificant for $R^* = 1$ (or vice versa), it can be interpreted that the change in R^* (meaning the changes in training receipt intensity or economic freedom) is associated with the effects of shock S_{it} on technical efficiency.

As is noticed, in dealing with endogenous portion of training / autonomy variables R_{it}, variables related to R_{it} are excluded in (6) unlike in (2), but are instead incorporated in IPW component (5).

3.3.2 Karakaplan & Kutlu (2017) panel SFA

The second panel SF model we employ is developed by Karakaplan & Kutlu (2017). In this specification, unlike Paul & Shankar (2020), key variables of interests can still be endogenous to efficiency shocks, even after controlling for time-variant fixed effects of the farmer. Following Karakaplan & Kutlu (2017),

$$\begin{gathered}
Y_{it} = \beta_y + \beta_k K_{it} + \beta_d D_{it} + \beta_x X_{it} + v_{it} - u_{it} \\
X_{it} = \gamma_x + \gamma_k K_{it} + \gamma_d D_{it} + \gamma_s S_{it} + \varepsilon_{it} \\
\begin{bmatrix} \tilde{\varepsilon}_{it} \\ v_{it} \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \sigma_v \rho \\ \sigma_v \rho' & \sigma_v^2 \end{bmatrix} \right) \\
u_{it} = h(\delta_x X_{it}) u_i^* \\
u_i^* \sim N^+(\mu, \sigma_u^2) \\
h(\delta_x X_{it}) > 0
\end{gathered} \quad (7)$$

in which X_{it} is the potentially endogenous variables that are expected to affect production frontier, as well as technical efficiency. S_{it} is the set of excluded IV, i.e., the price of chemical fertilizer and oil/diesel. v_{it}, ε_{it} are two-sided error terms with correlations $\boldsymbol{\rho}$, $\tilde{\varepsilon}_{it}$ is a standardized ε_{it} (standardized with variance of 1). δ_x is an estimated parameter.

In specification (7), a farm first exhibits heterogeneity in production frontier that is time-invariant and specific to the farm, u_i^*, which follows one-sided normal distribution with standard deviation σ_u. At each period t, the efficiency further fluctuates by $u_{it}(\geq 0)$ as a certain function of u_i^*, X_{it}, parameters δ_x and its transformation characterized by a certain function h. u_{it} is assumed uncorrelated with v_{it}, and is also conditionally independent of ε_{it} given K_{it}, X_{it}, Z_{it} and p_{it}.

Linking technical efficiency with input variable X

Following Karkaplan & Kutlu (2017) approach, we then assess the association between efficiency and input variables X_{it} by regressing predicted efficiency scores obtained from (7) on X_{it} and a constant term.

3.4 Variables

We focus on two key exposure variables R^* and two key production inputs X_{it}. Specifically, for R^*, we focus on (a) the intensity of knowledge / skill training received in 2022, and (b) the level of autonomy farmers had in various aspects of farm decision-making. Similarly, for inputs X_{it}, we focus on (c) fuels / diesel, and (d) chemical fertilizer.

The exposure variables (a) and (b) both relate to important quasi-public goods, i.e., information and enabling environment. As is described earlier, effective provisions of these public goods can significantly contribute to enhanced productivity and resilience. The input variables (c) and (d) are, while often important inputs in modernizing the agricultural sector in developing countries, also increasingly considered harmful, when excessively used from both economic and environmental sustainability standpoints.

Outcome variables

Key outcome variables y_{it} are the total production revenues, which are total production quantity times the price per unit for each crop, aggregated across all crops produced.

Other control variables for the first stage regression

Variables $Z_{i,2018}$, factors considered associated with the probability of exposure variables in 2018, in (3), include key demographic characteristics of farm manager (age, year of education completed), farming experiences (whether having special education in agriculture or farm management, years of experiences in agriculture), gender composition of farm enterprise workforce, total farmland endowment, access to public irrigation water, total farm business asset values, in the baseline year of 2018.

Variables $Z_{i,2018}$ also include the receipt of mandated training. This variable is likely to significantly affect the overall exposure to training received that also includes many voluntary trainings. Variables $Z_{i,2018}$ also include the year when the farm was established, as this may affect the level of autonomy in production decisions granted.

4 Dataset

Our primary data are panel data of farm enterprises collected through a survey of farm managers conducted within the framework of AGRICHANGE[2] and SUSADICA projects[3] in Kazakhstan (Turkistan province) and Uzbekistan (Samarkand province) in March-April 2019 and in April-May 2022. The Kazakhstan samples in the Turkistan province were collected through two-stage stratified sampling. First, 3 sub-districts (Auls) were selected within the province. Second, 150 farm managers were randomly chosen from each Aul. In Uzbekistan (Samarkand province), 450 farm managers were randomly selected from the roster of all farm lists within the province.[4] In total, 2019 round data consists of 900 farm enterprises (450 in Kazakhstan and 450 in Uzbekistan). In 2022, we re-visited and were able to interview 578 farm enterprises, including 269 from Kazakhstan and 309 from Uzbekistan samples. Our analyses primarily focus on these 578-panel farm enterprises, including 339-panel cotton producers and 302-panel wheat producers.

The interviewed farmers responded to a comprehensive questionnaire on socio-demographic information, farm, field, crop cultivation, and geographical factors. The farm survey covered questions on the types of training farmers received, their perceptions about rights to operate and sell/rent their farmland, and decision-making autonomy in the choice of crops, agronomic methods, and marketing channels.

4.1 Descriptive statistics

Table 1 through Table 4 summarize the descriptive statistics of our data. Table 1 shows that sample farmers in 2018 typically cultivated 26 ha of farmland and produced outputs worth around 1000 USD / ha, using 27 person-day / ha of family labor, incurring 187 USD / ha for other inputs, including seeds, agrochemicals, machine hiring services and hired labor, maintenance costs of own machines, irrigation costs, as well as chemical fertilizer and oil/diesels. Among other expenses, spending on chemical fertilizer, oil/diesels accounted for about 5 ~ 10%, while a majority of other expenses were incurred on hiring labor. Farmers typically had 183 USD / ha of farm business assets (including various machines and facilities).

By 2021, these farmers had shown considerable changes in production practices; they typically increased the cultivated area, spending similar expenses per ha and generating similar outputs per ha while reducing family labor use per ha. Conversely, farmers slightly reduced their overall spending on chemical fertilizers and oil/diesel.

Table 2 shows the use of chemical fertilizer and oil/diesel. Importantly, the use of these inputs declined relatively substantially as their prices increased between 2018 and 2021. Specifically, the use rate of chemical fertilizer declined sharply from 47 kg/ha to 28 kg/ha, facing a price increase of about 60% from 0.17 (USD / kg) to 0.28. Similarly, the use of oil/diesel declined from 6 kg/ha to 2 kg/ha, as the price increased by about 50% from 0.6 (USD / kg) to 0.9. These price change rates are significantly greater than the inflation rates in Kazakhstan and Uzbekistan during the same period (approximately 40% / 3 years for Uzbekistan and 18% / 3

[2] AGRICHANGE – Institutional change in land and labour relations of Central Asia's irrigated agriculture: https://www.iamo.de/en/research/projects/details/agrichange/

[3] SUSADICA – Structured doctoral programme on Sustainable Agricultural Development in Central Asia: https://www.iamo.de/en/research/projects/details/susadica/

[4] Each province is characterized by a mixture of cotton-growing farm enterprises and non-cotton farming enterprises. Maktaaral and Shardara districts in Turkistan and Pastdargam and Payarik districts in Samarkand are specialized in cotton cultivation. Sariagash district in Turkistan and Jomboy district in Samarkand have diversified non-cotton farming systems.

years for Kazakhstan (World Bank 2023)). While the decline in use rate per ha is partly driven by significant expansion of cultivated area between 2018 and 2021 as was shown in Table 1, the extent of decrease is still remarkable.

