Agricultural Insurance Association with Farm Technology and Technical Efficiency

Francis Tsiboe*, Research Agricultural Economist, Economic Research Service, U.S. Department of Agriculture, 805 Pennsylvania Avenue, Kansas City, MO 64105, USA

Eric Njuki, Research Agricultural Economist, Economic Research Service, U.S. Department of Agriculture, 805 Pennsylvania Avenue, Kansas City, MO 64105, USA

*Correspondence to Francis Tsiboe, Economic Research Service, U.S. Department of Agriculture, 805 Pennsylvania Avenue, Kansas City, MO 64105, USA (Email: francis.tsiboe@usda.gov).

Acknowledgments

The findings and conclusions in this publication are those of the author(s) and should not be construed to represent any official USDA or U.S. Government determination or policy. This research was supported by the Economic Research Service, U.S. Department of Agriculture.

Abstract

This paper addresses divergent interpretations of agricultural insurance's association with on-farm production variability by conducting an exhaustive analysis of the U.S. Federal Crop Insurance Program and its effect on farm technology levels and efficiency. We utilize a meta-stochastic frontier approach and employ nearest-neighbor matching of insured and uninsured farms to minimize the self-selection issue in insurance participation. Analyzing 106,551 farm-level observations from the Agricultural Resource Management Survey spanning 2001–2023, we find that insured farms exhibit an 8.50% higher technology level and a 6.36% greater efficiency in resource usage compared to uninsured farms. This technology level gap associated with insurance is weakly linked to its ability to strengthen producers' financial positions, making them more reliable candidates for credit and potentially promoting the use of technologies that yield relatively higher output. Additionally, significant variations in the benefits of insurance across different farm types and operator demographics are documented, underscoring the necessity for agricultural policy to be responsive to the heterogeneous needs of the farming community to optimize the impact of insurance programs.

Keywords: agricultural insurance; farm technology; technical efficiency; Federal Crop Insurance Program (FCIP); risk management; credit access

JEL codes: Q12, Q18, G22, Q14, O33, Q16

Agricultural Insurance Association with Farm Technology and Technical Efficiency

1. Introduction

Agricultural production, inherently vulnerable to the volatility of climate conditions and market dynamics, faces amplified risks in recent years due to growing uncertainty surrounding climate change and market conditions, posing threats to producers' livelihoods. Although producers adopt various strategies (e.g., irrigation, savings, and diversification) to mitigate these challenges, the escalating threats emphasize the enduring importance of government safety net programs. Among these safety net programs, agricultural insurance has emerged as an essential resource, growing rapidly in both developed and developing countries as an integral part of support mechanisms for farmers and ranchers (Mahul and Stutley 2010; Smith and Glauber 2012; Turner et al. 2023). In 2007, approximately half of all countries had some form of agricultural insurance, collectively generating a total of $15.10 billion in premiums (Mahul and Stutley 2010). By 2024, the U.S. alone—which represented over half of the global premiums in 2007—had seen this figure more than double to $17.27 billion (Tsiboe and Turner 2023b). This expansion is indicative of the growing recognition of agricultural insurance as a pivotal tool to buffer the increasing risks inherent in agricultural production. However, divergent interpretations of its impacts on observed on-farm production variability across varied producers persist, establishing a dichotomy in understanding.

One school of thought suggests that because of asymmetric information agricultural insurance potentially facilitates “opportunistic behavior”—that is, adverse selection (Goodwin and Kastens 1993; Just, Calvin and Quiggin 1999; Makki and Somwaru 2001; Hou, Hoag and Mu 2011), moral hazard (Smith and Goodwin 2017; Roberts, Key and O’Donoghue 2006), or both— leading to inefficient resource use among insured farmers. [1] Proponents of this theory argue that the subsidized risk coverage supplied by agricultural insurance might inadvertently promote resource weakening innovations (Miao 2020; Woodard et al. 2012) and inefficient input and technology utilization (Walters et al. 2015; Castro et al. 2023; Giannakas, Schoney and Tzouvelekas 2001) due to the safety net against potential losses. In contrast, the alternate perspective posits that insured producers—predominantly risk-averse—employ on-farm management strategies to mitigate production variability. Advocates of this theory believe such farmers demonstrate greater efficiency in resource allocation (Roll 2019; Shaik 2013; Zubor-Nemes et al. 2018; Zhu and Lansink 2010) and exhibit higher propensity to embrace new and advanced technologies (Foltz, Useche and Barham 2013; Freudenreich and Mußhoff 2018; Comstock 2022; Tang et al. 2019; Carter, Cheng and Sarris 2016), presumably because of the peace of mind from coverage supplied by agricultural insurance.

Considering these contradictory viewpoints, the current study endeavors to reconcile this discord by undertaking an exhaustive analysis of the impact of agricultural insurance on two sources of observed on-farm production variability—technology level (a system, method or technique for transforming inputs into outputs) and technical efficiency (i.e., the ability to produce the maximum possible output from a given input bundle or, alternatively, a given level of output using the minimum amount of resources). We specifically explored these linkages in the United States (U.S.) Federal Crop Insurance Program (FCIP), the largest agricultural insurance portfolio worldwide and a key component of the U.S. farm safety net. At a subsidized premium, FCIP offers a wide variety of options for producers to customize a farm safety net instrument that addresses risk

[1] Adverse selection in crop insurance occurs when the insured hides information to gain greater returns, like using loaded dice unknowingly to the insurer. Moral hazard arises when insured parties amplify their risk-taking, such as using riskier farming practices, after getting insured.

specific to their unique operating environment in the current year. Common options include type of outcome protected (yield, price, revenue, or margin); type of risk pooling (individual or group-based); level of on-farm risk aggregation (e.g., field, farm, or enterprise); level of coverage (catastrophic [50%] up to 95%); and commodity (row crop, livestock, or specialty crop). For the 2024 crop year, there were over two million unique potential customized policy offerings available for producers to purchase according to their needs.

This study employs a Stochastic Meta-Frontier (SMF) approach, utilizing a sample of 106,551 farms from the Agricultural Resource Management Survey (ARMS) that represents two decades (2001 to 2023) of agricultural production experience in the U.S. Our primary objective is to evaluate if the production variability observed across farms, segregated by FCIP participation status, is associated with differences in resource utilization efficiency, technological gaps, or some blend of the two. To minimize self-selection bias in FCIP participation and to reduce model dependency, a matching approach is utilized, pairing each insured with an uninsured farm exhibiting similar characteristics. This strategy allows us to directly associate any observed production disparities to the FCIP participation status. To manage the intricate task of matching farms with multiple covariates, we utilize Nearest-Neighbor Matching (NNM).

The analysis reveals that insured farms have an average technological level index of 0.925, compared to 0.852 for uninsured farms, resulting in a technology gap of 8.5% associated with agricultural insurance in U.S. agricultural production. Evaluating the managerial capacity relative to their respective frontiers, insured farms have an average score of 0.657, while uninsured farms score 0.617. This suggests that insured farms are achieving, on average, 65.7% of their attainable frontier outputs, whereas uninsured farms are achieving 61.7%. However, against a common benchmark—the meta-frontier—we find that insured and uninsured farms operate at 60.6% and

54.2% of the best performing technology, respectively. This reflects a gap of 11.7% favoring insured farms due to differences in both production technology level (8.5%) and its efficient usage (6.4%). The technology level difference associated with agricultural insurance is later shown to be weakly linked to its ability to strengthen producers' financial positions, making them more reliable candidates for credit and potentially promoting the use of technology that produces relatively higher output.

Decomposed results by subsamples within the data also showed significant heterogeneity in the association of agricultural insurance with farm performance, revealing that high-level aggregated estimates may obscure important variations linked to farm characteristics and operator demographics. While insured farms generally outperform uninsured ones, the benefits are not uniformly distributed across all categories. Temporal dynamics indicate a declining gap in performance in favor of the insured over the years, with fluctuations corresponding to different Farm Bill periods. Sub-sample analysis shows that regions with higher insurance penetration tend to have larger performance advantages for insured farms. Moreover, operator characteristics such as gender, education level, and land ownership play a significant role in the magnitude of the performance gap associated with insurance. The variability across farm typologies, commodities, and linkage to other federal initiatives suggests that the association is multifaceted and influenced by a complex interplay of factors. These heterogeneities highlight the role of more nuanced policy designs that consider the diverse needs and circumstances of various farming operations to optimize the outcomes of agricultural insurance programs.

Our research enriches the existing body of literature in three significant ways. First, while numerous studies have investigated the effects of agricultural insurance on input usage and yield, only a few have examined whether insurance affects a farm’s technical efficiency. Moreover, most of these studies focus on a single commodity (Castro et al. 2023; Giannakas et al. 2001; Roll 2019) or evaluate programs that are small or still in a somewhat pilot stage (Zubor-Nemes et al. 2018), often using samples that are not nationally representative. To our knowledge, no study has investigated these issues as they apply to an established large insurance scheme that covers a country's entire primary agricultural production sector. In this paper, we broaden the scope by providing nationally representative insights from the FCIP—the largest agricultural insurance portfolio worldwide and a key component of the U.S. farm safety net—using a sample that is representative of the entire U.S. farm economy.

Our second contribution addresses how prior studies model insurance. Specifically, previous research often estimates the association of insurance on observed on-farm productivity by including insurance as an explanatory variable in the inefficiency function (Giannakas et al. 2001) or estimating efficiency indicators from a homogenous production function for the entire sample before conducting two sample t-test to assess the impact on insurance (Castro et al. 2023). These approaches do not account for the potential impacts of farm-level technological heterogeneity on agricultural production, which may arise from disparities in the enabling environment for production plausibly associated with agricultural insurance. Failing to consider these distinctions in production technology may lead to incorrectly attributing production shortfalls due to uneven distribution of technologies (i.e., technology gaps) to managerial inefficiency (Battese, Rao and O'Donnell 2004). Since output shortfalls from these two sources require different policy interventions, by accommodating both the technology level and its usage, we provide an in-depth understanding of the potential contributions of each source. This insight may prove useful in designing suitable policies for farms based on their insurance status.

Finally, our study benefits from a large sample size that spans over two decades of production experience across the entire United States. This rich, nationally representative dataset offers broader coverage of farms across time and space than any previous U.S. studies. As such, it provides a unique opportunity to empirically assess the spatial distribution and temporal dynamics of production parameters—such as elasticities, returns to scale (RTS), technological gaps, and productivity trends—as well as the efficiency with which existing technology is used. To the best of our knowledge, (Shaik 2013) is the only study with a similar spatial scope us ours, but with a longer temporal scope. However, it is worth noting that, the cross-sectional units were at the state level while ours is at the farm level. This is particularly important, by using more granular level data (i.e., farm level vs state level), our study minimizes the potential for aggregation bias. This coupled with the attention to endogeneity (self-selection into FCIP) means this study address two potential sources of bias.

2. Conceptual considerations

We draw from the productivity and efficiency literature, with this study focusing on Technical Efficiency (TE) - a farm's ability to maximize output from a given set of inputs. A farm or farmer's TE is measured through output orientation (comparing actual to potential output given inputs), or input orientation (comparing observed input levels to the minimum required for a given output) (Belotti et al. 2013). Both methods are implemented using Stochastic Frontier Analysis (SFA) (Meeusen and van Den Broeck 1977; Aigner, Lovell and Schmidt 1977) or Data Envelopment Analysis (DEA) (Charnes, Cooper and Rhodes 1978; Charnes, Cooper and Rhodes 1981). While DEA does not impose a functional form on data and assumes output variability is purely due to inefficiency, it is susceptible to outliers and lacks direct statistical properties for inferences. The SFA, on the other hand, is less susceptible to outliers but requires a well-specified functional form.

In the U.S. context, both SFA (C. J. M. Paul, Nehring and Banker 2004; Jonathan R. McFadden, Rosburg and Njuki 2022; Murova and Chidmi 2013) and DEA (C. Paul et al. 2004; Murova and Chidmi 2013) have been applied in empirical studies. However, in the spirit of this study, research on U.S. dairies and federal government programs using 2005 ARMS survey data found that the two methods yielded similar results for most examined variables (Murova and Chidmi 2013). Furthermore, it has been asserted that since the true level of efficiency is unknown, it's unfeasible to ascertain the superiority of one method over another, making the choice of method partly empirical and partly dependent on the available data and research goals (Battese, Heshmati and Hjalmarsson 2000). This study employs an adaptation of the output oriented SFA approach due to the absence of reliable price data.

The SFA approach assumes that a homogenous farm technology, coupled with the adoption of best management practices that allow maximum potential output for a given set of inputs, situates all farmers on the same production frontier. Thus, any production performance below this frontier is attributed to technical inefficiency(Bokusheva and Hockmann 2005). However, it has been observed that farmers in the same agricultural systems use differentiated technologies due to farmer characteristics (Asravor et al. 2024; Adaku, Tsiboe and Clottey 2023), resource availability, government regulation, input prices, and their environment (Hayami and Ruttan 1971; Tsiboe 2021; Ansah, Appiah-Twumasi and Tsiboe 2023), among others. Studies have also indicated that agricultural insurance potentially improves access to credit (Ifft, Kuethe and Morehart 2015a; Tsiboe and Turner 2023a), presumptively promoting enhanced technology adoption—a critical aspect of agricultural insurance utility worth considering. Failure to account for technological differences in each farm’s circumstance leads to falsely attributing technological gap-related production shortfalls to inefficient input use (Battese et al. 2004). Consequently, since the introduction of the Stochastic Meta-Frontier (SMF) approach (Hayami 1969) and further developments (Hayami and Ruttan 1970; Hayami and Ruttan 1971), it has been used to capture technological differences among farms.