Table 3 and Table 4 show the prevalence of the receipt of different types of training, as well as the levels of autonomy in decision-making across various aspects of farm economic activities in year 2018. Regarding the training receipt in Table 3, respondents were asked "if they participated in sets of training on the following topics during the last 3 years". The levels of autonomy in Table 4 are measured as Likert scales from 1 to 5, indicating the degree of autonomy to exercise a particular right (Akhmadiyeva & Herzfeld 2021). For example, respondents were asked 'How free are you to enter the agricultural land of your farm?' The answers to such questions ranged from across five options such as from 'I cannot enter' (1) to 'I can enter always' (5). The economic freedoms of interviewed farmers on other aspects are assessed in similar ways.

Table 5 summarizes the descriptive statistics of other covariates $z_{i,t=2018}$ that are assumed to be associated with the level of training receipts and autonomy on production decisions in 2018. Most farm enterprises are of medium sizes, with 10 ~ 50 ha of farms, and typically with 10,000 ~ 50,000 USD of business assets.[5]

Table 6 summarizes the descriptive statistics of other covariates $z_{i,t=2018}$ that are assumed to be associated with the level of training receipts and autonomy on production decisions in 2018. It shows descriptive statistics based on both raw sample and IPW sample. The raw samples suggest that receipt of training and the level of economic freedom are significantly associated with farm enterprise characteristics. Once adjusted by IPW, however, the differences become statistically insignificant for all covariates, suggesting that IPW-SFA models discussed can attribute any remaining differences in technical efficiency to the receipt of training and/or economic freedom.

5 Results

5.1 Simple panel fixed-effects instrumental variable regression

Table 7 summarizes results based on the simple panel-fixed effects IV regression (1). Coefficients on interaction terms between input prices (oil/diesel, fertilizer) and intensity of training received or level of autonomy in production decision-making are statistically significantly positive for revenue and profit per area. These results imply that training and autonomy generally mitigate adverse effects, if any, of input price increases on revenue and profit per area (which we use as key indicators of productivity as described earlier). Table 8 summarizes the same sets of main results as Table 7, but for crop-specific regressions for cotton and wheat. Results in Table 8 are largely consistent with the aggregated results in Table 7, suggesting that the patterns also hold at major crops levels.

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[5] There are considerable variations in sample characteristics between those on the Uzbek side of the border, and the Kazakh side of the border, despite similar agroecological conditions. Importantly, these cross-border variations together with within-country variations may imply that there are inherent differences in sample characteristics between each side of the border. As was described in the empirical methodology section, we control for such inherent differences through the inclusion of country dummy variable. In IPW-SFKK, constructing IPW based on variables including country dummy variable assures that weighted samples are comparable across country border. We also offer results for wheat which is exclusively grown among Uzbek sample, which is free from any country-specific effects.

Results on Table 7 suggest that the training and autonomy can potentially have meaningfully significant effects on alleviating the shocks due to input price increases. They motivate a more in-depth assessment of the effects on technical efficiency in subsequent sections and assure that findings in subsequent sections are not mere artifacts of methodological complexities.

5.2 Stochastic frontier regressions

Table 9 presents the main results of SFPS model (2). Specifically, we present the estimated coefficients for γ_s and γ_{sz}, corresponding measurements in terms of elasticity of average technical efficiency with respect to input price increase, and the extent of mitigation of elasticity change due to one-standard increase in mandatory training intensity.

Table 9 (top panel) suggests that technical efficiency is negatively associated with higher input prices, particularly fertilizer price (albeit insignificant for oil/diesel price). However, receiving more mandatory training in 2018 partly mitigates such negative associations, as shown by statistically significant positive coefficients on the interaction term. The elasticity of the average technical efficiency with respect to fertilizer price is -0.256. However, one standard deviation increases in the number of types of mandatory training received mitigated this elasticity by 0.089. Similarly, the same increase in mandatory training is associated with 0.128 increase in the elasticity with respect to oil/diesel price. The aforementioned results (for all crops combined) are generally consistent with crop-specific results for cotton and wheat (Table 9, lower panels). For cotton production, the elasticity of average technical efficiency with respect to fertilizer price is –0.109 with statistical significance, but this is mitigated by 0.012 through a one-standard deviation increase in mandatory training received. For wheat production, the elasticity of average technical efficiency with respect to oil/diesel price, which is –0.144 (albeit statistically insignificant), is mitigated by 0.044 a one-standard deviation increases in mandatory training received. While results are somewhat less precise for cotton and wheat production due to smaller sample sizes, there is no statistically significant evidence that training aggravates the negative elasticity.

Similarly, Table 9 (top panel) presents the results for the potential effects of having greater autonomy. These results suggest that farms that had less autonomy in production decision-making (restricted farms) experienced significant reduction in technical efficiency due to higher oil/diesel price, while farms with more autonomy did not experience such effects. Similarly, for cotton production specifically, restricted farms experienced a significant reduction in technical efficiency due to price increases for chemical fertilizer, while farms with more autonomy did not experience similar reduction in technical efficiency. Since IPW method makes farms with more autonomy and farms with less autonomy comparable, these qualitative differences in technical efficiency response to input price increases are more clearly attributable to the level of autonomy farms were granted in production related decisions.

Altogether, these results are consistent with the hypotheses that receiving mandatory training partly mitigates the negative effects of increased input prices on technical efficiency.

IPW-SFKK model

Table 10 presents the main results based on IPW-SFKK (3), (4) and (7). As was described above, since results are based on IPW-balanced samples, the differences between samples are directly attributable to the level of respondents' exposure to training and/or their level of autonomy in production decision making in 2018. For example, the first 4 columns in Table 10 show that, receiving more intensive training in 2018 raised average technical efficiency scores for the rest of 2018 as well as in 2021, under either specification of production frontiers (7) with X_{it} being oil / diesel or chemical fertilizer. Similarly, the latter 4 columns imply that being granted greater autonomy in production decisions raised average technical efficiency scores.

Table 10 shows how the technical efficiency is resilient against or sensitive to the changes in the key inputs, oil/diesel and chemical fertilizer, and how the training and autonomy affected these. In all cases, estimated coefficients are statistically significantly negative for less intensive trainees or more restricted farms; in other words, for these farmers, reducing the use of oil/diesel and/or chemical fertilizer in 2021 (in response to their increased prices) significantly lowered technical efficiency. On the other hand, they are not statistically significant for other groups of farmers; in other words, intensive trainees and farms with more autonomy have been more resilient so that reducing oil/diesel and/or chemical fertilizer in 2021 did not reduce their technical efficiency.

The bottom part of Table 10 shows similar results but focusing specifically on cotton and wheat production. These results suggest that results for all crops combined generally hold for these individual crops, although statistical significance somewhat declines due to smaller sample sizes. Specifically, for cotton production, receiving more training in 2018 and/or having more autonomy in production decisions in 2018 makes technical efficiency less vulnerable to reduced use of oil/diesel or chemical fertilizer. Similarly, for wheat production, receiving more training and/or having more autonomy in production decisions in 2018 helped technical efficiency less vulnerable to the reduced use of oil/diesel.

5.3 Other robustness checks

Further analyses show that our main results discussed above hold fairly robust across variations in our model specifications.

5.3.1 Using 40 or 60 percentiles instead of 50 percentiles as thresholds

Table 11 shows the same set of results for IPW-SFKK as Table 10, but using slightly different percentiles (40 and 60 percentiles) of training intensity and the level of economic freedom, instead of 50 percentiles used in Table 10. Results in Table 11 suggest that results are largely consistent with Table 10, i.e., receiving less training and/or less autonomy in production decision-making is associated with greater vulnerability in their technical efficiency when facing increased prices and are forced to reduce the use of oil/diesel and chemical fertilizer.