Based on the dichotomy in understanding discussed in the introduction and the observed differences in covariates described in the data section that follows, this study considers an SMF (Huang, Huang and Liu 2014), to capture farmers' adoption of specific technologies based on their agricultural insurance participation status. We assume that there are two broad groupings of farms: insured and uninsured. Given this assumed structure, our conceptual model is an SMF where two agricultural insurance participation specific stochastic-frontier (SF) are enveloped under a national meta-stochastic-frontier. The SF for the j group (1 = uninsured and 2 = insured) faced by the i^{th} farm is denoted as:

$$y_{i,j} = f\left(\boldsymbol{x}_{i,j}; \boldsymbol{\alpha}_j\right) + \varepsilon_{i,j}, \qquad \varepsilon_{i,j} = v_{i,j} - u_{i,j} \qquad \forall j \in 1,2 \qquad (1)$$

here $y_{i,j}$ denotes the level of output, and function $f(\cdot)$ captures the deterministic relationship ($\boldsymbol{\alpha}_j$) between the production inputs ($\boldsymbol{x}_{i,j}$) and satisfy all the properties of a regular production technology. The term $\varepsilon_{i,j}$ drives the stochasticity in output and is decomposed into technical inefficiency ($u_{i,j}$) and idiosyncratic ($v_{i,j}$) effects, and their distributional assumptions underpin the estimation of Equation (1).

The term $u_{i,j}$ is non-negative, independent of $v_{i,j}$, and considered to be truncated at zero, accommodating several distributions and specifications, including the half normal, scaled, or unscaled truncated normal, exponential, uniform, gamma, Weibull, truncated skewed Laplace, Rayleigh, log normal, and generalized exponential. Key parameters in these distributions may also shift based on farmer demographics to evaluate their impact on technical inefficiency (Battese, Rambaldi and Wan 1997; Tsiboe 2021). On the other hand, $v_{i,j}$ is generally assumed to follow a normal distribution with a zero mean. Finally, the *j*th group specific technical efficiency of the *i*th farm ($TE_{i,j}$), is calculated as:

$$TE_{i,j} = E\left[\exp\left(-u_{i,j}\right) | \varepsilon_{i,j}\right]. \tag{2}$$

Next, the stochastic meta frontier that captures the output from all farms (regardless of insurance status), after having accounted for technical inefficiency ($u_{i,j}$) and idiosyncratic shocks ($v_{i,j}$) is given by.

$$\hat{y}_{i,j} = f\left(\boldsymbol{x}_{i,j}; \boldsymbol{\alpha}_j\right) = m\left(\boldsymbol{x}_{i,j}; \boldsymbol{\beta}\right) + \omega_i - \vartheta_i \tag{3}$$

Where $\boldsymbol{\beta}$ captures the deterministic relationship between the production inputs, ϑ_i has the same properties as $u_{i,j}$, and $f\left(\boldsymbol{x}_{i,j}; \boldsymbol{\alpha}_j\right) \leq m\left(\boldsymbol{x}_{i,j}; \boldsymbol{\beta}\right), \forall j \in 1,2$. Thus, the ratio of group *j*'s frontier to the meta-frontier is the technology gap ratio ($TGR_{i,j}$) is:

$$TGR_{i,j} = \frac{f\left(\boldsymbol{x}_{i,j}; \boldsymbol{\alpha}_j\right)}{m\left(\boldsymbol{x}_{i,j}; \boldsymbol{\beta}\right)}. \tag{4}$$

The technology gap depends on the adoption level of the best available technology, which in turn depends on producer/farm characteristics and the enabling environment for adoption. Together, each farm's meta-frontier technical efficiency (MTE) is:

$$MTE_{i,j} = TGR_{i,j} \times TE_{i,j}. \tag{5}$$

The three scores - $MTE_{i,j}, TE_{i,j}$, and $TGR_{i,j}$ - are performance measures that range from zero to one ([0,1]), where values closer to one indicate relatively better performance. The $TE_{i,j}$ assesses each farm's performance relative to their peer group, defined by insurance status. This score reflects the 'pure farm technical efficiency' for each farm, independent of the technology level potentially influenced by insurance status. After accounting for pure farm technical efficiency, the $TGR_{i,j}$ measures the differences in technology level solely driven by insurance status. Here, values closer to one suggest that these farms are operating near the best-performing frontier in terms of output level.

In what follows, we use micro data on U.S. farms of all forms and sizes to assess the extent to which agricultural insurance made available via the FCIP drives on-farm output variability linked to technology differential, technical efficiency, and their combination via the differences in $TGR_{i,j}$, $TE_{i,j}$, and $MTE_{i,j}$, respectively.

3. Data

This study employs data from the Agricultural Resource Management Survey (ARMS) provided by the USDA. Serving as the USDA's principal informational source on the financial standing, production practices, and resource usage of U.S. farm businesses, as well as the economic health of farm households, ARMS is a nationally representative survey. These data have been used in several previous studies to analyze various productivity issues in the U.S (C. Paul et al. 2004; C. J. M. Paul et al. 2004; Nehring et al. 2021; Darlington Sabasi, Shumway and Astill 2019; Jonathan R. McFadden et al. 2022; Mayen, Balagtas and Alexander 2010). The survey is conducted in three phases: a sample screening phase [Phase I], a field-level phase [Phase II], and a farm-level phase [Phase III], targeting approximately 5,000 fields and 30,000 farms annually. We pool farm level data from Phase III of ARMS, which provides information on farms producing crops or some combination of crops and livestock for the years 2001 to 2023.

Aside land and labor, we represented all other inputs in monetary terms, adjusted by the producer price index (with 2023 as base) obtained from the USDA, National Agricultural Statistics Service

(NASS). However, we calculated total production output for each farm via a two-part process. In the first step, we generated a commodity price index. For this index, we determined the basket at the state level, based on the weighted average production quantity for the commodities included in our sample. These averages were drawn from all conducted surveys. The baseline price for the index was set as the average commodity price at the state level for the year 2023. Next, we calculated the price index for each state and year. This was done by valuing the basket at the current price and then dividing it by the value of the same basket at the base price. Finally, we formulated the quantity index. This was achieved by dividing the total farm production value for each farm by the corresponding state-year price index.

The impact of insurance likely differs between crop and livestock sectors due to distinct management dynamics. Livestock management involves factors such as adjustments in herd size, feed cost variability, veterinary care, and reproduction rates. In contrast, crop yields mainly depend on weather conditions, land quality, and input use. Insurance uptake in crop production may affect input usage (e.g., fertilizer application), whereas in livestock production, insurance primarily mitigates financial risk, facilitating herd expansion or increased investment in animal health.

Moreover, there is a notable gap between crops and livestock in terms of policy availability and utilization of the FCIP during our analysis period. Historically, three major field crops—corn, soybeans, and wheat—dominated both the area insured and the total insured value under FCIP. In contrast, livestock-related liabilities significantly increased from approximately $1 billion in 2011 to $6 billion in 2024, largely driven by substantial changes in funding mechanisms beginning in 2019. Furthermore, starting around 2016-2017, insured acreage for forage crops, such as hay and pasture, increased steadily due to rising popularity of Pasture, Rangeland, and Forage (PRF) coverage. By 2024, forage crops accounted for more than half of all insured acres—surpassing even the combined acreage of the top three field crops—yet represented only around 4% of the total insured value.

Since our analysis employs a meta-frontier approach to account for technological differences between insured and uninsured farms, combining livestock and crop production into a single analysis raises concerns regarding aggregation bias. Such bias could obscure or distort the unique insurance effects specific to each sector. Given these fundamental differences in production organization, as well as disparities in FCIP availability and utilization during our study period, we restricted the ARMS sample to farms deriving 50% or more of their total production value from crops. Additionally, we further narrowed the sample to farms for which more than half of their total crop production value originates from specific crops: corn, soybeans, cotton, wheat, rice, potato, tobacco, peanut, sugar beet, sugarcane, sorghum, barley, canola, and oats. Collectively, these crops accounted for over 90% of FCIP-insured liabilities from 2001 to 2024.

We further excluded farms exhibiting zero values for the output index and any input. After cleaning, our final sample consisted of 106,551 farms.[2] Within this sample, 77,900 farms, representing 73% of the total, were insured under FCIP. We identified these FCIP-participating farms as those with either expenditures on FCIP premiums or indemnity receipts from the FCIP. Table 1 describes the sample, including operator/farm characteristics, production inputs/output, weather/climate, and FCIP rating parameters, showing their temporal and insurance status variation. In assessing the differences in these variables across insurance status and seasons, we used linear regression for continuous variables and a logit model for dummies. A trend variable,

[2] The mean share of crop production value (in parenthesis) are soybeans (28%), corn (16.37%), wheat (12.5%), cotton (7.39%), rice (3.51%), tobacco (2.56%), peanut (1.84%), potato (1.11%), sorghum (0.81%), barley (0.78%), sugar beet (0.7%), sugarcane (0.47%), canola (0.24%), and oats (0.2%).

and a fixed effect for insurance status, as well as their interactions, were included in the estimations.

The insurance participation rate shows an annual significant increasing trend of about 1.50%. In contrast, the rate of receipt of payments from countercyclical program (e.g., Price Loss Coverage [PLC] and Agriculture Risk Coverage [ARC]) and Ad-Hoc programs are 38% and 29% respectively and show statistically significant annual decreases of about 2% and 7% respectively. Regarding the primary operator characteristics, female operators constitute 2% but demonstrate a significant annual growth rate of about 4%. The mean age of primary operators is around 56 years with a moderate annual increase of 0.7%. When it comes to the level of education, about 4% have less than a high school education, 39% have completed high school, 31% have some college education, and 27% are college graduates or beyond. All education levels show a decreasing trend, except for college graduates, which is increasing at 1.7% per annum. Beginner farms constitute 6% of the total, with a significant annual decrease of about 0.7%. The proportion of family farms in the sample is 95% with the majority of these classified as large (19%) to very large (44%) farms. All except very large and non-family farms are decreasing over time.

The mean output to input value ratio (a crude measure of factor productivity) is 0.92 with a positive annual trend of 0.85%. The average total operated land amounts to 1,910 acres, with an annual increase of 0.42%. As for land ownership, 15% of farms are fully owned (significant annual increase of 1.8%), 68% are partly owned, and 17% are rented, with fully owned showing a significant annual increase. The total real value of farm production from the value of real output produced is about $740 per operated acres with a significant decrease of about 1.23% annually. Labor (operator, family, and hired), materials (seed, plants, livestock purchases, other livestock-related expenses, fertilizer, chemicals, feed, utilities, fuel, oils, repairs, maintenance, machine-hire, custom work, and other variable expenses), capital (interest expense, rent and lease, and depreciation) variable inputs show means of 70 (hours per acre), 400 (U.S. real dollars per acre), and 190 (U.S. real dollars per acre) respectively, with all showing significant annual decreases. The mean farm asset value is 660 (U.S. real dollars per acre), also showing a 1% significant increase annually. Irrigated production is present in 6% of farms, with a significant annual increase of 2.2%.

A comparison between insured and uninsured farms shows distinctive patterns. countercyclical program participation is higher among uninsured farms, while insured farms lead in Ad-Hoc program participation. Insured farms have a higher percentage of female operators and operators with less than high school education or have completed high school. Conversely, uninsured farms show a higher proportion of operators with some college education and those with degrees. Uninsured farms have more very large farms, higher output to input ratio, and larger operational land areas, but insured farms demonstrate a higher percentage of fully owned land. Both variable production inputs (labor, materials, and capital) and fixed assets all in per acre terms are higher in insured farms. Differences in FCIP rating parameters (i.e., risk rating) and weather anomalies between insured and uninsured farms are minor.

It is important to note that a substantial number of these differences are statistically significant at the 1% level, which implies the presence of systematic dissimilarities between the characteristics and operational methodologies of insured and uninsured farms. These differences partly provide valuable contributions to the design and implementation of policies and programs intending to cater to the distinct requirements of these farming groups. Furthermore, this understanding emphasizes the importance of considering these differences when evaluating divergent outcomes between insured and uninsured farms.

4. Empirical specification

Previous studies have consistently captured micro-level U.S. agricultural output using either the Cobb-Douglas (Darlington Sabasi et al. 2019; Jonathan R. McFadden et al. 2022), or Translog (C. Paul et al. 2004; C. J. M. Paul et al. 2004; Nehring et al. 2021; Mayen et al. 2010) production function. However, due to its relative flexibility, we utilize the latter to capture both the insurance status and meta frontiers previously conceptualized. Nonetheless, since Cobb-Douglas is nested within the Translog, the former was tested after estimation and was soundly rejected at $p<0.01$ (see Table 2). If estimated production functions via SFA are theoretically inconsistent, it affects meaningful interpretation of the efficiency measures. Preliminary analysis showed that our estimated production frontiers did not meet the theoretically necessary characteristics for monotonicity (1 to 97% observations violated) and quasi-concavity (1 to 94% observations violated). Consequently, we impose monotonicity for all observations via a commonly used three step approach (Henningsen and Henning 2009; Koebel, Falk and Laisney 2003).[3] Imposing monotonicity resulted in about 99% of our estimating sample to satisfy quasi-concavity (see Table 2).

Our stylized Translog stochastic production frontier for the j^{th} agricultural insurance participation status is specified as:

$$\ln y_{ijt} = \alpha_{0j} + \sum_k \alpha_{kj} \ln x_{ikjt} + \frac{1}{2}\sum_k \sum_s \alpha_{jkr} \ln x_{ikjt} \ln x_{isjt} + \alpha_{tj} t + \frac{1}{2}\alpha_{ttj} t^2 + \sum_k \alpha_{ktj} \ln x_{ikjt}\, t + \boldsymbol{\alpha}_{zj} \mathbf{z}_{ijt} + v_{ijt} - u_{ijt}$$

[3] First, estimate the unrestricted model. Second, use the estimated parameters and covariance matrix from Step 1 to determine restricted parameters via quadratic optimization, ensuring positive marginal products at each observation. Third, measure efficiency and identify its determinants using a theoretically consistent frontier, with the maximum possible output from restricted parameters as the exogenous variable. Variables affecting inefficiency are reintroduced into the model as in Step 1.

$$u_{ijt} \sim N^{+}\left[0, \exp\left(\boldsymbol{\alpha}_{hj} \boldsymbol{h}_{ijt}\right)\right], \quad v_{ijt} \sim N\left[0, \sigma_{v_j}^2\right] \qquad \forall j \in 1,2 \tag{6}$$

where, y_{ijt} denotes real monetary value of total farm revenue from crops and livestock production of the i^{th} farm, in the j^{th} group representing insurance status, at a given time t; x_{ikjt} represents the inputs used, including land, labor hours, real monetary value of materials, and real monetary value of capital. The vector $\boldsymbol{z}_{ijt}$ contains structural shifters including, farm typology, USDA Economic Research Service Farm Resource Regions (here after "ERS resource regions") (Heimlich 2000), irrigation status, crop production value share, binary variables for specific commodities, and county level weather variables (quadratic precipitation and extreme/killing degree-day variables used in related works (Schlenker and Roberts 2009; Shew et al. 2020; Tack, Barkley and Nalley 2015)).