5.3.2 Robustness against potential violation of conditional independence assumption of IPW

IPW relies on the assumption of conditional independence (or sometimes also called *ignorability*, *selection on observables*) (Imbens & Wooldridge 2009). IPW estimates can be biased if there are unobservable confounders that are associated with both the training receipt or autonomy on production decision, and technical efficiency. To see if our results are affected by potential biases, we conduct sensitivity analyses (Li et al. 2011) which assess how IPW estimates change depending on the extent to which estimated propensity score $\widehat{p_i}$ from (3) deviates from the true propensity score. Table 12 summarizes how key results on the change in technical efficiency due to reduced inputs uses from Table 10, vary depending on the deviations in true propensity scores. Table 12 shows that the statistical significance or insignificance continue to hold against deviations in propensity scores, even when deviations are 30% (in other words, estimated propensity scores are 30% different from the true propensity scores), which can suggest that results are reasonably robust against the violation in conditional independence assumption of IPW (Li et al. 2011).

5.3.3 Attrition

Our data also includes a significant number of farm enterprises who were interviewed in 2019 but did not respond in 2022. This information allows us to assess if sample attrition is an issue in our analyses. We estimate a probit regression in which we regress a binary indicator of attrition (whether the sample originally interviewed in 2019 was also interviewed in 2022) on all exogenous variables in 2019 data.

Table 13 shows the results of probit regression. The results show that attrition is not statistically significantly associated with any covariates, suggesting that the non-response in 2022 was relatively random and therefore do not bias our results.

5.4 Interpretation of production frontier

Our primary focus is the effects of training and greater autonomy on technical efficiency in the presence of higher oil/diesel prices and fertilizer prices, and the results on other covariates are of secondary importance. We therefore show the results for other covariates in Appendix Table 15 and Table 16. Both tables suggest that in production functions for all crops combined, as well that for cotton and wheat, land and other expenditures are generally more statistically significant, while family labor and agricultural capital are somewhat more weakly significant. The generally statistically insignificant effects of family labor may reflect that there is somewhat surplus labor, similar to experiences in other parts of Asia in earlier years (e.g., Wan & Cheng 2001). Results in these tables also suggest that greater temperature anomaly generally negatively affects productivity. Results for SFKK in Table 16 suggests that the heterogeneity of technical efficiency (u_{it} in equation (7)) is greater among smaller farms. Results for SFKK in Table 16 also suggests that the use of oil/diesel or chemical fertilizer is significantly associated with excluded IVs and the use of other inputs like land, family labor and other expenditures.

6 Conclusions

Economic resilience within the agrifood system is becoming increasingly crucial for assuring sustainable development. This is particularly so in developing regions with volatile and fragile environments, including Central Asia. Evidence remains scarce regarding what factors can enhance the economic resilience of agents within the agrifood system, including the resilience of productivity and technical efficiency. We partly fill this knowledge gap using the unique panel datasets of farm enterprises in Uzbekistan and southern Kazakhstan, collected in 2018 and 2021, during which these enterprises experienced significant economic shocks in input prices.

Our results consistently show that receiving critical public goods, including information and knowledge (through training) and enabling environment (that grant greater production-related decision-making power) have enhanced resilience of farm enterprises against economic shocks represented by increased prices of key inputs like oil/diesel and chemical fertilizer. The persistence of high technical efficiency against the shocks is one pathway of such resilience. Our results further confirm that farm enterprises that received more training and/or decision-making power could better maintain their technical efficiency while reducing oil/diesel and chemical fertilizer inputs in response to higher prices. These results are generally robust and hold across various model specifications, in both reduced form specifications and structural form specifications.

Lastly, our findings have several policy implications that underscore the importance of proactive measures to strengthen the economic resilience of farm enterprises in irrigated areas of Central Asia. To enhance the economic resilience of agrifood systems, it remains important for the Kazakhstan and Uzbekistan governments to prioritize investments in critical public goods by incorporating more training as part of the complementary strategies to transition into a more environmentally sustainable production system while retaining technical efficiency. To allow farm enterprises to better navigate economic shocks, policymakers should implement initiatives aimed at information and knowledge dissemination by expanding training programs and providing access to agricultural extension services.

Furthermore, governments should pay attention to creating an institutional environment that grants farmers greater autonomy in their farming operations to adapt effectively to economic shocks and changing input prices. Our results on the role of economic freedom of farmers in their resilience are particularly relevant for the government of Uzbekistan. Over the recent few years, the government of Uzbekistan has been promoting a shift toward more competitive, market- and export-oriented agriculture under the Agrifood Development Strategy 2020-2030, which aims at diversifying agricultural portfolio, attracting private investments, and improving land tenure security. Such approaches that should also elaborate greater decision-making autonomy of farmers will be particularly effective in maintaining resilience against economic shocks, including those triggered by today's regional geopolitical uncertainty in Central Asia. In addition, policymakers should invest in micro-level data collection and analysis to monitor and evaluate the impacts of policies and interventions on farm resilience. Continuous data collection, as demonstrated in the panel dataset used in this study, can help policymakers make informed decisions and tailor their strategies to the specific needs of their agricultural sector. Finally, policymakers in other regions facing similar socioeconomic challenges can draw insights from our two-country empirical analysis suggesting that investments in public goods and empowering farmers can be effective strategies to enhance the resilience of agrifood systems, regardless of the region's economic context.

References

Akhmadiyeva Z & T Herzfeld. 2021. How does practice matches land laws in Central Asia? *Land Use Policy 109*:105726.

Araujo-Enciso SR & T Fellmann. 2020. Yield variability and harvest failures in Russia, Ukraine and Kazakhstan and their possible impact on food security in the Middle East and north Africa. *Journal of Agricultural Economics 71*(2):493-516.

Asfaw EB. 2021. State-led cotton deregulation in Uzbekistan: Reforms and effects. *Central Asian Journal of Water Research 7*(2):121-37.

Baliki G, T Brück, NT Ferguson & SW Kebede. 2022. Fragility exposure index: Concepts, measurement, and application. *Review of Development Economics 26*(2):639-60.

Barrett CB, K Ghezzi-Kopel, J Hoddinott, N Homami, E Tennant, J Upton & T Wu. 2021. A scoping review of the development resilience literature: Theory, methods and evidence. *World Development 146*:105612.

Bizikova L, P Larkin, S Mitchell & R Waldick. 2019. An indicator set to track resilience to climate change in agriculture: a policy-maker's perspective. *Land Use Policy 82*, 444-56.

Briguglio L, G Cordina, N Farrugia & S Vella. 2009. Economic vulnerability and resilience: concepts and measurements. *Oxford Development Studies 37*(3):229-47.

Callais JT & JB Pavlik. 2022. Does economic freedom lighten the blow? Evidence from the great recession in the United States. *Economics of Governance*, in press.

Cavatassi R, L Salazar, M González-Flores & Winters P. 2011. How do agricultural programmes alter crop production? Evidence from Ecuador. *Journal of Agricultural Economics 62*(2):403-28.

Cullen R. 2017. Evaluating renewable energy policies. *Australian Journal of Agricultural and Resource Economics 61*(1):1-18.

Djanibekov N, S Charyyeva, G Sanaev. 2020. Cotton sector reforms in Central Asia. *IAMO Annual 22, Halle (Saale):*46-54.

Efron B. 1979. Bootstrap methods: Another look at the jackknife. *Ann. Stat. 7*:101-18.

Fellmann T, S Hélaine & O Nekhay. 2014. Harvest failures, temporary export restrictions and global food security: the example of limited grain exports from Russia, Ukraine and Kazakhstan. *Food Security 6*:727-42.

Fischer RA & DJ Connor. 2018. Issues for cropping and agricultural science in the next 20 years. *Field Crops Research 222*:121-42.

Food and Agriculture Organization (FAO). (2023). *FAOSTAT*. Rome, Italy.

Foster A & M Rosenzweig. 1995. Learning by doing and learning from others: Human capital and technical change in agriculture. *Journal of Political Economy 103*(6):1176-1209.

Fuwa N, C Edmonds, P Banik. 2007. Are small-scale rice farmers in eastern India really inefficient? Examining the effects of microtopography on technical efficiency estimates. *Agricultural Economics 36*(3):335-46.

Glauber JW & D Laborde. 2023. *The Russia-Ukraine conflict and global food security.* Washington, DC: IFPRI.

IFPRI. 2020. *COVID-19 & Global Food Security*. Washington DC.

Huber M. 2014. Treatment evaluation in the presence of sample selection. *Econometric Reviews 33*(8):869-905.

Imbens G & J Woolridge. 2009. Recent developments in the econometrics of program evaluation. *Journal of Economic Literature 47*(1):5-86.

Karakaplan MU & L Kutlu. 2017. Endogeneity in panel stochastic frontier models: an application to the Japanese cotton spinning industry. *Applied Economics 49*(59):5935-39.

Karakaplan MU. 2022. Panel stochastic frontier models with endogeneity. *Stata Journal 22*(3):643-63.

Kazbekov J & AS Qureshi. 2011. *Agricultural extension in Central Asia: Existing strategies and future needs* (Vol. 145). IWMI.

Khan MA, A Wahid, M Ahmad, MT Tahir, M Ahmed, S Ahmad & M Hasanuzzaman. 2020. *World cotton production and consumption: An overview.* In *Cotton production and uses: Agronomy, crop protection, and postharvest technologies*, by S Ahmad & M Hasanuzzaman. Springer.

Khatri-Chhetri A, TB Sapkota, S Maharjan, NC Konath & P Shirsath. 2023. Agricultural emissions reduction potential by improving technical efficiency in crop production. *Agricultural Systems 207*:103620.

Kienzler KM, N Djanibekov & JP Lamers. 2011. An agronomic, economic and behavioral analysis of N application to cotton and wheat in post-Soviet Uzbekistan. *Agricultural Systems 104*(5), 411-18.

Kuhl L. 2018. Potential contributions of market-systems development initiatives for building climate resilience. *World Development 108*:131-44.

Kurbanov Z, A Tadjiev & N Djanibekov. 2022. Adoption of sustainable agricultural practices and investments in productive assets in irrigated areas of Central Asia: Farm–survey evidence from Kazakhstan and Uzbekistan. *Leibniz Institute of Agricultural Development in Transition Economies (IAMO) Annual 24*:69-79.

Kutlu L. 2022. Spatial stochastic frontier model with endogenous weighting matrix. *Empirical Economics 63*(4):1947-68.

Laborde JP, CS Wortmann, H Blanco-Canqui, CA Baigorria & JL Lindquist. 2020. Identifying the drivers and predicting the outcome of conservation agriculture globally. *Agricultural Systems 177*:102692.

Li L, C Shen, AC Wu & X Li. 2011. Propensity score-based sensitivity analysis method for uncontrolled confounding. *American Journal of Epidemiology 174*(3):345-53.

Organisation for Economic Co-operation and Development (OECD) (2020). *States of Fragility 2020.* Paris: OECD. 126p.

Paul S & S Shankar. 2020. Estimating efficiency effects in a panel data stochastic frontier model. *Journal of Productivity Analysis 53*:163-80.

Pellegrini P & RJ Fernández. 2018. Crop intensification, land use, and on-farm energy-use efficiency during the worldwide spread of the green revolution. *Proceedings of the National Academy of Sciences 115*(10):2335-40.

Petrick M, D Oshakbaev & J Wandel. 2017. *More than pouring money into an ailing sector? Farm-level financial constraints and Kazakhstan's 'Agribusiness 2020'strategy*. In S Gomez y Paloma, S Mary, S Langrell & P Ciaian (Eds.). The Eurasian wheat belt and food security (pp. 103–118). Springer, Cham.

Robins JM & A Rotnitzky. 1995. Semiparametric Efficiency in Multivariate Regression Models with Missing Data. *Journal of the American Statistical Association 90*(429):122-29.

Sadoulet E & A de Janvry. 1995. *Quantitative Development Policy Analysis.* Johns Hopkins University Press, Baltimore and London.

Salam MA, S Rahman, AR Anik & SC Sharna. 2023. Exploring competitiveness of surface water versus ground water irrigation and their impacts on rice productivity and efficiency: An empirical analysis from Bangladesh. *Agricultural Water Management 283*:108298.

Shtaltovna A & AK Hornidge. 2014. *A comparative study on cotton production in Kazakhstan and Uzbekistan*. Center for Development Research (ZEF), University of Bonn.

Smith TA & CE Landry. 2021. Household Food Waste and Inefficiencies in Food Production. *American Journal of Agricultural Economics 103*(1):4-21.

Sondermann D. 2018. Towards more resilient economies: The role of well-functioning economic structures. *Journal of Policy Modeling 40*(1):97-117.

Steinke J, J van Etten, A Müller, B Ortiz-Crespo, J van de Gevel, S Silvestri & J Priebe. 2021. Tapping the full potential of the digital revolution for agricultural extension: an emerging innovation agenda. *International Journal of Agricultural Sustainability 19*(5-6):549-565.

Swinnen JFM. 2009. Reforms, globalization, and endogenous agricultural structures. *Agricultural Economics 40*(6):719-32.

Swinnen JF, A Vandeplas & M Maertens. 2010. Liberalization, endogenous institutions, and growth: a comparative analysis of agricultural reforms in Africa, Asia, and Europe. *World Bank Economic Review 24*(3):412-45.

Takeshima H. 2017. Custom-hired tractor services and returns to scale in smallholder agriculture: A production function approach. *Agricultural Economics 48*(3):363-72.

Takeshima H, N Houssou, X Diao. 2018. Effects of tractor ownership on returns-to-scale in agriculture: Evidence from maize in Ghana. *Food Policy 77*:33-49.

Takeshima H. 2019. Geography of plant breeding systems, agroclimatic similarity, and agricultural productivity: an insight from Northern Nigeria. *Agricultural Economics 50*(1):67-78.

Takeshima H, K Akramov, A Park, J Ilyasov, Y Liu & T Ergasheva. 2020a. Agriculture–nutrition linkages with heterogeneous, unobserved returns and costs: Insights from Tajikistan. *Agricultural Economics 51*(4):553-65.

Takeshima H, P Hatzenbuehler, H Edeh. 2020b. Effects of agricultural mechanization on economies of scope in crop production in Nigeria. *Agricultural Systems 177*, 102691.

Takeshima H, B Balana, J Smart, HO Edeh, MA Oyeyemi & KS Andam. 2022. Subnational public expenditures, short-term household-level welfare and economic flexibility: Evidence from Nigeria. *Agricultural Economics 53*(5):739-55.

Wan GH & E Cheng. 2001. Effects of land fragmentation and returns to scale in the Chinese farming sector. *Applied Economics 33*(2):183-194.

World Bank. 2007. *World Development Report 2008: Agriculture for Development*. Washington, DC: World Bank.

World Bank. 2023. *World Development Indicators.* Washington, DC: World Bank.

Zorya S, N Djanibekov & M Petrick. 2019. *Farm restructuring in Uzbekistan: How did it go and what is next?* World Bank Group, Washington, D.C.

Table 1. Production characteristics (panel samples, both countries combined)

Variables	All		Kazakhstan		Uzbekistan	
	2018	**2021**	**2018**	**2021**	**2018**	**2021**
	Mean	Mean	Mean	Mean	Mean	Mean
Area cultivated (ha)	26	38	12	10	37	62
Revenue	964	1097	2124	1565	658	1029
Family labor (person-day / ha)	27	12	74	29	15	10
Other expenses	187	199	289	211	150	197
Fertilizer	10	9	11	12	9	8
Oil / diesel	3	2	6	1	3	2
Farm business asset	183	188	401	226	123	183

Source: Authors.

Note: All values are in USD / per ha, unless specified otherwise.

Table 2. Use and price of fertilizer and oil/diesel (sample median)

Input	Use / price	All		Kazakhstan		Uzbekistan	
		2018	**2021**	**2018**	**2021**	**2018**	**2021**
Chemical fertilizer	Use (kg / ha)	47	28	73	53	41	25
	Price (USD / kg)	0.164	0.278	0.153	0.253	0.188	0.278
Oil / diesel	Use (kg / ha)	6	2	11	3	5	2
	Price (USD / kg)	0.600	0.880	0.492	1.505	0.613	0.880

Source: Authors.