The terms u_{ijt} and v_{ijt} describe the deviations from the efficient frontier due to technical inefficiency and production risk, respectively. Due to its ease of convergence for several subsample estimations, we also assume that u_{ijt} follows a half-normal distribution (i.e., $u_{ijt} \sim N^{+}\left[0, \exp\left(\boldsymbol{\alpha}_{hj} \boldsymbol{h}_{ijt}\right)\right]$) but later show that our core findings for the full sample are generally robust to other commonly used distributions. The $\boldsymbol{h}_{ijt}$ and $\boldsymbol{\alpha}_{hj}$, are vectors of explanatory variables and estimated parameters, respectively (Battese et al. 1997; Tsiboe 2021). Vector $\boldsymbol{h}_{ijt}$ contains covariates that control for; operator's characteristics (age, education, and gender), farm typology, land tenure status, whether the farm has received Federal ad-hoc or disaster assistance, whether the farm has received countercyclical payments (e.g., PLC and ARC), and farm bill period. The term v_{ijt} is assumed to follow a normal distribution with zero mean and a variance $\sigma_{v_j}^2$. With known parameters ($\boldsymbol{\alpha}$), the technical efficiency level ($TE_{i,j}$) is calculated as outlined in the conceptual considerations.

The predicted output levels from Equation (6) at $v_{ijt} = 0$ and $u_{ijt} = 0$ were used as the observations for a pooled frontier that captures all farms regardless of insurance status to estimate the meta-frontier specified as:

$$\ln y_{ijt} = \beta_0 + \sum_k \beta_k \ln x_{ikt} + \frac{1}{2}\sum_k \sum_s \beta_{kr} \ln x_{ikt} \ln x_{ist} +$$
$$\beta_t t + \frac{1}{2}\beta_{tt} t^2 + \sum_k \beta_{kt} \ln x_{ikt}\, t + \boldsymbol{\beta}_z \boldsymbol{z}_{it} + \omega_{it} - \vartheta_{it}$$
$$\vartheta_{it} \sim N^+\left[0, \exp\left(\boldsymbol{\beta}_{hj} \boldsymbol{h}_{it}\right)\right], \qquad \omega_{it} \sim N[0, \sigma_\omega^2] \tag{7}$$

All terms have been previously described above with the key differences being that the deviation from the efficient frontier due to technology gaps is defined by ϑ_{it}, and ω_{it} is the random error.

Assessing risk is a crucial aspect in pricing any insurance product, yet its quantification often presents a challenge to insurers. Each policyholder's risk profile varies, compelling insurance providers to rely on observable characteristics that correspond with risk. The FCIP, for example, estimates risk by comparing an insured's average on-farm yields with their peers, operating under the assumption that risk aligns with this average. The insurance premium - the price for a specific coverage amount selected by the insured - is subsequently calculated using an actuarially derived formula (Risk Management Agency [RMA] 2000; Tsiboe and Tack 2022; Turner et al. 2024). This price is influenced by both the coverage choices of the insured and their associated risk level. It is important to note that the observed data regarding insurance prices is influenced by these factors.

A significant inference from our study is that producers are likely to opt in or out of agricultural insurance based on their privately understood risk profile. This means, they might participate if they feel their risk is undervalued or withdraw if they think it's overvalued. Therefore, the empirical model we proposed earlier must address a quintessential self-selection issue, resulting from a mix of adverse selection (Goodwin and Kastens 1993; Just et al. 1999; Makki and Somwaru 2001; Hou et al. 2011) and moral hazard (Smith and Goodwin 2017; Roberts et al. 2006). Previous studies have addressed self-selection and endogeneity issues by employing methods such as instrumental variable (IV) regression (Schoengold, Ding and Headlee 2015; Connor and Katchova 2020; Wang, Rejesus and Aglasan 2021; Tsiboe and Turner 2023a; Tsiboe and Turner 2023b) or Heckman-type models of participation (Shaik et al. 2008). As typically done in similar studies using SMF plagued by self-selection in technology adoption (Mayen et al. 2010; Crespo-Cebada, Pedraja-Chaparro and Santín 2014; Asmare, Jaraitė and Kažukauskas 2022; Bravo-Ureta et al. 2021; Tiedemann and Latacz-Lohmann 2013), we address the potential selection bias concerns using a matched sample in estimating the meta frontier (Equation [6]).

Our approach incorporates the pairing of each insured farm with a counterpart that is uninsured and shares similar non-production characteristics. Our objective diverges from traditional matching imputation methods, which involve substituting the missing potential outcomes for each farm with the observed outcomes of its paired unit (Abadie and Imbens 2006; Abadie and Imbens 2016). Instead, we strive to refine our sample to create a balanced subset. This balanced subset will serve as the basis for estimating the meta frontier (Equation [6]). We match on attributes such as operator's characteristics (age, education, and gender), total operated land, land tenure status, beginner farm status, and the value of farm equipment. We also consider factors such as the farm's irrigation status, the production share of specific commodities, whether the farm has received Federal ad-hoc or disaster assistance, whether the farm has received countercyclical payments, similarity in climatic conditions, and RMA county-level rating parameters like the reference rate, fixed rate, and rating exponent, which are averaged across all crops and policies. Importantly, our observations were paired strictly within the same ARMS wave, farm typology, and ERS resource region. This matching process enables us to associate any observed technological differences to the agricultural insurance status.

Pairing farms is straightforward with a single ideal conditioning covariate, as the counterfactual for each treated farm is the untreated farm most similar in value. However, the task becomes significantly more complex as the number and types (scalar and categorical) of conditioning covariates increase. To navigate this complexity, we employ one-to-one nearest-neighbor-matching to establish similarity metrics that identify comparable observations. We considered distance between pairs computed using either propensity scores (with the binomial link function specified as Logit, Probit, Complementary log-log, or Cauchit), Euclidean, Scaled Euclidean, Mahalanobis, or the Robust Mahalanobis metric. The balancing diagnostics for all alternative distance measures are presented in Figure S1 in the appendix. The standardized differences (i.e., the difference in terms of standard deviations) for the matched farms are close to zero, and the variance ratios are all close to one. According to the literature (Rubin 2001; Stuart 2010), the common thresholds for the variance ratio for balanced groups are 0.5 and 2, although ratios closer to one are preferred. From Figure S1 we observed that nearest-neighbor-matching with the Mahalanobis distance yield the best match across both measures overall.

Finally, since the ARMS is based on a stratified sample design, it requires weighted estimation of sample statistics; thus, USDA recommended delete-a-group (out of 30 groups) jackknife procedure was used to estimate standard errors in all estimations. Additional rational for using the jackknife procedure was due to the inability of the approach used in imposing theoretical consistency in our frontiers to estimate a conventional variance covariance matrix. For each of the 30 iterations, we draw the sample, estimate the Equation (6), match the data, and estimate the Equation (7) while incorporating the correction for monotonicity and quasi-concavity when estimating Equations (6) and (7).

5. Results and Discussions

Our analysis examines the impact of agricultural insurance on technology levels and its utilization efficiency in the U.S., with comprehensive results provided across various tables and figures. The full parameters estimated for Equations (6) and (7) are available in Tables S1 and S2 in the online Appendix. Table 2 outlines our model diagnostics, while Tables 3 and 4 respectively evaluates the disparities in input elasticities and production performance scores associated with agricultural insurance, with related elasticity trends depicted in Figure S2. Figure 1 displays the differences in production input and debt use by agricultural insurance. Figure 2 illustrates the distribution of production performance scores within our sample, and Figures 3 highlight the temporal variations in agricultural insurance effects on production performance scores. Figure 4 examines the heterogeneity by farm typology, ERS resource regions, commodities, operator and farm characteristics, and participation in other federal programs. Lastly, Figure S4 tests the robustness of our core findings against various analytical adjustments.

5.1 Model diagnostics

The stochastic frontier analysis (SFA) used in this study relies on maximum likelihood techniques which require that technical efficiency error specification be negatively skewed. If the error is not negatively skewed, then we are back to an ordinary least squares (OLS) production function with no technical inefficiency. In this context, we conducted three tests to confirm the error specification for SFA: two skewness tests on OLS residuals (Schmidt and Lin 1984; Coelli 1995) and a one-sided generalized likelihood-ratio test for technical inefficiency (Gutierrez, Carter and Drukker 2001). According to Table 2, all three tests rejected the suitability of a basic naïve SF model that disregards peer group segregation, based on insurance status, in the estimation. When peer group segregation was considered, all still indicated rejection. These results collectively confirm the negative skewness of the error, validating the use of SFA for estimating models in U.S. farms as per the ARMS data. Consequently, the study advances with the SMF approach.

The study consistently rejected the null hypothesis that technical inefficiency is unaffected by variables in the inefficiency function (i.e., $H_o\colon \boldsymbol{\alpha} = 0$) across all models, lending statistical support to the technical inefficiency function. Moreover, the likelihood-ratio test strongly opposed the null hypothesis that the production frontiers of the two peer groups are identical with a significant LR test statistic. This outcome reinforces the initial assumption that U.S. farms operate using diverse technologies, which are distinctly shaped by their FCIP status. Table 2 also shows that the mean proportion of agricultural production variance due to technical inefficiency (γ) is 0.77 and 0.85 for the insured and uninsured farms, respectively, indicating a significant portion of agricultural output variation is due to inefficient input use. Other contributing factors to this variation include production risk factors, data measurement errors, and model specification. This study specifically found that the mean estimated γ for the meta-frontier was 0.94, indicating that nearly all on-farm agricultural output variation is attributable to technological gaps associated with agricultural insurance participation, after adjusting for insurance status driven technical inefficiency.

5.2 Output elasticities

Table 3 illustrates that the responsiveness of the real value of total farm output to each factor input are generally statistically significant at the 1% level and consistently shows positive output elasticities across all models, echoing the findings of several studies on U.S. agriculture (O'Donnell 2016; D. Sabasi, Shumway and Astill 2019; J.R. McFadden, Rosburg and Njuki 2022). In these models, materials inputs showed the largest effect on total farm output, followed sequentially by land, labor, and capital. Disaggregated by agricultural insurance status, the elasticity of materials is higher for insured farms (0.447) than for the uninsured (0.520), showing a 14.15% decrease. The elasticities of land and labor also show decreases for insured farms— -15.80% for labor and -27.69% for land — indicating that insured farms generally tend to gain more from their labor and land resources than their uninsured counterparts. Conversely, the most pronounced difference is for capital use, where insured farms exhibit an elasticity of 0.030, relative to 0.019 for the uninsured, a difference of 59.27%. Lastly, the returns to scale for insured farms (0.744) is 14.05% lower than that of the uninsured (0.865).

5.3 Technological level

The technological level of insured and uninsured farms, which is represented by the estimated technology gap ratios (TGRs) is summarized in Table 4. Findings from the matched sample reveal an average TGR of 0.925 and 0.852 for insured and uninsured farms, respectively. This implies that these farms generally produce, on average, 93% and 85% of the potential industrial output, respectively. This culminates into an 8.50% agricultural insurance associated technology gap in the real value of total farm output in the U.S.

The disparity in technology levels induced by agricultural insurance aligns with findings from other studies. For example, in a sample of Minnesota and Wisconsin farmers from 2006 and 2007, those who were risk-averse enough to purchase crop insurance were also the most willing to pay for drought tolerance as a trait built into seeds (Foltz et al. 2013). Similarly, insurance significantly increases the adoption of higher-yielding seeds among Mexican farmers (Freudenreich and Mußhoff 2018). Another study using Phase 2 of the 2018 ARMS data indicates that producers enrolled in the FCIP may be more likely to have adopted precision agriculture technologies earlier than those not enrolled (Comstock 2022). This suggests that producers may not view the FCIP as a substitute for other risk management options or may not perceive these technologies in the same risk-reducing manner as they do the FCIP.

The TGR estimates are echoed by the disparity in the elasticity estimates which suggest that insured farmers are generally more productive than their uninsured counterparts. If we assume that U.S farmers are relatively risk-averse, this is not surprising, as insurance allows them to operate more like a risk-neutral producer: increasing productivity. Based on Figure 1 from our sample, which uses the matched dataset, we find that agricultural insurance significantly influences the per-acre use of farm assets (9.33% more), capital (2.08%), and labor (26.72%). Conversely, the difference in land area between insured and uninsured farmers is statistically negative (-15.68%), while that of materials is negligible (-1.64%). These results suggest that agricultural insurance leads farmers to adopt a mix of production inputs that maximize output. This aligns with the findings suggesting that crop insurance subsidies encourage farms to purchase crop insurance, thereby increasing the expected return on insured risky crops (Yu, Smith and Sumner 2018).