Table 3. Types of training received in 2018 among panel samples

Types	Unit	Kazakhstan	Uzbekistan
Application of manure and fertilizers	Yes = 1	0.026	0.104
Laser leveling	Yes = 1	0.000	0.000
Crop rotation	Yes = 1	0.011	0.036
Chemical protection of plants	Yes = 1	0.019	0.039
Biological protection of plants	Yes = 1	0.026	0.019
Agro technics of wheat production	Yes = 1	0.000	0.524
Agro technics of cotton production	Yes = 1	0.019	0.385
Agro technics of vegetable production	Yes = 1	0.019	0.071
Agro technics of fruit production	Yes = 1	0.011	0.016
Quality and export procedures	Yes = 1	0.004	0.291
Other	Yes = 1	0.082	0.007
Total types of training received	**Average count**	**0.215**	**1.230**

Source: Authors.

Table 4. Type of autonomy in 2018 among panel samples

Types	Unit	Kazakhstan	Uzbekistan
Enter agricultural land of your farm	Yes = 1	0.996	0.990
Collect harvest from your land	Yes = 1	0.996	0.618
Change the purpose of land use within agriculture	Yes = 1	0.970	0.269
Decide which crop to cultivate	Yes = 1	0.993	0.340
Decide which cultivation methods to use	Yes = 1	0.993	0.909
Decide how much to invest in land	Yes = 1	0.993	0.932
Prohibit other farmers and households from producing crops on your land	Yes = 1	0.955	0.926
decide where/how, whom and for how much to sell main harvested crops	Yes = 1	1.000	0.372
Grant another person permission to use your land	Yes = 1	0.758	0.246
Sell land to others	Yes = 1	0.721	0.003
Use the land of other farmers who lease land from government	Yes = 1	0.862	0.146
Give your land as a heritage	Yes = 1	0.888	0.392
Average types of autonomy	**Average**	**0.928**	**0.512**

Source: Authors.

Table 5. Descriptive statistics of exogenous variables in baseline year 2018

Variables	Kazakhstan sample		Uzbekistan sample		Total	
	Mean	Std.dev.	Mean	Std.dev	Mean	Std.dev.
Age	48.238	(13.233)	43.916	(10.151)	45.891	(11.847)
Year of education	11.362	(2.883)	12.440	(2.507)	11.947	(2.736)
Had farming education or not	0.312	(0.464)	0.359	(0.481)	0.337	(0.473)
Farming experiences (years)	20.796	(10.100)	13.259	(8.008)	16.703	(9.768)
Share of female workers	0.090	(0.202)	0.035	(0.127)	0.060	(0.168)
Farmland endowment in 2018 (ha)	15.175	(45.057)	38.449	(28.322)	27.814	(38.670)
Access to irrigation water (1=head, 2=middle, 3=tail, 4=outside)	1.977	(0.742)	1.952	(0.685)	1.964	(0.712)
total farm business asset values (USD)	10,362.250	(25,418.690)	43444.520	(34,059.700)	28327.840	(18509.610)
Number of mandatory trainings received	0.004	(0.064)	0.301	(0.681)	0.163	(0.524)
Years since farm was established (years, natural log)	19.685	(5.097)	10.877	(6.757)	5.902	(7.476)
Sample size	260		309		569	

Source: Authors. ***1% **5% *10%.

Table 6. IPW – Balancing properties of IPW-samples

Variables	Separated by training status				Separated by autonomy			
	Raw sample		IPW sample		Raw sample		IPW sample	
	More intensive trainees	Less intensive trainees	More intensive trainees	Less intensive trainees	More autonomy	Less autonomy	More autonomy	Less autonomy
Age	45.007*	46.741	45.795	45.816	47.768***	44.420	44.560	45.458
Year of education	12.222**	11.683	12.061	11.933	11.432***	12.351	12.089	12.045
Had farming education or not	0.423***	0.255	0.385	0.369	0.328	0.345	0.431	0.384
Farming experiences	15.358***	17.997	16.855	16.758	20.588***	13.658	16.872	16.821
Share of female workers	0.050	0.069	0.068	0.060	0.091***	0.035	0.055	0.046
Farmland endowment in 2018 (ha, natural log)	3.290***	2.483	2.919	2.828	2.353***	3.290	2.901	2.880
Access to irrigation water (1=head, 2=middle, 3=tail, 4=outside)	1.985	1.943	2.028	1.974	1.976	1.953	2.029	2.012
total farm business asset values (USD, natural log)	7.584***	4.344	5.998	5.584	3.823***	7.587	5.662	5.712
Number of mandatory trainings received	0.197***	0.000	0.098	0.000				
Years since farm was established (years, natural log)					2.729***	2.194	2.450	2.461
Country (Uzbekistan = 1)	0.835***	0.262	0.552	0.483	0.100***	0.890	0.506	0.519

Source: Authors. ***1% **5% *10%.

Table 7. Results from simple panel fixed-effects regression (1)

Variables	Dependent variables			
	Ln (Revenue per area)		Ln (profit per area)	
Training	0.313***	-0.320	0.175	–0.331
	(0.111)	(0.234)	(0.236)	(0.314)
Oil / diesel price	–.096		0.043	
	(.109)		(0.048)	
Fertilizer price		-1.421**		-1.735**
		(0.611)		(0.883)
Oil / diesel price * Training	0.493**		0.205***	
	(0.244)		(0.066)	
Fertilizer price * Training		1.223*		1.635**
		(0.658)		(0.835)
Year dummy	Included	Included	Included	Included
Year dummy * Uzbekistan dummy	Included	Included	Included	Included
Temperature anomalies	Included	Included	Included	Included
Intercept	Included	Included	Included	Included
p-value (H_0: coefficients jointly insignificant)	.000	.000	.000	.000
p-value (H0: model underidentified)	.001	.000	.001	.000
Autonomy	1.805	0.417	0.519	1.520**
	(1.196)	(0.625)	(1.152)	(0.689)
Oil / diesel price	–0.734		-0.954	
	(0.484)		(0.817)	
Fertilizer price		–0.884*		–1.051
		(0.494)		(1.058)
Oil / diesel price * Autonomy	1.715*		2.145*	
	(1.036)		(1.358)	
Fertilizer price * Autonomy		2.047**		3.018***
		(0.997)		(0.753)
Year dummy	Included	Included	Included	Included
Year dummy * Uzbekistan dummy	Included	Included	Included	Included
Temperature anomalies	Included	Included	Included	Included
Intercept	Included	Included	Included	Included
p-value (H_0: coefficients jointly insignificant)	.000	.000	.000	.000
p-value (H0: model underidentified)	.001	.000	.066	.077
Sample	1,086	1,086	986	986

Source: Authors. ***1% **5% *10%.
Numbers in parentheses are heteroskedasticity-robust standard errors.