The increase in per-acre input use may result from agricultural insurance acting as a safety net, encouraging risk-averse farmers to adopt innovative technologies (Foltz et al. 2013; Freudenreich and Mußhoff 2018; Comstock 2022; Tang et al. 2019; Carter et al. 2016). However, some studies have shown it may also lead to resource-weakening innovations (Miao 2020; Woodard et al. 2012). Research on risk balancing suggests that producers might take on more financial risk as business risk decreases (Featherstone et al. 1988; Ifft, Kuethe and Morehart 2015b). Thus, agricultural insurance, as a safeguard against unexpected losses, influences agricultural credit and the broader financial landscape. Agricultural insurance enhances producers' creditworthiness in several ways. It reduces borrowing risk by protecting against income volatility and potential losses due to adverse weather or market fluctuations, making farmers more attractive to lenders (Ifft et al. 2015a;

Tsiboe and Turner 2023a; Pflueger and Barry 1985; Gaku and Tsiboe 2024). It also improves producers' ability to repay loans by providing compensation during challenging times, enhancing their debt-servicing capacity (Anon n.d.). Participation in agricultural insurance signals to lenders that farmers are proactive in managing risks, further boosting their creditworthiness. Figure 1 from our matched dataset shows that agricultural insurance is mostly insignificantly associated with the amount of debt accessed (standardized by operated area) by producers. The only type of debt positively associated with agricultural insurance is short term debt lasting less than one year (9.00% more), and total non-farm debt (21.13%). Similar trends are observed among uninsured farmers if they were insured. These trends show that agricultural insurance strengthens producers' financial positions, making them more reliable candidates for credit and potentially promoting technology adoption.

5.4 Pure farmer technical efficiency

Evaluating farm performance of each farm group relative to its own technology, which is represented by the pure farm technical efficiency (TE) scores as displayed in Table 4 reveal an average of 0.657 and 0.617 for the insured and uninsured farms, respectively. This suggests that, on average, insured and uninsured farms had the potential to increase their output by 34% and 38% respectively, by using their inputs more efficiently relative to their respective potential frontier outputs. This culminates into a 6.36% agricultural insurance associated pure farmer technical efficiency gap in the real value of total farm output in the U.S.

Our finding that agricultural insurance is associated with a technical efficiency gap aligns with results from empirical studies in developed countries, which generally show that insurance improves technical efficiency. For example, insurance enhanced production and efficiency among Norwegian salmon farmers (Roll 2019). A state-level analysis of 48 U.S. states from 1960 to 2004 indicated that crop insurance improved efficiency (Shaik 2013). Similarly, in Hungary, insured crop-producing farms were more efficient than uninsured ones (Zubor-Nemes et al. 2018). A study on the European Union's Common Agricultural Policy (CAP) found that from 1995 to 2004, crop subsidies negatively impacted technical efficiency in Germany but positively in Sweden, with no significant effect in the Netherlands (Zhu and Lansink 2010).

Research suggests that insurance influences technical efficiency in two contrasting ways (Roll 2019). On one hand, it enhances a farmer's efficiency by enabling greater specialization, especially when the farmer might diversify to manage unique risks. This specialization leads to efficiency gains. On the other hand, the presence of moral hazard might cause farmers to change their behavior in ways that reduce expected profits after accounting for insurance payouts (Smith and Goodwin 2017; Roberts et al. 2006). Since it is not possible to separate these opposing effects, the observed differences in technical efficiency represent the net impact of insurance. In related studies, the effects of agricultural insurance were mainly attributed to factors like farm size and specialization in Germany, and to specialization and reliance on subsidies in the Netherlands and Sweden (Zhu and Lansink 2010).

Our agricultural insurance associated pure farm technical efficiency gap finding is however inconsistent with other empirical studies (Castro et al. 2023; Giannakas et al. 2001). Notably, in a developed country context, Saskatchewan farmers were found to be operating at 0.769 efficiency (Giannakas et al. 2001). However, amongst these same farmers, crop insurance income (included as an explanatory variable in the inefficiency function) was associated with low efficiency scores, suggesting reduced incentives to maximize income. Since all farms are evaluated under the same production function, this relationship may be due to adverse weather affecting both insurance payouts (higher under adverse weather) and efficiency estimates (low output under adverse weather), making the linkage unclear. In our analysis, insurance is considered as an indicator (insured or uninsured) regardless of indemnification, and we formulated separate production functions for insured or uninsured farms. This allowed us to evaluate farms with the same insurance status when computing the TE scores.

5.5 Overall performance

Combining the TGR and TE effects into a single comparable measure (meta-frontier technical efficiency [MTE = TE × TGR] scores) across both groups shows that insured and uninsured farms operate at 60.60% and 54.20% of the industrial frontier, respectively. This corresponds to a statistically significant MTE difference of 11.68%, indicating that insured farms are generally more efficient than their uninsured peers. Since the agricultural insurance induced disparity in TGR (8.50%) is larger than that of the TE (6.35%), the prime source of the variation in the estimated MTE for insured and uninsured farms is attributed more to technological level rather than the differences in how well each group uses their technology.

5.6 Robustness of main findings

Our core findings of the existence of an agricultural induced gap in technology and its efficient use remain robust across various dimensions of the analysis: (1) the choice of production function, distributional assumption on the inefficiency term, calculation method for observational level scores (TGR, TE, and MTE), matching algorithm, restriction of sample based on crop production share, and whether the production function is restricted or freely estimated (see Figure S3).

5.7 Observed heterogeneity.

Estimating our empirical model across the entire sample provides average effects for all producers within each insurance group. However, such high-level aggregated estimates might obscure variations linked to factors like differences in insurance policy offerings across commodities and counties, and varying incentives for insurance and technology adoption influenced by producer demographics. Figure 2 illustrates the distribution of sources of farm-level real production value variation by agricultural insurance participation, revealing a nearly multimodal distribution of our key efficiency measures.

Inaccuracies in both estimated efficiency and the ranking of units arise if the data generating process deviates from a unimodal inefficiency distribution, yet a model assumes a half-normal distribution for inefficiency (Kumbhakar et al. 2021). Such a scenario might occur with diverse management styles or might suggest model misspecification. If the actual inefficiency varies over time and is not modeled with sufficient flexibility, the correlation between true and estimated inefficiency might be low or even negative (Duygun, Kutlu and Sickles 2016). A significant challenge with model misspecification is that although symptoms are noticeable, pinpointing the 'true' model by identifying the source or cause remains challenging.

Our robustness checks, however, confirm that our core findings are consistent across several model configurations, including the choice of production function and the distributional assumptions of the inefficiency term. Nevertheless, the multimodal nature of the performance score distribution suggests potential heterogeneity within the sample, an indication of multiple types of managers. To explore this, we conducted additional estimations for subsamples defined by farm typology, ERS resource region, commodity harvested, operator characteristics (gender, age, education, farming experience, and land tenure), and participation in other Federal programs. The results, presented in Figures 3 and 4, confirm that generally, insured farms perform better than uninsured farms, even within these subsamples.

Figure 3 illustrates the temporal dynamics of differences in MTE, TGR, and TE driven by agricultural insurance from 2001 to 2023, along with estimates specific to four farm bill periods during the same timeframe. We observe an overall decline in the agricultural insurance-driven gap in MTE, which began at 20.08% in 2001, peaked at 36.30% in 2020, and then decreased to 14.65% by 2023. During the tenure (2001-2007) of the 2000 Farm Bill (The Agricultural Risk Protection Act of 2000), the gap was 12.64%. The 2014 Farm Bill (Agricultural Act of 2014) and 2018 Farm Bill (Agriculture Improvement Act of 2018) show statistically similar gaps estimated at 14.96% and 12.57%, respectively. The 2008 farm bill gap level estimated at 2.55% was however smaller than the other farm bills. The dynamics in MTE are similarly reflected in the TGR, with the gap favoring insured farms at 9.91% in 2001, then shifting to favor uninsured farms by 4.23% by 2023. In contrast to the trends observed in MTE and TGR, the TE gap has widened in favor of insured farms, indicating increasing disparities in technical efficiency over the period analyzed.

Figure 4 presents gaps by ERS resource region, examining the differences in MTE, TGR, and TE driven by agricultural insurance throughout the analysis period, alongside insurance penetration and actuarial performance. Across all regions, we find a positive difference in MTE and TE in favor of insured farms. However, negative differences in TGR are only observed in the Eastern uplands. The Southern Seaboard region shows the highest agricultural insurance-induced difference in overall farm performance (MTE) at 29.13 %, followed closely by the Eastern uplands at 15.56 %. Other regions show the following MTE differences: Heartland (10.46%), Northern Great Plains (7.96%), Northern Crescent (7.58%), Basin and Range (5.86%), Prairie Gateway (2.37%), Fruitful Rim (2.26%), and Mississippi Portal (-0.04%). Figure S4 shows that this ranking of differences aligns with the regions of high insurance penetration, as measured by the share of cropland insured, indicating a correlation between insurance uptake and the observed benefits in MTE.

Regarding operator characteristics, our findings on Figure 4 reveal an MTE gap in favor of the insured is most pronounced among female operators, those with relatively moderate levels of education, and operators who own all the land they farm. Figure 4, however, shows no statistical difference in the MTE gap based on farming experience or age of the operator. The analysis further demonstrates significant heterogeneity in the MTE gap when operations are classified by farm typology, particularly indicating that the effects are not linear with respect to the complexity of the resources and organizational structure of the farm. For example, farms classified as limited resource/retirement residential/lifestyle exhibit a significant MTE gap of 13.51% in favor of the insured. Similarly, farming occupation lower sales farms show a gap of 4.32%, and non-family farms show a gap of 0.65%, all in favor of the insured. In contrast, very large farms, large farms, and farming occupation higher sales farms show insignificant or negative gaps (-3.76%, -2.75%, and -1.88% respectively), indicating a gap in favor of the uninsured. Additionally, farmers reporting harvests of wheat, sorghum, corn, and soybeans show MTE gaps of 13.42%, 12.81%, 10.05%, and 8.48% respectively, in favor of the insured. Conversely, those harvesting rice and cotton respectively exhibit gaps of 4.39% and 1.36% but in favor of the uninsured. This variability suggests that the impact of agricultural insurance on efficiency varies significantly across different types of agricultural production.

The FCIP in the U.S. intricately intertwines with various federal initiatives, establishing a robust safety net for agriculture while also reinforcing environmental and economic policies. One critical aspect is conservation compliance; farmers face a premium penalty or lose their premium subsidy if they fail to adhere to specific conservation practices, integrating environmental stewardship directly into the risk management framework. Insurance eligibility and the choice of supplemental plans like the Supplemental Coverage Option (SCO) and the Enhanced Coverage Option (ECO) are also strategically linked with Farm Bill decisions—specifically, whether a farm has elected the Agricultural Risk Coverage (ARC) or the Price Loss Coverage (PLC). For instance, opting for ARC on certain crops restricts the use of SCO for those same crops, while PLC does not impose such limitations. Furthermore, emergency response programs like the Wildfire and Hurricane Indemnity Program (WHIP) and its successor, WHIP+, mandate that recipients secure at least 60% crop insurance coverage to qualify for aid, reinforcing the role of insurance in disaster recovery. The integration extends to financial avenues as well; the FCIP often serves as a prerequisite for obtaining agricultural loans from federal credit programs such as those offered through the Farm Credit System, demonstrating how risk management is closely linked to financial stability in the farming sector. Through these layered connections, the FCIP not only provides direct financial relief but also promotes a sustainable, compliant, and economically secure agricultural environment.

Figure 4 illuminates the intricate interplay between the FCIP and other federal initiatives, demonstrating the varied impact on the MTE for insured farms. Overall, farms receiving any form of federal payments show a 3.98% higher MTE in favor of the insured. Notably, farms benefiting from marketing loan initiatives exhibit the largest MTE gap of 16.21%. These farms are followed by those receiving counter-cyclical payments from programs like the PLC and ARC with an estimated gap of 7.06%. Farms engaged in conservation programs like the Conservation Reserve Program (CRP) and the Environmental Quality Incentives Program (EQIP) display an MTE gap of 6.39%, while those receiving Ad-hoc or disaster payments show a gap of 2.68% but in favor of the uninsured.

6. Conclusion

Agricultural production is subject to increasing risk, underscoring the essential role of agricultural insurance. However, perspectives on its impact on farm productivity are mixed. Some argue that it may encourage opportunistic behaviors such as adverse selection and moral hazard, due to asymmetric information, potentially leading to inefficient use of resources. On the other hand, proponents believe that insurance mitigates risk for farmers, encouraging them to implement efficient management practices and to invest in advanced technologies. This study offers a detailed examination of the production-related effects of agricultural insurance, with a specific focus on technology adoption and technical efficiency. We analyze the United States Federal Crop Insurance Program (FCIP)—the world's largest agricultural insurance portfolio and a pivotal component of the U.S. agricultural safety net.

Our empirical analysis uses a Stochastic Meta-Frontier (SMF) approach to analyze data from 106,551 farms collected by the Agricultural Resource Management Survey (ARMS) over two decades (2001-2023), aiming to determine whether production variability among U.S. farms is mainly due to differences in resource utilization efficiency, technological gaps, or a combination of both. To address self-selection bias in agricultural insurance participation and reduce model dependency, we employ a Nearest-Neighbor Matching method, pairing each insured farm with a similar uninsured one, thus directly attributing any observed production disparities to insurance participation.

Our results indicate that the average technology gap between insured and uninsured farms to be 11.68%. In other words, the representative technology frontier for an insured farm is 11.68 percentage points higher than their uninsured counterpart. Because we define a production technology as a system, method or technique for transforming inputs into outputs we conclude that this technology difference—which is statistically different from zero—is driven by the ability of insured farms to adapt the best available production technology. These structural differences between insured and uninsured farms extend to technical efficiency levels. The technical efficiency level for the average insured farm was 65.7% compared to 61.7% for the uninsured. These managerial efficiency differences are striking, indicating that insured farms are more proficient at using their technology—that is, they are more skilled at combining various inputs at their disposal to maximize output.

Some limitations of our analysis warrant consideration. Firstly, the study encountered challenges related to self-selection in agricultural insurance participation, which led to the adoption of matching techniques to enhance balance and comparability between insured and uninsured farms. This method reduces reliance on the model's functional form and lessens the impact of omitted variable bias, positioning our findings as a detailed examination of the association between agricultural insurance and production, rather than as a definitive demonstration of causality. Secondly, while agricultural insurance policies in the US are typically commodity-specific, our data primarily permit analysis at the enterprise level, covering indemnity receipts or premium payments without consistently including all eligible commodities. Despite this, our sub-sample analyses by harvested commodity and location reveal that agricultural insurance contributes to disparities in farm technology and technical efficiency. It is crucial, therefore, to interpret our results within the context of broad enterprise-level participation. Future research should seek to expand data sources and methodologies to more accurately assess the impacts of agricultural insurance to potentially establish causality, focusing on validated measures of commodity-specific agricultural insurance participation at the farm level.

Despite the limitations, the analysis indicates that agricultural insurance has a multifaceted impact on farm production variability. It not only mitigates risk but also promotes technological advancement and efficient resource utilization. These implications highlight the importance of integrating insurance programs into agricultural policies aimed at enhancing productivity, sustainability, and resilience in the farming sector.

References

Abadie, A., and G.W. Imbens. 2006. “Large Sample Properties of Matching Estimators for Average Treatment Effects.” *Econometrica* 74(1):235–267.

Abadie, A., and G.W. Imbens. 2016. “Matching on the Estimated Propensity Score.” *Econometrica*.

Adaku, A.A., F. Tsiboe, and J. Clottey. 2023. “Taking stock of gender gaps in crop production technology adoption and technical efficiency in Ghana.” *Agrekon*:1–18.

Aigner, D., C.A.K. Lovell, and P. Schmidt. 1977. “Formulation and estimation of stochastic frontier production function models.” *Journal of Econometrics* 6(1):21–37.

Anon. “The impact of crop insurance on farm financial outcomes - DeLay - 2023 - Applied Economic Perspectives and Policy - Wiley Online Library.” Available at: https://onlinelibrary.wiley.com/doi/full/10.1002/aepp.13223 [Accessed April 15, 2024].

Ansah, I.G.K., M. Appiah-Twumasi, and F. Tsiboe. 2023. “Starchy staples production shortfalls in Ghana: Technical inefficiency effects outweigh technological differences across ecologies” M. T. Sohail, ed. *PLOS ONE* 18(4):e0284780.

Asmare, F., J. Jaraitė, and A. Kažukauskas. 2022. “Climate change adaptation and productive efficiency of subsistence farming: A bias-corrected panel data stochastic frontier approach.” *Journal of Agricultural Economics* 73(3):739–760.

Asravor, J., F. Tsiboe, R.K. Asravor, A.N. Wiredu, and M. Zeller. 2024. “Technology and managerial performance of farm operators by age in Ghana.” *Journal of Productivity Analysis*. Available at: https://link.springer.com/10.1007/s11123-023-00679-y.

Battese, G.E., A. Heshmati, and L. Hjalmarsson. 2000. “Efficiency of labour use in the Swedish banking industry: a stochastic frontier approach.” *Empirical Economics* 25(4):623–640.

Battese, G.E., A.N. Rambaldi, and G.H. Wan. 1997. “A Stochastic Frontier Production Function with Flexible Risk Properties.” *Journal of Productivity Analysis* 8(3):269–280.

Battese, G.E., D.S.P. Rao, and C.J. O’Donnell. 2004. “A Metafrontier Production Function for Estimation of Technical Efficiencies and Technology Gaps for Firms Operating Under Different Technologies.” *Journal of Productivity Analysis* 21(1):91–103.

Belotti, F., S. Daidone, G. Ilardi, and V. Atella. 2013. "Stochastic frontier analysis using Stata." *The Stata Journal* 13(4):719–758.

Bokusheva, R., and H. Hockmann. 2005. "Production risk and technical inefficiency in Russian agriculture." *European Review of Agricultural Economics* 33(1):93–118.

Bravo-Ureta, B.E., M. González-Flores, W. Greene, and D. Solís. 2021. "Technology and Technical Efficiency Change: Evidence from a Difference in Differences Selectivity Corrected Stochastic Production Frontier Model." *American Journal of Agricultural Economics* 103(1):362–385.

Carter, M.R., L. Cheng, and A. Sarris. 2016. "Where and how index insurance can boost the adoption of improved agricultural technologies." *Journal of Development Economics* 118:59–71.

Castro, M., A. Reyes Duarte, A. Villegas, and L. Chanci. 2023. "The effect of crop insurance in Ecuadorian rice farming: a technical efficiency approach." *Agricultural Finance Review* 83(3):478–497.

Charnes, A., W.W. Cooper, and E. Rhodes. 1981. "Evaluating Program and Managerial Efficiency: An Application of Data Envelopment Analysis to Program Follow Through." *Management Science* 27(6):668–697.

Charnes, A., W.W. Cooper, and E. Rhodes. 1978. "Measuring the efficiency of decision making units." *European Journal of Operational Research* 2(6):429–444.

Coelli, T. 1995. "Estimators and hypothesis tests for a stochastic frontier function: A Monte Carlo analysis." *Journal of Productivity Analysis* 6(3):247–268.

Comstock, H.A. 2022. *THE EFFECTS OF GOVERNMENT FARM SUPPORT PROGRAMS ON THE ADOPTION OF FARM TECHNOLOGY AND SUSTAINABLE PRODUCTION PRACTICES*. thesis. Purdue University Graduate School. Available at: https://hammer.purdue.edu/articles/thesis/THE_EFFECTS_OF_GOVERNMENT_FARM_SUPPORT_PROGRAMS_ON_THE_ADOPTION_OF_FARM_TECHNOLOGY_AND_SUSTAINABLE_PRODUCTION_PRACTICES/19666332/1 [Accessed December 13, 2023].

Connor, L., and A.L. Katchova. 2020. "Crop insurance participation rates and asymmetric effects on U.S. Corn and soybean yield risk." *Journal of Agricultural and Resource Economics* 45(1):1–19.

Crespo-Cebada, E., F. Pedraja-Chaparro, and D. Santín. 2014. "Does school ownership matter? An unbiased efficiency comparison for regions of Spain." *Journal of Productivity Analysis* 41(1):153–172.

Duygun, M., L. Kutlu, and R.C. Sickles. 2016. "Measuring productivity and efficiency: a Kalman filter approach." *Journal of Productivity Analysis* 46(2):155–167.

Featherstone, A.M., C.B. Moss, T.G. Baker, and P.V. Preckel. 1988. “The Theoretical Effects of Farm Policies on Optimal Leverage and the Probability of Equity Losses.” *American Journal of Agricultural Economics* 70(3):572–579.

Foltz, J.D., P. Useche, and B.L. Barham. 2013. “Bundling Technology and Insurance: Packages versus Technology Traits.” *American Journal of Agricultural Economics* 95(2):346–352.

Freudenreich, H., and O. Mußhoff. 2018. “Insurance for Technology Adoption: An Experimental Evaluation of Schemes and Subsidies with Maize Farmers in Mexico.” *Journal of Agricultural Economics* 69(1):96–120.

Gaku, S., and F. Tsiboe. 2024. “Evaluation of alternative farm safety net program combination strategies.” *Agricultural Finance Review* ahead-of-print(ahead-of-print). Available at: https://doi.org/10.1108/AFR-11-2023-0150 [Accessed August 22, 2024].

Giannakas, K., R. Schoney, and V. Tzouvelekas. 2001. “Technical Efficiency, Technological Change and Output Growth of Wheat Farms in Saskatchewan.” *Canadian Journal of Agricultural Economics/Revue canadienne d’agroeconomie* 49(2):135–152.

Goodwin, B.K., and T.L. Kastens. 1993. “Adverse Selection, Disaster Relief, and the Demand for Multiple Peril Crop Insurance.” *Contract Report for the Federal Crop Insurance Corporation*.

Gutierrez, R.G., S. Carter, and D.M. Drukker. 2001. “On boundary-value likelihood-ratio tests.” *Stata Technical Bulletin* 10(60). Available at: https://econpapers.repec.org/article/tsjstbull/y_3a2001_3av_3a10_3ai_3a60_3asg160.htm [Accessed October 21, 2017].

Hayami, Y. 1969. “Sources of Agricultural Productivity Gap among Selected Countries.” *American Journal of Agricultural Economics* 51(3):564.

Hayami, Y., and V.W. Ruttan. 1971. “Agricultural development: an international perspective.” *Agricultural development: an international perspective.* Available at: https://www.cabdirect.org/cabdirect/abstract/19721890134 [Accessed July 19, 2018].

Hayami, Y., and V.W. Ruttan. 1970. “Agricultural Productivity Differences among Countries.” *The American Economic Review* 60:895–911. Available at: https://www.jstor.org/stable/1818289 [Accessed July 19, 2018].

Heimlich, R.E. 2000. “Farm resource regions.”

Henningsen, A., and C.H.C.A. Henning. 2009. “Imposing regional monotonicity on translog stochastic production frontiers with a simple three-step procedure.” *Journal of Productivity Analysis* 32(3):217–229.

Hou, L., D.L.K. Hoag, and Y. Mu. 2011. “Testing for adverse selection of crop insurance in northern China” H. Holly Wang, ed. *China Agricultural Economic Review* 3(4):462–475.

Huang, C.J., T.-H. Huang, and N.-H. Liu. 2014. "A new approach to estimating the metafrontier production function based on a stochastic frontier framework." *Journal of Productivity Analysis*.

Ifft, J.E., T. Kuethe, and M. Morehart. 2015a. "Does federal crop insurance lead to higher farm debt use? Evidence from the Agricultural Resource Management Survey (ARMS)." *Agricultural Finance Review* 75(3):349–367.

Ifft, J.E., T. Kuethe, and M. Morehart. 2015b. "Does federal crop insurance lead to higher farm debt use? Evidence from the Agricultural Resource Management Survey (ARMS)." *Agricultural Finance Review* 75(3):349–367.

Just, R.E., L. Calvin, and J. Quiggin. 1999. "Adverse Selection in Crop Insurance: Actuarial and Asymmetric Information Incentives." *American Journal of Agricultural Economics* 81(4):834–849.

Koebel, B., M. Falk, and F. Laisney. 2003. "Imposing and Testing Curvature Conditions on a Box-Cox Cost Function." *Journal of Business & Economic Statistics* 21(2):319–335.

Kumbhakar, S.C., A. Peresetsky, Y. Shchetynin, and A. Zaytsev. 2021. "Technical efficiency and inefficiency: Reliability of standard SFA models and a misspecification problem." *Econometrics and Statistics*. Available at: https://www.sciencedirect.com/science/article/pii/S2452306221001507 [Accessed September 26, 2024].

Mahul, O., and C.J. Stutley. 2010. *Government Support to Agricultural Insurance*. The World Bank. Available at: http://elibrary.worldbank.org/doi/book/10.1596/978-0-8213-8217-2 [Accessed June 4, 2020].

Makki, S.S., and A. Somwaru. 2001. "Evidence of Adverse Selection in Crop Insurance Markets." *The Journal of Risk and Insurance* 68(4):685.

Mayen, C.D., J.V. Balagtas, and C.E. Alexander. 2010. "Technology Adoption and Technical Efficiency: Organic and Conventional Dairy Farms in the United States." *American Journal of Agricultural Economics* 92(1):181–195.

McFadden, Jonathan R., A. Rosburg, and E. Njuki. 2022. "Information inputs and technical efficiency in midwest corn production: evidence from farmers' use of yield and soil maps." *American Journal of Agricultural Economics* 104(2):589–612.

McFadden, J.R., A. Rosburg, and E. Njuki. 2022. "Information Inputs and Technical Efficiency in Midwest Corn Production: Evidence from Farmers' Use of Yield and Soil Maps." *American Journal of Agricultural Economics* 104(2):589–612.

Meeusen, W., and J. van Den Broeck. 1977. "Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error." *International Economic Review* 18(2):435.

Miao, R. 2020. "Climate, insurance and innovation: the case of drought and innovations in drought-tolerant traits in US agriculture." *European Review of Agricultural Economics* 47(5):1826–1860.

Murova, O., and B. Chidmi. 2013. "Technical efficiency of US dairy farms and federal government programs." *Applied Economics* 45(7):839–847.

Nehring, R.F., J. Gillespie, C. Greene, and J. Law. 2021. "The Economics and Productivity of Organic versus Conventional U.S. Dairy Farms." *Journal of Agricultural and Applied Economics* 53(1):134–152.

O'Donnell, C.J. 2016. "Using Information About Technologies, Markets and Firm Behaviour to Decompose a Proper Productivity Index." *Journal of Econometrics* 190(2):328–340.

Paul, C., R. Nehring, D. Banker, and A. Somwaru. 2004. "Scale Economies and Efficiency in U.S. Agriculture: Are Traditional Farms History?" *Journal of Productivity Analysis* 22(3):185–205.

Paul, C.J.M., R. Nehring, and D. Banker. 2004. "Productivity, Economies, and Efficiency in U.S. Agriculture: A Look at Contracts." *American Journal of Agricultural Economics* 86(5):1308–1314.

Pflueger, B., and P.J. Barry. 1985. "Crop Insurance And Credit: A Farm Level Simulation Analysis." *1985 Regional Committee NC-161, October 9-10, 1985, St. Louis, Missouri*. Available at: https://ideas.repec.org//p/ags/nc1985/140940.html [Accessed April 14, 2024].

Risk Management Agency [RMA]. 2000. "Premium Rate Calculations for the Continuous Rating Model."

Roberts, M.J., N. Key, and E. O'Donoghue. 2006. "Estimating the extent of moral hazard in crop insurance using administrative data." In *Review of Agricultural Economics*.

Roll, K.H. 2019. "Moral hazard: the effect of insurance on risk and efficiency." *Agricultural Economics* 50(3):367–375.

Rubin, D.B. 2001. "Using propensity scores to help design observational studies: Application to the tobacco litigation." *Health Services and Outcomes Research Methodology* 2(3–4):169–188.