Table 8. Results from simple panel fixed-effects regression (1) by crops

Cotton

Variables	Ln (Revenue per area)		Ln (profit per area)	
Training	0.131***	-0.103	0.505**	0.158
Oil / diesel price	0.044		–0.386	
Fertilizer price		-0.142		-0.264
Oil / diesel price * Training	0.277***		1.051*	
Fertilizer price * Training		0.485		0.626*
Year dummy	Included	Included	Included	Included
Year dummy * Uzbekistan dummy	Included	Included	Included	Included
Temperature anomalies	Included	Included	Included	Included
Intercept	Included	Included	Included	Included
p-value (H_0: jointly insignificant)	.000	.000	.000	.000
p-value (H0: model underidentified)	.034	.000	.031	.000
Autonomy	0.268	0.367***	0.697	0.554***
Oil / diesel price	–0.185		0.027	
Fertilizer price		–0.169***		–0.236***
Oil / diesel price * Autonomy	0.351		0.961*	
Fertilizer price * Autonomy		0.164**		0.222**
Year dummy	Included	Included	Included	Included
Year dummy * Uzbekistan dummy	Included	Included	Included	Included
Temperature anomalies	Included	Included	Included	Included
Intercept	Included	Included	Included	Included
p-value (H_0: jointly insignificant)	.000	.000	.000	.000
p-value (H0: model underidentified)	.001	.000	.000	.000
Sample	678	678	648	648

Wheat

Training	0.948	0.605***	0.353	0.578**
Oil / diesel price	0.576		–0.818*	
Fertilizer price		-2.314***		-2.274**
Oil / diesel price * Training	–0.395		0.068*	
Fertilizer price * Training		1.453***		1.391**
Year dummy	Included	Included	Included	Included
Year dummy * Uzbekistan dummy	Included	Included	Included	Included
Temperature anomalies	Included	Included	Included	Included
Intercept	Included	Included	Included	Included
p-value (H_0: jointly insignificant)	.000	.000	.000	.000
p-value (H0: model underidentified)	.008	.004	.008	.004
Autonomy	1.217**	0.364	–0.708	0.815*
Oil / diesel price	–1.452***		–3.879**	
Fertilizer price		0.449		0.582
Oil / diesel price * Autonomy	1.071*		3.204**	
Fertilizer price * Autonomy		1.184**		1.639**
Year dummy	Included	Included	Included	Included
Year dummy * Uzbekistan dummy	Included	Included	Included	Included
Temperature anomalies	Included	Included	Included	Included
Intercept	Included	Included	Included	Included
p-value (H_0: jointly insignificant)	.000	.000	.000	.000
p-value (H0: model underidentified)	.008	.010	.000	.014
Sample	604	604	588	588

Source: Authors. ***1% **5% *10%

Year dummy, Year dummy * Uzbekistan dummy, Temperature anomalies and Intercepts are included.

Table 9. Results for the SFPS model (2)

Category	All crops combined		Cotton		Wheat	
	Oil / diesel price	**Fertilizer price**	**Oil / diesel price**	**Fertilizer price**	**Oil / diesel price**	**Fertilizer price**
Efficiency changes due to higher inputs prices	–0.091** (0.040)	–0.633** (0.250)	–0.032** (0.015)	–0.425*** (0.185)	–0.153* (0.090)	–0.114 (0.226)
Elasticity of average technical efficiency with respect to input price increase (at sample mean)	–0.021**	–0.256**	–0.007**	–0.109***	–0.054*	-0.045
Training						
Efficiency changes due to higher inputs prices * More training in 2018	0.096** (0.043)	0.243** (0.142)	0.037** (0.018)	0.047* (0.028)	0.211** (0.097)	0.057* (0.030)
Mitigation of elasticity change due to 1sd increase in mandatory training intensity	0.033**	0.089**	0.013**	0.012*	0.044**	0.022*
Autonomy						
Efficiency changes due to higher inputs prices * More autonomy in 2018	0.077* (0.045)	0.215* (0.132)	0.229** (0.109)	0.242*** (0.093)	0.131** (0.056)	0.187** (0.095)
Mitigation of elasticity change due to 1sd increase in mandatory training intensity	0.027*	0.039*	0.046**	0.046***	0.013**	0.008**

Source: Authors. ***1% **5% *10%
Numbers in parentheses are heteroskedasticity-robust standard errors.

Table 10. IPW-SFKK model

Category	Groups by training in 2018				Groups by autonomy in 2018			
	Oil / diesels		Chemical fertilizer		Oil / diesels		Chemical fertilizer	
	Intensive trainees	Less intensive trainees	Intensive trainees	Less intensive trainees	More autonomy	Less autonomy	More autonomy	Less autonomy
All crops combined								
Mean efficiency score[a]	0.834***	0.772	0.804*	0.784	0.820**	0.784	0.831***	0.786
	(0.009)	(0.017)	(0.010)	(0.012)	(0.011)	(0.012)	(0.011)	(0.011)
Efficiency changes due	-0.059	-0.040*	-0.006	-0.063**	-0.037	-0.083***	0.019	-0.107**
to reduced inputs use	(0.056)	(0.021)	(0.058)	(0.030)	(0.025)	(0.026)	(0.057)	(0.053)
% increase in inefficiency due to 10% reduction in inputs use		1.8		2.9		3.8		5.0
Cotton								
Efficiency changes due	–0.039	–0.013**	–0.064	–0.051*	0.016	–0.051***	0.008	–0.065***
to reduced inputs use	(0.025)	(0.007)	(0.064)	(0.029)	(0.044)	(0.014)	(0.010)	(0.016)
Wheat								
Efficiency changes due	–0.055	–0.078**	-0.008	–0.070**	0.007	–0.067**	0.008	–0.015**
to reduced inputs use	(0.044)	(0.033)	(0.036)	(0.035)	(0.007)	(0.033)	(0.005)	(0.007)

Source: Authors. ***1% **5% *10%

[a]Asterisks in this row indicate statistically significant differences from 'less-intensive trainees' or 'restricted farm' samples. Numbers in parentheses are heteroskedasticity-robust standard errors.

Table 11. Results for Table 10 (all crops combined) but using 40 and 60 percentiles instead of 50 percentile as thresholds

Category	Groups by training in 2018				Groups by autonomy in 2018			
	Oil / diesels		Chemical fertilizer		Oil / diesels		Chemical fertilizer	
	Intensive trainees	Less intensive trainees	Intensive trainees	Less intensive trainees	More autonomy	Less autonomy	More autonomy	Less autonomy
60 percentiles								
Mean efficiency score[a]	0.800** (0.010)	0.768 (0.012)	0.985*** (0.001)	0.779 (0.010)	0.869*** (0.009)	0.735 (0.013)	0.861*** (0.010)	0.756 (0.012)
Efficiency changes due to reduced inputs use	–0.059 (0.056)	–0.025*** (0.002)	-0.001 (0.001)	-0.036*** (0.010)	–0.006 (0.004)	–0.031*** (0.012)	0.005 (0.008)	–0.048*** (0.015)
% increase in inefficiency due to 10% reduction in inputs use		1.1		1.6		1.2		2.0
40 percentiles								
Mean efficiency score[a]	NA	NA	NA	NA	0.971** (0.002)	0.832 (0.009)	0.989*** (0.002)	0.816 (0.010)
Efficiency changes due to reduced inputs use					-0.004 (0.003)	-0.013*** (0.001)	0.001 (0.005)	-0.002** (0.001)
% increase in inefficiency due to 10% reduction in inputs use						0.8		1.1

Source: Authors. ***1% **5% *10%
Numbers in parentheses are heteroskedasticity-robust standard errors.