Sabasi, Darlington, C.R. Shumway, and G.M. Astill. 2019. "Off-farm work and technical efficiency on U.S. dairies." *Agricultural Economics* 50(4):379–393.

Sabasi, D., C.R. Shumway, and G.M. Astill. 2019. "Off-Farm Work and Technical Efficiency on U.S. Dairies." *Agricultural Economics* 50(4):379–393.

Schlenker, W., and M.J. Roberts. 2009. “Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change.” *Proceedings of the National Academy of Sciences of the United States of America* 106(37):15594–15598.

Schmidt, P., and T.-F. Lin. 1984. “Simple tests of alternative specifications in stochastic frontier models.” *Journal of Econometrics* 24(3):349–361.

Schoengold, K., Y. Ding, and R. Headlee. 2015. “The Impact of AD HOC Disaster and Crop Insurance Programs on the Use of Risk-Reducing Conservation Tillage Practices.” *American Journal of Agricultural Economics* 97(3):897–919.

Shaik, S. 2013. “Crop Insurance Adjusted Panel Data Envelopment Analysis Efficiency Measures.” *American Journal of Agricultural Economics* 95(5):1155–1177.

Shaik, S., K.H. Coble, T.O. Knight, A.E. Baquet, and G.F. Patrick. 2008. “Crop Revenue and Yield Insurance Demand: A Subjective Probability Approach.” *Journal of Agricultural and Applied Economics* 40(3):757–766.

Shew, A.M., J.B. Tack, L.L. Nalley, and P. Chaminuka. 2020. “Yield reduction under climate warming varies among wheat cultivars in South Africa.” *Nature Communications* 11(1):4408.

Smith, V.H., and J.W. Glauber. 2012. “Agricultural Insurance in Developed Countries: Where Have We Been and Where Are We Going?” *Applied Economic Perspectives and Policy* 34(3):363–390.

Smith, V.H., and B.K. Goodwin. 2017. “Crop insurance, moral hazard, and agricultural chemical use.” In *The Economics of Agri-Environmental Policy*.

Stuart, E.A. 2010. “Matching Methods for Causal Inference: A Review and a Look Forward.” *Statistical Science* 25(1):1–21.

Tack, J., A. Barkley, and L.L. Nalley. 2015. “Effect of warming temperatures on US wheat yields.” *Proceedings of the National Academy of Sciences* 112(22):6931–6936.

Tang, Y., Y. Yang, J. Ge, and J. Chen. 2019. “The impact of weather index insurance on agricultural technology adoption evidence from field economic experiment in China.” *China Agricultural Economic Review* 11(4):622–641.

Tiedemann, T., and U. Latacz-Lohmann. 2013. “Production Risk and Technical Efficiency in Organic and Conventional Agriculture - The Case of Arable Farms in Germany.” *Journal of Agricultural Economics* 64(1):73–96.

Tsiboe, F. 2021. “Chronic sources of low cocoa production in Ghana: new insights from meta-analysis of old survey data.” *Agricultural and Resource Economics Review*:1–26.

Tsiboe, F., and J. Tack. 2022. "Utilizing Topographic and Soil Features to Improve Rating for Farm-Level Insurance Products." *American Journal of Agricultural Economics* 104(1):52–69.

Tsiboe, F., and D. Turner. 2023a. "Econometric identification of crop insurance participation." *Agricultural and Resource Economics Review* 52(3):476–797.

Tsiboe, F., and D. Turner. 2023b. "The Crop Insurance Demand Response to Premium Subsidies: Evidence from U.S. Agriculture." *Food Policy* 119:102505.

Turner, D., F. Tsiboe, K. Baldwin, B. Williams, E. Dohlman, G. Astill, S. Raszap Skorbiansky, V. Abadam, A. Yeh, and R. Knight. 2023. "Federal Programs for Agricultural Risk Management." *EIB-259, U.S. Department of Agriculture, Economic Research Service.* Available at: https://www.ers.usda.gov/publications/pub-details/?pubid=108166.

Turner, D., F. Tsiboe, H. Biram, and L. Connor. 2024. "Actuarial implications of prevented planting coverage." *Applied Economic Perspectives and Policy* n/a(n/a). Available at: https://onlinelibrary.wiley.com/doi/abs/10.1002/aepp.13471 [Accessed August 22, 2024].

Walters, C.G., C.R. Shumway, H.H. Chouinard, and P.R. Wandschneider. 2015. "Asymmetric Information and Profit Taking in Crop Insurance." *Applied Economic Perspectives and Policy* 37(1):107–129.

Wang, R., R.M. Rejesus, and S. Aglasan. 2021. "Warming Temperatures, Yield Risk and Crop Insurance Participation." *European Review of Agricultural Economics* 48(5):1109–1131.

Woodard, J.D., A.D. Pavlista, G.D. Schnitkey, P.A. Burgener, and K.A. Ward. 2012. "Government Insurance Program Design, Incentive Effects, and Technology Adoption: The Case of Skip-Row Crop Insurance." *American Journal of Agricultural Economics* 94(4):823–837.

Yu, J., A. Smith, and D.A. Sumner. 2018. "Effects of Crop Insurance Premium Subsidies on Crop Acreage." *American Journal of Agricultural Economics* 100(1):91–114.

Zhu, X., and A.O. Lansink. 2010. "Impact of CAP Subsidies on Technical Efficiency of Crop Farms in Germany, the Netherlands and Sweden." *Journal of Agricultural Economics* 61(3):545–564.

Zubor-Nemes, A., J. Fogarasi, A. Molnár, and G. Kemény. 2018. "Farmers' responses to the changes in Hungarian agricultural insurance system." *Agricultural Finance Review* 78(2):275–288.

Tables and Figures

Table 1. Descriptive Statistics of U.S. Farms Differentiated by Federal Crop Insurance Program (FCIP) participation status (2001-2023)

Variable	Sample mean (standard deviation)			Sample annual trend [standard error] (%) [a]		
	All farms (n= 106,551)	FCIP farms (n= 77,900)	non-FCIP farms (n= 28,651)	All farms (n= 106,551)	FCIP farms (n= 77,900)	non-FCIP farms (n= 28,651)
FCIP participation (binary) [b, c, d, e]	0.73 (0.44)	-	-	1.50*** [0.03]	-	-
Received PLC/ARC payment (binary) [b, d]	0.38 (0.49)	0.34 (0.47)	0.39 (0.49)	-1.64*** [0.07]	-0.69*** [0.07]	-4.35*** [0.18]
Received Ad-Hoc payment (binary) [b, d]	0.29 (0.45)	0.44 (0.50)	0.23 (0.42)	-6.55*** [0.08]	-5.86*** [0.10]	-8.94*** [0.16]
Primary operator						
Female (binary) [b, d]	0.02 (0.14)	0.03 (0.16)	0.02 (0.13)	4.21*** [0.37]	4.42*** [0.45] †	3.63*** [0.65] †
Age (years) [b, d]	56.29 (12.20)	57.03 (12.67)	56.01 (12.02)	0.69*** [0.01]	0.69*** [0.01] †	0.68*** [0.02] †
Less than high school (categorical) [b, d]	0.04 (0.18)	0.05 (0.23)	0.03 (0.17)	-5.70*** [0.29]	-6.87*** [0.35]	-2.52*** [0.49]
High school (categorical) [b, d]	0.39 (0.49)	0.43 (0.50)	0.37 (0.48)	-0.65*** [0.06]	-0.65*** [0.08] †	-0.66*** [0.13] †
Some college (categorical) [b, d]	0.31 (0.46)	0.28 (0.45)	0.32 (0.47)	-0.14* [0.08]	-0.16* [0.08] †	-0.10 [0.17] †
College graduate/beyond (categorical) [b, d]	0.27 (0.44)	0.23 (0.42)	0.28 (0.45)	1.73*** [0.08]	1.69*** [0.09] †	1.84*** [0.19] †
Beginner farm (binary) [b]	0.06 (0.24)	0.07 (0.26) †	0.06 (0.23) †	-0.68** [0.28]	-1.03*** [0.33] †	0.29 [0.49] †
Farm typology (categorical) [b, c, d]						
Limited resources	0.00 (0.06)	0.01 (0.08)	0.00 (0.05)	-17.76*** [1.20]	-17.36*** [1.44] †	-18.84*** [2.13] †
Retirement	0.03 (0.16)	0.05 (0.21)	0.02 (0.13)	-2.06*** [0.32]	-2.39*** [0.40] †	-1.15** [0.50] †
Residential/lifestyle	0.08 (0.27)	0.15 (0.35)	0.06 (0.23)	-0.55*** [0.18]	-0.53** [0.23] †	-0.61** [0.26] †
Farming occupation/lower sales	0.08 (0.27)	0.13 (0.34)	0.06 (0.24)	-3.35*** [0.19]	-4.59*** [0.23]	0.03 [0.28]
Farming occupation/higher sales	0.13 (0.33)	0.14 (0.34)	0.13 (0.33)	-4.16*** [0.14]	-4.87*** [0.16]	-2.22*** [0.29]
Large Farm	0.19 (0.39)	0.16 (0.37)	0.20 (0.40)	-2.06*** [0.11]	-2.16*** [0.12] †	-1.78*** [0.26] †
Very large Farm	0.44 (0.50)	0.31 (0.46)	0.49 (0.50)	2.58*** [0.06]	2.70*** [0.06]	2.31*** [0.15]
Non-family farm	0.05 (0.22)	0.06 (0.23)	0.05 (0.22)	2.52*** [0.23]	3.06*** [0.27]	1.05** [0.44]
Total operated land (1000 acres) [c]	1.91 (2.59)	1.28 (2.09)	2.14 (2.71)	0.42*** [0.07]	0.21*** [0.07]	0.98*** [0.18]
Land ownership (categorical)						
Fully owned [b, d]	0.15 (0.36)	0.25 (0.43)	0.11 (0.31)	1.83*** [0.13]	1.77*** [0.16] †	1.97*** [0.18] †
Partly owned [b, d]	0.68 (0.47)	0.60 (0.49)	0.71 (0.45)	-0.08** [0.04]	0.08** [0.04]	-0.54*** [0.09]
Rented [b, d]	0.17 (0.38)	0.15 (0.36)	0.18 (0.38)	-1.40*** [0.12]	-1.43*** [0.13] †	-1.31*** [0.27] †
Output (1000 US real dollars per acre) [c, d]	0.74 (1.19)	0.84 (2.07)	0.70 (0.60)	1.23*** [0.07]	1.38*** [0.05] †	0.86*** [0.20] †
Labor (100 hours per acre) [c]	0.07 (0.31)	0.12 (0.55)	0.05 (0.12)	-0.78*** [0.17]	-1.32*** [0.14] †	0.72 [0.50] †
Materials (1000 US real dollars per acre) [c]	0.40 (0.55)	0.46 (0.94)	0.37 (0.31)	-0.25*** [0.07]	-0.12** [0.05] †	-0.62*** [0.23] †
Capital (1000 US real dollars per acre) [c]	0.19 (0.43)	0.23 (0.78)	0.17 (0.18)	-0.38*** [0.11]	-0.22*** [0.06] †	-0.83** [0.39] †

* Significance levels: * p<0.10, ** p<0.05, ***p<0.01. † Indicate insignificant (p<0.05) variation across FCIP participation status.

[a] The trend was estimated via a linear regression for continuous variables and a logit model for dummies.

[b, c, d, e] denotes variables used in the matching features, in the production function, in the technical inefficiency function, and in the production risk function, respectively.

Data Sources: Agricultural Resource Management Survey (ARMS) [2001-2023]

Table 1. Descriptive Statistics of U.S. Farms Differentiated by Federal Crop Insurance Program (FCIP) participation status (2001-2023) – continued

Variable	Sample mean (standard deviation)			Sample annual trend [standard error] (%) [a]		
	All farms (n= 296,257)	**FCIP farms (n= 120,522)**	**non-FCIP farms (n= 175,735)**	**All farms (n= 296,257)**	**FCIP farms (n= 120,522)**	**non-FCIP farms (n= 175,735)**
Output to input value ratio	0.92 (0.42)	0.89 (0.45)	0.93 (0.41)	0.85*** [0.02]	1.04*** [0.03]	0.33*** [0.05]
Farm assets (1000 US real dollars per acre) [b]	0.66 (1.00)	0.80 (1.57)	0.61 (0.67)	0.99*** [0.08]	1.03*** [0.07] †	0.89*** [0.24] †
Irrigated production (binary) [c, d]	0.06 (0.23)	0.06 (0.23)	0.05 (0.23)	2.22*** [0.21]	0.39 [0.24]	7.13*** [0.42]
FCIP actuarial parameters [e]						
County reference rate	0.09 (0.06)	0.09 (0.05)	0.09 (0.06)	-2.91*** [0.04]	-3.22*** [0.04]	-1.95*** [0.07]
County fixed rate	0.03 (0.01)	0.03 (0.01)	0.03 (0.01)	-2.97*** [0.02]	-3.04*** [0.02]	-2.77*** [0.05]
Weather [c]						
Precipitation	16.41 (7.20)	16.85 (7.07)	16.25 (7.24)	0.52*** [0.02]	0.52*** [0.03] †	0.53*** [0.05] †
Degree Days: 0-10C	1233.80 (228.77)	1251.33 (222.36)	1227.35 (230.75)	-0.08*** [0.01]	-0.08*** [0.01] †	-0.10*** [0.02] †
Degree Days: 10-30C	1215.11 (384.39)	1214.23 (376.98) †	1215.44 (387.08) †	0.05*** [0.02]	0.04** [0.02] †	0.08** [0.03] †
Degree Days: +30C	26.12 (27.95)	24.70 (27.62)	26.64 (28.04)	-0.43*** [0.05]	-0.73*** [0.06]	0.39*** [0.12]
Climate [b]						
Precipitation	16.29 (5.37)	16.67 (5.27)	16.15 (5.40)	0.17*** [0.02]	0.22*** [0.02]	0.04 [0.03]
Degree Days: 0-10C	1230.04 (157.95)	1243.14 (148.65)	1225.22 (160.97)	-0.03*** [0.01]	-0.05*** [0.01]	0.00 [0.01]
Degree Days: 10-30C	1196.99 (331.97)	1194.60 (313.32)	1197.87 (338.57)	-0.15*** [0.01]	-0.18*** [0.02]	-0.06** [0.03]
Degree Days: +30C	24.91 (23.31)	23.74 (23.12)	25.34 (23.37)	-0.90*** [0.05]	-1.15*** [0.05]	-0.21* [0.11]
Anomaly [e]						
Precipitation	0.50 (28.81)	1.02 (28.21) †	0.31 (29.02) †	-20.46 [53.48]	-15.18 [38.24]	-36.64 [130.95]
Degree Days: 0-10C	0.28 (13.20)	0.66 (13.13)	0.14 (13.22)	-68.48 [2274.17]	-95.22 [2721.19]	60.41 [1152.68]
Degree Days: 10-30C	1.54 (15.37)	1.50 (15.56)	1.55 (15.30)	13.04 [14.81]	16.62 [25.02]	11.83*** [3.70]
Degree Days: +30C	6.31 (70.53)	3.09 (71.45)	7.49 (70.16)	0.19 [0.97]	-2.55*** [0.45]	7.26** [3.14]

* Significance levels: * p<0.10, ** p<0.05, ***p<0.01. † Indicate insignificant (p<0.05) variation across FCIP participation status.
[a] The trend was estimated via a linear regression for continuous variables and a logit model for dummies.
[b, c, d, e] denotes variables used in the matching features, in the production function, in the technical inefficiency function, and in the production risk function, respectively.
Data Sources: Agricultural Resource Management Survey (ARMS) [2001-2023]

Table 2. Hypothesis Tests and Sources of Variability for U.S Federal Crop Insurance Program (FCIP)- and Meta-Frontier Models for Agricultural Production in the U.S. (2001-2023)

	Naïve frontier	Group frontier		Meta frontier	
		FCIP farms	**non-FCIP farms**	**Unmatched sample**	**Matched sample**
Sample size	105,174	76,806	28,368	105,174	49,962
Cobb-Douglas vs Translog test	-	534529.71***	-	83685.411***	43761.070***
Monotonicity satisfaction (%)	100.00	100.00	99.99	99.80	99.84
Curvature satisfaction (%)	99.98	99.98	99.06	98.93	99.33
Skewness test					
Schmidt & Lin (1984) [a]	-1.461***	-1.147***	-1.700***	0.745***	0.463***
Coelli, (1995) [ab]	-193.408***	-129.718***	-116.914***	98.643***	42.212***
Gutierrez (2001) [a]	26321.616**	14374.549**	9211.913**	22311.142**	5888.256**
Inefficiency variance [σ_u^2]	0.285*** (0.011)	0.218*** (0.068)	0.418*** (0.003)	0.006 (0.072)	0.016 (0.101)
Total variance [σ^2]	0.595*** (0.010)	0.533*** (0.121)	0.700*** (0.002)	0.095 (0.141)	0.132 (0.175)
Gamma [$\gamma = \sigma_u^2/\sigma^2$]	0.805*** (0.007)	0.768*** (0.094)	0.852*** (0.001)	0.690*** (0.120)	0.941*** (0.024)
Model log likelihood	-45,722	-28,889	-15,165	143,837	61,560
No. of parameters	44	43	51	63	70
Meta frontier LR test				291007.74***	126454.54***

Significance levels: * p<0.10, ** p<0.05, ***p<0.01
[a] Null hypothesis of no one-sided error (i.e., no inefficiency) was tested.
[b] Values less than the critical value of -1.96 confirm the rejection of the null hypothesis.
Data Sources: Agricultural Resource Management Survey (ARMS) [2001-2023]

Table 3. Input Elasticities for U.S. Federal Crop Insurance Program (FCIP)- and Meta-Frontier Models for Agricultural Production in the US (2001-2023)

	Total operated land (acres)	**Labor (hours)**	**Materials (US real dollars)**	**Capital (US real dollars)**	**Trend**	**Returns to scale [a]**
Naïve frontier on unmatched sample	0.223***	0.050***	0.504***	0.028***	0.005***	0.805***
	(0.002)	(0.001)	(0.007)	(0.004)	(0.000)	(0.002)
Matched sample						
Group frontier						
FCIP farms [A]	0.223***	0.044***	0.447***	0.030	0.004	0.744***
	(0.059)	(0.005)	(0.134)	(0.042)	(0.039)	(0.156)
Non-FCIP farms [B]	0.265***	0.061***	0.520***	0.019*	0.008***	0.865***
	(0.002)	(0.001)	(0.014)	(0.009)	(0.001)	(0.004)
Percentage difference [A-B]	-15.801	-27.68***	-14.154	59.274	-	-14.045
	(22.314)	(9.349)	(25.319)	(85.907)		(17.955)
Meta frontier	0.228***	0.053***	0.464***	0.028	0.006	0.772***
	(0.014)	(0.004)	(0.027)	(0.017)	(0.016)	(0.028)
Unmatched sample						
Group frontier						
FCIP farms [A]	0.211***	0.047***	0.480***	0.032	0.005	0.770***
	(0.053)	(0.007)	(0.156)	(0.049)	(0.048)	(0.166)
Non-FCIP farms [B]	0.271***	0.061***	0.517***	0.017*	0.007***	0.866***
	(0.002)	(0.001)	(0.015)	(0.009)	(0.001)	(0.004)
Percentage difference [A-B]	-22.299	-22.956*	-7.053	82.059	-	-11.152
	(19.733)	(11.402)	(29.915)	(107.554)		(19.059)
Meta frontier	0.212***	0.050***	0.485***	0.030	0.005	0.777***
	(0.038)	(0.007)	(0.095)	(0.034)	(0.032)	(0.107)

Significance levels: * p<0.10, ** p<0.05, ***p<0.01
[a] Null hypothesis of constant returns to scale was tested.
Values in parenthesis are standard errors estimated via USDA recommended delete-a group (out of 30 groups) jackknife procedure.
Data Sources: Agricultural Resource Management Survey (ARMS) [2001-2023]

Table 4. Technology and Efficiency Scores for U.S. Federal Crop Insurance Program (FCIP)- and Meta-Frontier Models for Agricultural Production in the US (2001-2023)

	Naïve technical efficiency	**Technology gap ratio (TGR)**	**Technical efficiency (TE)**	**Meta-frontier technical efficiency (MTE)**
Matched sample				
FCIP farms [A]	0.661*** (0.002)	0.925*** (0.118)	0.657*** (0.085)	0.606*** (0.029)
Non-FCIP farms [B]	0.598*** (0.002)	0.852*** (0.056)	0.617*** (0.001)	0.542*** (0.040)
Gap [A-B] (%)	10.535*** (0.223)	8.498 (7.922)	6.356 (13.793)	11.679*** (3.602)
Unmatched sample				
FCIP farms [A]	0.708*** (0.006)	0.977*** (0.064)	0.708*** (0.028)	0.694*** (0.039)
Non-FCIP farms [B]	0.570*** (0.004)	0.866*** (0.028)	0.592*** (0.002)	0.531*** (0.020)
Gap [A-B] (%)	24.158*** (0.306)	12.823** (4.950)	19.474*** (4.524)	30.725*** (4.591)

Significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$
Values in parenthesis are standard errors estimated via USDA recommended delete-a group (out of 30 groups) jackknife procedure.
Data Sources: Agricultural Resource Management Survey (ARMS) [2001-2023]

Figure 1. Production Input and Debt use Parity Associated with Agricultural Insurance in the U.S. (2001-2023)

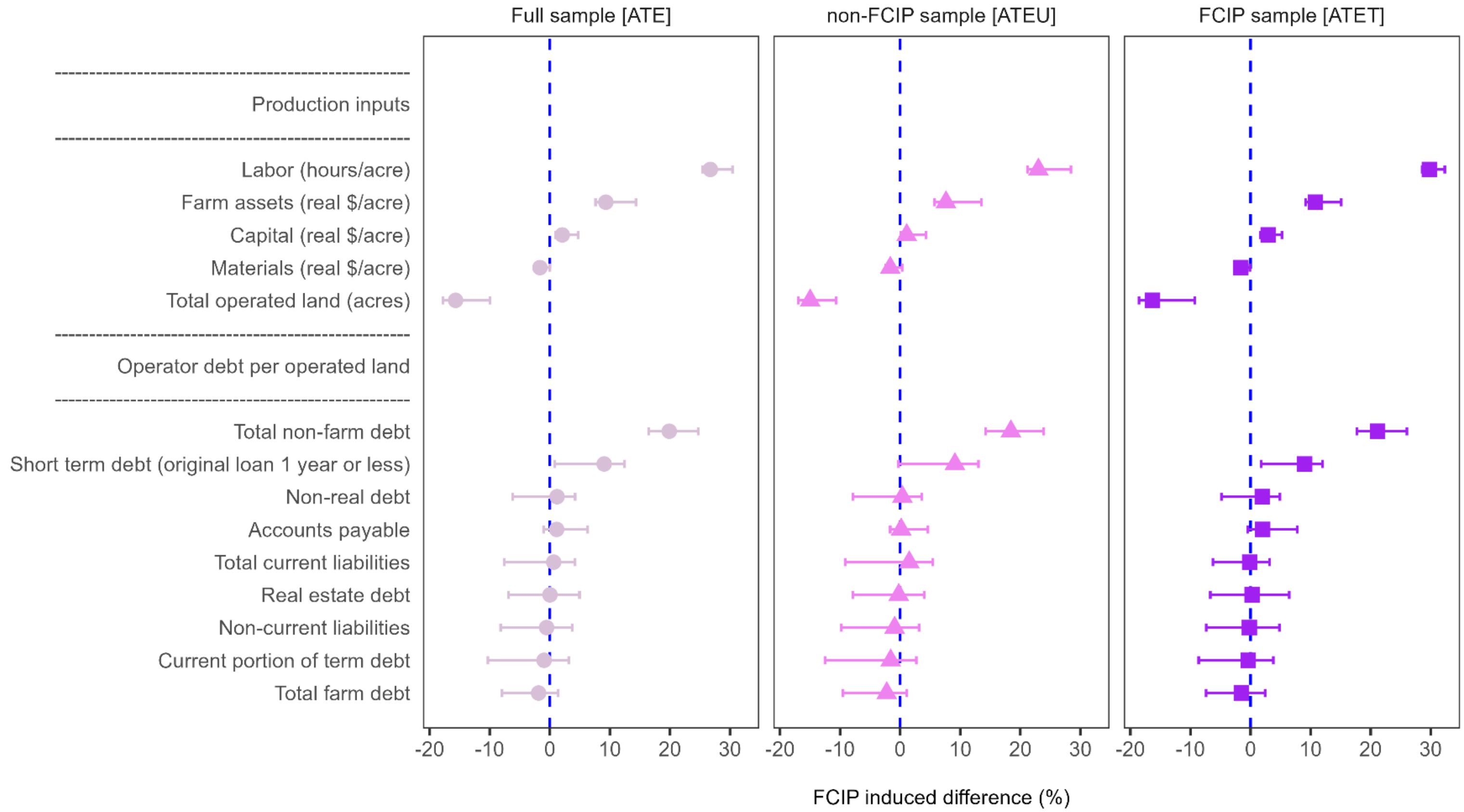

Figure 2. Distribution of Sources of Farm Level Real Production Value Variation by Agricultural Insurance Participation in the U.S. (2001-2023)

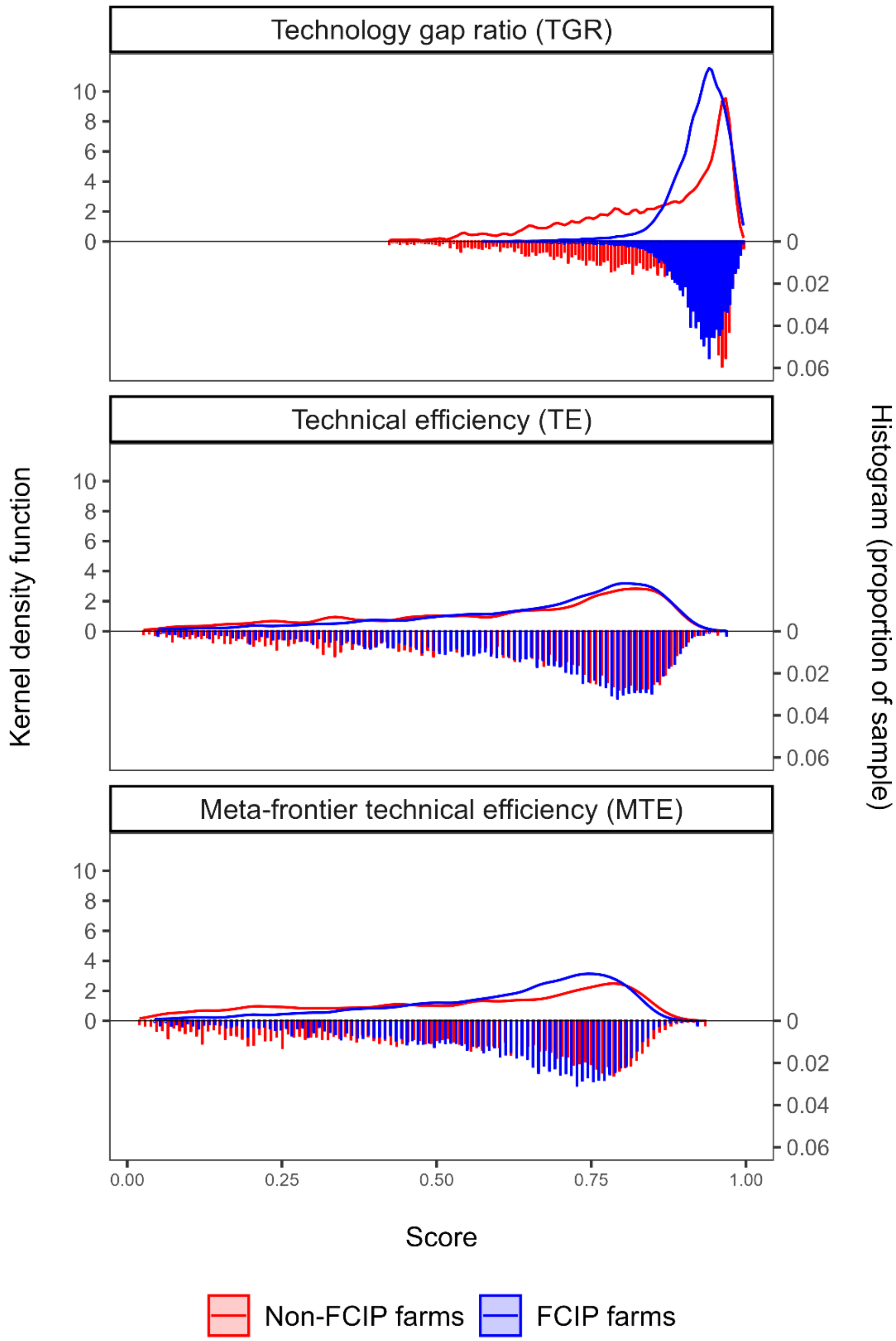

Figure 3. Temporal Dynamics in Agricultural Insurance Driven Differences in Farm Level Real Production Value in the U.S. (2001-2023)