Table 12. Sensitivity of IPW-SFKK model results for Table 10

Category		Groups by training in 2018				Groups by autonomy in 2018			
		Oil / diesels		Chemical fertilizer		Oil / diesels		Chemical fertilizer	
Efficiency change due to reduced inputs use	Deviations in true propensity scores	**Intensive trainees**	**Less intensive trainees**	**Intensive trainees**	**Less intensive trainees**	**More autonomy**	**Less autonomy**	**More autonomy**	**Less autonomy**
All crops combined	0%	–0.059	–0.040*	–0.006	–0.063**	–0.037	–0.083***	0.019	–0.107**
		(0.056)	(0.021)	(0.058)	(0.030)	(0.025)	(0.026)	(0.057)	(0.053)
	10%	–0.050	–0.038*	–0.005	–0.063**	–0.038	–0.088***	0.020	–0.117**
		(0.046)	(0.021)	(0.052)	(0.027)	(0.026)	(0.027)	(0.058)	(0.057)
	20%	–0.037	–0.036*	–0.004	–0.062**	–0.039	–0.093***	0.020	–0.128**
		(0.034)	(0.020)	(0.043)	(0.027)	(0.027)	(0.029)	(0.059)	(0.061)
	30%	–0.020	–0.034*	–0.002	–0.060**	–0.040	–0.098***	0.021	–0.137**
		(0.019)	(0.019)	(0.030)	(0.026)	(0.027)	(0.031)	(0.060)	(0.065)
Cotton	0%	–0.039	–0.013**	–0.064	–0.051*	0.016	–0.051***	0.008	–0.065***
		(0.025)	(0.007)	(0.064)	(0.029)	(0.044)	(0.014)	(0.010)	(0.016)
	10%	–0.036	–0.012**	–0.055	–0.048*	0.015	–0.057***	0.008	–0.062***
		(0.025)	(0.006)	(0.056)	(0.027)	(0.046)	(0.014)	(0.011)	(0.015)
	20%	–0.030	–0.011**	–0.045	–0.045*	0.015	–0.064***	0.008	–0.058***
		(0.018)	(0.005)	(0.048)	(0.025)	(0.047)	(0.015)	(0.011)	(0.013)
	30%	–0.019	–0.010**	–0.036	–0.043*	0.015	–0.072***	0.009	–0.051***
		(0.016)	(0.005)	(0.040)	(0.024)	(0.048)	(0.016)	(0.024)	(0.011)
Wheat	0%	–0.055	–0.078**	-0.008	–0.070**	0.007	–0.067**	0.008	–0.015**
		(0.044)	(0.033)	(0.036)	(0.035)	(0.007)	(0.033)	(0.005)	(0.007)
	10%	–0.057	–0.080**	0.002	–0.069**	0.023	–0.057**	0.006	–0.014**
		(0.045)	(0.035)	(0.047)	(0.035)	(0.014)	(0.027)	(0.006)	(0.007)
	20%	–0.021	–0.055**	0.035	–0.069**	0.025	–0.047**	0.006	–0.012*
		(0.048)	(0.025)	(0.071)	(0.035)	(0.016)	(0.021)	(0.004)	(0.007)
	30%	–0.025	–0.015**	0.092	–0.068**	0.026	–0.039**	0.010	–0.006*
		(0.048)	(0.007)	(0.103)	(0.034)	(0.016)	(0.017)	(0.010)	(0.003)

Source: Authors. ***1% **5% *10%.
Numbers in parentheses are heteroskedasticity-robust standard errors.

Table 13. Correlates of sample attrition in 2022

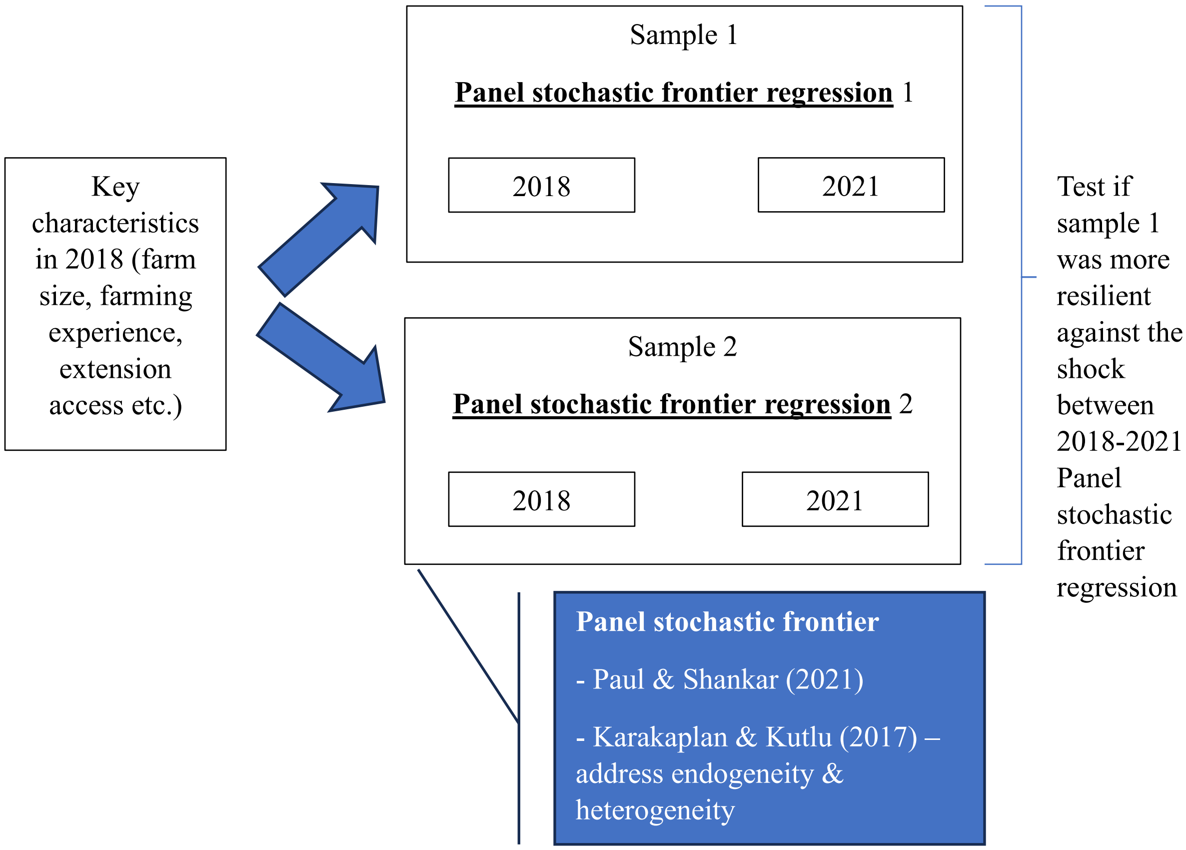
Variables	Coefficients	(std.err)
Age	0.000	(0.003)
Year of education	–0.012	(0.038)
Had farming education or not	0.022	(0.027)
Farming experiences	–0.004	(0.003)
Share of female workers	–0.127	(0.130)
Farmland endowment in 2018 (ha, natural log)	0.005	(0.034)
Access to irrigation water (1=head, 2=middle, 3=tail, 4=outside)	0.022	(0.029)
total farm business asset values (USD, natural log)	–0.004	(0.003)
Number of mandatory trainings received	–0.011	(0.046)
Years since farm was established (years, natural log)	0.004	(0.005)
Fertilizer price	–0.020	(0.018)
Oil/diesel price	0.024	(0.031)
Country (Uzbekistan = 1)	–0.131	(0.092)
Pseudo-R2	0.030	
Number of observations	915	

Source: Authors. ***1% **5% *10%

Marginal effects are evaluated at the means of all variables.

Numbers in parentheses are heteroskedasticity-robust standard errors.

Figure 1. Illustration of empirical approach



Source: Authors.

Appendix: Full results

Table 14. IPW correlates of training participation intensity and autonomy of production decisions

Variables	Training participation status		Autonomy of production decisions	
	Marginal elasticity	(std.err)	Marginal elasticity	(std.err)
Age	–0.116	(0.163)	–0.840**	(0.333)
Year of education	–0.103	(0.154)	–0.083	(0.311)
Had farming education or not	0.085***	(0.025)	0.027	(0.053)
Farming experiences	0.078	(0.080)	0.237	(0.169)
Share of female workers	0.010	(0.014)	0.044**	(0.022)
Farmland endowment in 2018 (ha, natural log)	0.178†	(0.123)	–0.069	(0.284)
Access to irrigation water (1=head, 2=middle, 3=tail, 4=outside)	0.084	(0.086)	–0.008	(0.188)
total farm business asset values (USD, natural log)	–0.004	(0.052)	0.019	(0.117)
Number of mandatory trainings received	0.337***	(0.024)		
Years since farm was established (years, natural log)			0.904**	(0.381)
Country (Uzbekistan = 1)	0.394***	(0.056)	–1.134***	(0.130)
Pseudo-R2	0.351		0.526	
Number of observations	548		548	

Source: Authors. ***1% **5% *10%

Marginal effects are evaluated at the means of all variables.

Numbers in parentheses are heteroskedasticity-robust standard errors.

Table 15. Full results for SFPS model in Table 9

Category	All crops combined		Cotton		Wheat	
	Oil / diesel price	Fertilizer price	Oil / diesel price	Fertilizer price	Oil / diesel price	Fertilizer price
Training						
Land	1.072***	1.058***	1.058***	1.064***	0.906***	0.903***
	(0.057)	(0.056)	(0.030)	(0.029)	(0.031)	(0.032)
Family labor	–0.005	–0.007	0.009	0.007	0.002	0.004
	(0.010)	(0.010)	(0.007)	(0.005)	(0.005)	(0.007)
Agricultural capital	0.001	0.004	0.002	0.002	0.007*	0.005*
	(0.008)	(0.008)	(0.006)	(0.002)	(0.004)	(0.003)
Other expenditures	0.171***	0.175***	–0.024	–0.028	0.002	–0.001
	(0.024)	(0.022)	(0.019)	(0.027)	(0.017)	(0.018)
Temperature anomaly	–0.011***	–0.010***	–0.005	–0.004*	–0.007	0.016
	(0.004)	(0.004)	(0.005)	(0.002)	(0.010)	(0.012)
Efficiency changes due to higher inputs prices	–0.091**	–0.633**	–0.032**	–0.425***	–0.153*	–0.114
	(0.040)	(0.250)	(0.015)	(0.185)	(0.090)	(0.226)
Training	0.005	0.008	0.028	–0.008	–0.668	0.051
	(0.009)	(0.009)	(0.145)	(0.007)	(0.634)	(0.043)
Efficiency changes due to higher inputs prices * More training in 2018	0.096**	0.243**	0.037**	0.047*	0.211**	0.057*
	(0.043)	(0.142)	(0.018)	(0.028)	(0.097)	(0.030)
Year dummy	Included	Included	Included	Included	Included	Included
Year dummy * Uzbekistan	Included	Included	Included	Included	Included	Included
Intercept	Included	Included	Included	Included	Included	Included
R-squared	.550	.554	.819	.822	.841	.825
Sample size	1,086	1,086	678	678	604	604
Autonomy						
Land	1.073***	1.046***	1.012***	1.030***	0.916***	0.914***
	(0.052)	(0.052)	(0.033)	(0.033)	(0.031)	(0.032)
Family labor	–0.007	–0.003	0.016**	0.014**	0.000	0.000
	(0.010)	(0.009)	(0.007)	(0.007)	(0.006)	(0.006)
Agricultural capital	0.003	0.006	0.006	0.006	0.004	0.006*
	(0.007)	(0.007)	(0.005)	(0.005)	(0.005)	(0.004)
Other expenditures	0.187***	0.177***	0.018	0.007	0.007	–0.004
	(0.024)	(0.025)	(0.019)	(0.019)	(0.019)	(0.019)
Temperature anomaly	–0.009**	–0.015***	–0.003	0.000	–0.010***	–0.019***
	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Efficiency changes due to higher inputs prices	–0.001	–0.459**	–0.085	–0.387***	–0.611***	–0.021
	(0.046)	(0.134)	(0.142)	(0.098)	(0.117)	(0.077)
Training	0.021	0.017*	0.009	0.019**	0.030***	0.010*
	(0.017)	(0.010)	(0.014)	(0.008)	(0.007)	(0.006)
Efficiency changes due to higher inputs prices * More training in 2018	0.076*	0.215*	0.229**	0.242**	0.131**	0.187**
	(0.045)	(0.132)	(0.109)	(0.093)	(0.056)	(0.095)
Year dummy	Included	Included	Included	Included	Included	Included
Year dummy * Uzbekistan	Included	Included	Included	Included	Included	Included
Intercept	Included	Included	Included	Included	Included	Included
R-squared	.551	.554	.812	.816	.846	.836
Sample size	1,086	1,086	678	678	604	604

Source: Authors. ***1% **5% *10%
Numbers in parentheses are heteroskedasticity-robust standard errors.

Table 16. Full results for SFKK model in Table 11

Variables	Groups by training in 2018				Groups by autonomy in 2018			
	Oil / diesels		Chemical fertilizer		Oil / diesels		Chemical fertilizer	
	Intensive trainees	Less intensive trainees	Intensive trainees	Less intensive trainees	More autonomy	Less autonomy	More autonomy	Less autonomy
Production frontier								
Land	0.795***	0.746***	0.867***	0.669***	0.941***	0.768***	0.718***	0.808***
	(0.069)	(0.118)	(0.055)	(0.073)	(0.305)	(0.053)	(0.081)	(0.052)
Family labor	0.023*	0.004	–0.013	0.015	–0.015	–0.013	0.015	–0.006
	(0.012)	(0.025)	(0.012)	(0.024)	(0.047)	(0.012)	(0.028)	(0.012)
Agricultural capital	–0.016	0.022	0.008	0.007	0.053	–0.004	0.013	0.000
	(0.013)	(0.024)	(0.009)	(0.010)	(0.064)	(0.009)	(0.011)	(0.008)
Other expenditures	0.128***	0.368***	0.179***	0.280***	0.364*	0.099*	0.260***	0.224***
	(0.034)	(0.135)	(0.054)	(0.087)	(0.193)	(0.053)	(0.079)	(0.072)
Temperature anomaly	0.001	0.003	–0.007	0.007	0.001	0.004	0.011	–0.004
	(0.007)	(0.009)	(0.006)	(0.009)	(0.017)	(0.006)	(0.016)	(0.006)
Oil/diesels	0.386**	–0.268			–0.526	0.256*		
	(0.173)	(0.336)			(0.749)	(0.136)		
Chemical fertilizer			–0.145	–0.016			–0.071	–0.112
			(0.200)	(0.220)			(0.257)	(0.173)
Year dummy	Included	Included	Included	Included	Included	Included	Included	Included
Year dummy*Uzbekistan	Included	Included	Included	Included	Included	Included	Included	Included
Intercept	Included	Included	Included	Included	Included	Included	Included	Included
Heteroskedasticity								
Land	–1.302***	–1.386***	–1.242***	–1.433***	–1.196***	–1.214***	–1.324***	–1.023***
	(0.355)	(0.384)	(0.272)	(0.397)	(0.431)	(0.312)	(0.441)	(0.287)
Intercept	Included	Included	Included	Included	Included	Included	Included	Included
Instrumenting regression								
Excluded IV	0.430***	0.178*	–0.154***	–0.177***	0.111	0.617***	–0.161***	–0.176***
	(0.096)	(0.102)	(0.041)	(0.052)	(0.118)	(0.091)	(0.058)	(0.034)
Land	0.244***	0.273***	–0.025	–0.212***	0.376***	0.090*	–0.198**	–0.004
	(0.073)	(0.106)	(0.066)	(0.070)	(0.123)	(0.055)	(0.081)	(0.051)
Family labor	0.018	–0.034	0.022	0.069**	–0.044	0.022	0.077**	0.028**
	(0.017)	(0.042)	(0.015)	(0.027)	(0.047)	(0.014)	(0.031)	(0.013)
Agricultural capital	0.051***	0.059***	0.011	0.010	0.080***	0.016	0.015	–0.006
	(0.012)	(0.021)	(0.011)	(0.013)	(0.023)	(0.010)	(0.015)	(0.009)
Other expenditures	0.032	0.405***	0.224***	0.366***	0.259***	0.306***	0.279***	0.375***
	(0.046)	(0.080)	(0.041)	(0.053)	(0.084)	(0.007)	(0.055)	(0.038)
Temperature anomaly	–0.016*	–0.020	–0.002	–0.032***	–0.019	–0.017**	–0.052***	–0.019***
	(0.009)	(0.015)	(0.008)	(0.010)	(0.018)	(0.007)	(0.012)	(0.006)
Year dummy	Included	Included	Included	Included	Included	Included	Included	Included
Year dummy*Uzbekistan	Included	Included	Included	Included	Included	Included	Included	Included
Intercept	Included	Included	Included	Included	Included	Included	Included	Included
p-value (H_0: variables jointly insignificant)	.000	.000	.000	.000	.000	.000	.000	.000
Sample size	543	543	543	543	543	543	543	543

Source: Authors. ***1% **5% *10%

Numbers in parentheses are heteroskedasticity-robust standard errors.

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