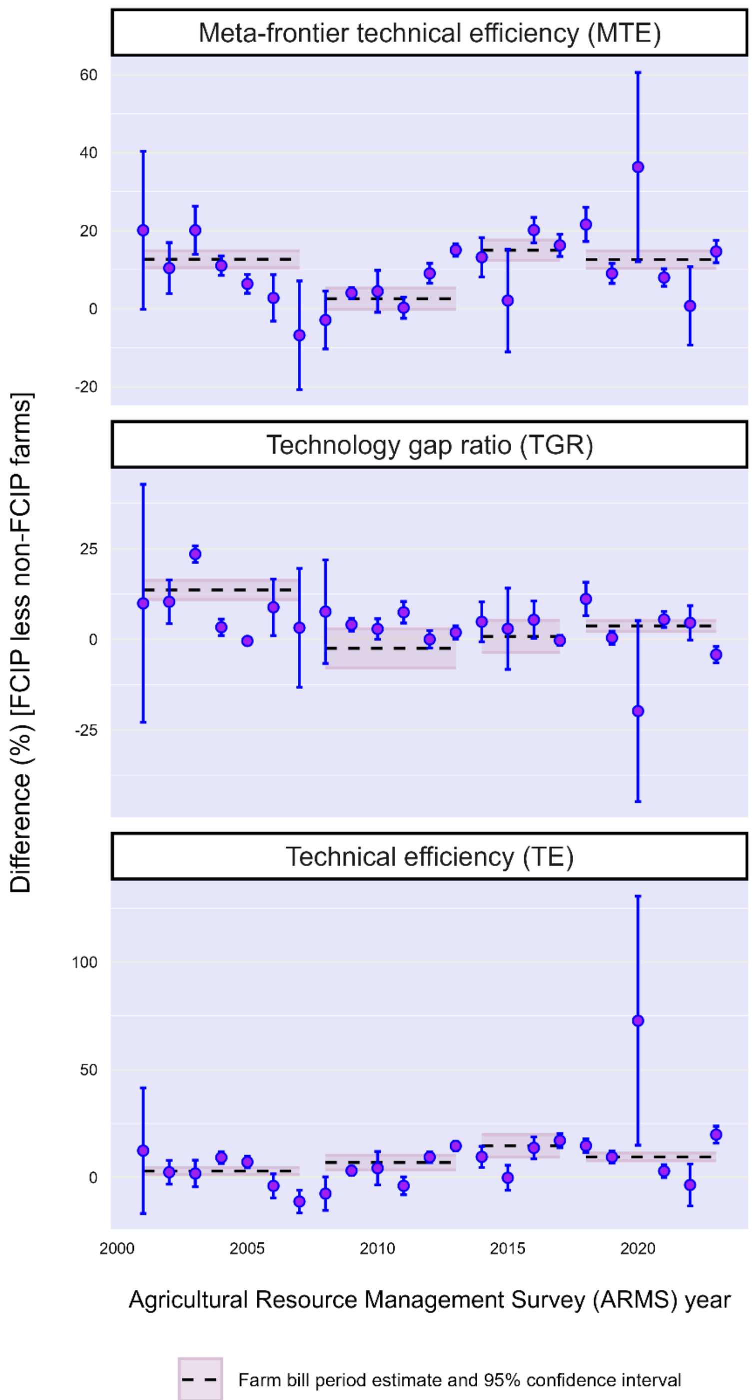

Figure 4. Observed Heterogeneity in Agricultural Insurance Driven Differences in Farm Level Real Production Value in the U.S. (2001-2023)

Appendix

Table S1: U.S. Federal Crop Insurance Program (FCIP)- and Meta-Frontier Stylized Translog Function Parameters for Real Agricultural Production Value in the US (2001-2023)

	Naïve frontier	**Group frontier**		**Meta frontier**	
		FCIP farms	**non-FCIP farms**	**Unmatched sample**	**Matched sample**
Total operated land (acres) [lnI1]	0.1969*** (0.0047)	0.1697** (0.0689)	0.2536*** (0.0042)	0.1832* (0.0919)	0.2178*** (0.0048)
Labor (hours) [lnI2]	0.0583*** (0.0023)	0.0517*** (0.0084)	0.0783*** (0.0029)	0.0611*** (0.0125)	0.0655*** (0.0031)
Materials (US real dollars) [lnI3]	0.4950*** (0.0080)	0.4666*** (0.0863)	0.4975*** (0.0114)	0.4831*** (0.1013)	0.4486*** (0.0426)
Capital (US real dollars) [lnI4]	0.0275*** (0.0066)	0.0273 (0.0479)	0.0099 (0.0122)	0.0251* (0.0130)	0.0289 (0.0210)
Trend [I5]	0.0042 (0.0041)	0.0034 (0.0039)	0.0093*** (0.0019)	0.0052 (0.0473)	0.0060 (0.0332)
1/2 * lnI1 * lnI1	-0.0182*** (0.0021)	-0.0473*** (0.0116)	0.0180*** (0.0020)	-0.0131** (0.0063)	0.0115*** (0.0025)
lnI1:lnI2	-0.0021*** (0.0004)	-0.0016 (0.0013)	-0.0005* (0.0003)	-0.0032*** (0.0008)	-0.0017* (0.0009)
lnI1:lnI3	-0.0080*** (0.0026)	0.0218*** (0.0032)	-0.0494*** (0.0024)	-0.0054 (0.0155)	-0.0294*** (0.0097)
lnI1:lnI4	-0.0025 (0.0016)	0.0001 (0.0054)	0.0008 (0.0006)	-0.0064** (0.0031)	-0.0022 (0.0051)
lnI1:I5	0.0007** (0.0003)	0.0007 (0.0010)	0.0017*** (0.0001)	0.0009 (0.0045)	0.0015** (0.0007)
1/2 * lnI2 * lnI2	0.0051*** (0.0004)	0.0044*** (0.0006)	0.0086*** (0.0002)	0.0061*** (0.0013)	0.0068*** (0.0003)
lnI2:lnI3	0.0018*** (0.0005)	0.0060*** (0.0005)	0.0004* (0.0002)	0.0044* (0.0022)	0.0039* (0.0020)
lnI2:lnI4	0.0015*** (0.0004)	0.0001 (0.0016)	-0.0001 (0.0001)	0.0014 (0.0017)	0.0000 (0.0003)
lnI2:I5	0.0001* (0.0001)	-0.0001 (0.0001)	0.0002* (0.0001)	-0.0001 (0.0010)	0.0001 (0.0002)
1/2 * lnI3 * lnI3	0.0491*** (0.0023)	0.0476 (0.0609)	0.0639*** (0.0029)	0.0600** (0.0293)	0.0851*** (0.0153)
lnI3:lnI4	0.0016* (0.0010)	0.0032 (0.0185)	0.0013* (0.0007)	-0.0010 (0.0068)	-0.0069* (0.0037)
lnI3:I5	-0.0002* (0.0001)	0.0002 (0.0019)	-0.0017*** (0.0002)	-0.0006 (0.0009)	-0.0007* (0.0004)
1/2 * lnI4 * lnI4	0.0023* (0.0013)	0.0010 (0.0169)	0.0004 (0.0025)	0.0090*** (0.0031)	0.0097*** (0.0028)
lnI4:I5	0.0002 (0.0001)	0.0002 (0.0054)	0.0010*** (0.0002)	0.0008 (0.0032)	0.0004 (0.0002)
1/2 * I5 * I5	0.0002 (0.0003)	0.0001 (0.0037)	0.0002*** (0.0001)	0.0000 (0.0060)	0.0002 (0.0043)

Significance levels: * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Values in parenthesis are standard errors estimated via USDA recommended delete-a group (out of 30 groups) jackknife procedure.

Data Sources: Agricultural Resource Management Survey (ARMS) [2001-2023]

Table S1: U.S. Federal Crop Insurance Program (FCIP)- and Meta-Frontier Stylized Translog Function Parameters for Real Agricultural Production Value in the US (2001-2023) – continued

	Naïve frontier	**Group frontier**		**Meta frontier**	
		FCIP farms	**non-FCIP farms**	**Unmatched sample**	**Matched sample**
Irrigated production (binary)	0.1029*** (0.0035)	0.1344*** (0.0279)	0.0437*** (0.0110)	0.1130*** (0.0043)	0.0717*** (0.0195)
Share of crops in value of production	0.2196*** (0.0076)	0.1903*** (0.0143)	0.2692*** (0.0212)	0.2211*** (0.0149)	0.2405*** (0.0141)
Weather					
Precipitation Level	3.9061*** (0.6104)	6.4638*** (0.8873)	0.8383** (0.3832)	3.6224* (1.9650)	2.4186* (1.2697)
Precipitation Squared	-62.8494*** (22.7704)	-115.8967*** (26.358)	-5.1988 (14.9590)	-54.9300 (47.5014)	-29.4436 (18.4254)
Extreme/Killing Degree Days: +30C	-1.5710*** (0.0175)	-1.8730*** (0.1335)	-0.9523*** (0.0792)	-1.6472*** (0.1620)	-1.1729*** (0.2812)
Farm typology (base= limited resources/retirement/residential/lifestyle farm)					
Farming occupation/lower sales	-0.0638*** (0.0100)	-0.0573* (0.0303)	-0.0354** (0.0157)	-0.0715*** (0.0235)	-0.0740*** (0.0172)
Farming occupation/higher sales	0.0683*** (0.0121)	0.0886 (0.1932)	0.0779*** (0.0042)	-0.0100 (0.1543)	0.0361 (0.0887)
Large farm	0.1926*** (0.0114)	0.2317 (0.3301)	0.1928*** (0.0123)	0.1262 (0.2481)	0.1776 (0.1203)
Very large farm	0.4452*** (0.0083)	0.5069 (0.5459)	0.4091*** (0.0104)	0.3888 (0.4382)	0.4221* (0.2177)
Non-family farm	0.6319*** (0.0077)	0.6539 (0.4828)	0.6390*** (0.0061)	0.6372 (0.4262)	0.6471** (0.2426)
Commodity harvested (binary)					
Corn	0.0858*** (0.0050)	0.0783 (0.0553)	0.0599*** (0.0019)	0.0803* (0.0404)	0.0670*** (0.0168)
Soybean	0.0588*** (0.0074)	0.0582*** (0.0098)	0.0355*** (0.0079)	0.0527*** (0.0129)	0.0495*** (0.0081)
Wheat	-0.0867*** (0.0014)	-0.0879 (0.0785)	-0.0443*** (0.001)	-0.0857 (0.0558)	-0.0652** (0.0247)
Rice	0.0374* (0.0199)	0.0240 (0.1102)	0.0473* (0.0261)	0.0279 (0.0932)	0.0360 (0.0608)
Cotton	-0.0461*** (0.0157)	-0.0489 (0.0995)	0.0055 (0.0128)	-0.0513 (0.0775)	-0.0227 (0.0342)
Barley	-0.0223*** (0.0068)	0.0011 (0.0621)	-0.0155 (0.0127)	-0.0136 (0.0469)	-0.0183 (0.0143)
Oats	-0.0668*** (0.0039)	-0.0556*** (0.0148)	-0.0680*** (0.010)	-0.0605*** (0.014)	-0.0618*** (0.011)
Sorghum	-0.0329*** (0.0060)	-0.0202 (0.0283)	-0.0389*** (0.012)	-0.0290 (0.0214)	-0.0368*** (0.009)
Peanut	-0.0412*** (0.0027)	-0.0413*** (0.0130)	0.0094*** (0.0031)	-0.0437*** (0.013)	-0.0253*** (0.004)
Tobacco	0.0283*** (0.0048)	0.0248 (0.0557)	0.1723*** (0.0072)	0.0228 (0.0222)	0.0984*** (0.0246)
Sugar beet	0.0751*** (0.0025)	0.0794 (0.0940)	0.0921*** (0.0090)	0.0743 (0.0679)	0.0878** (0.0328)
Canola	-0.1060*** (0.0026)	-0.1075*** (0.0225)	-	-0.1046*** (0.022)	#N/A
Intercept	-1.3621*** (0.0172)	-1.3763** (0.6183)	-1.3871*** (0.009)	-1.2843*** (0.184)	-1.2683*** (0.032)

Significance levels: * p<0.10, ** p<0.05, ***p<0.01
Values in parenthesis are standard errors estimated via USDA recommended delete-a group (out of 30 groups) jackknife procedure. Some models included fixed effects for ERS resource region
Data Sources: Agricultural Resource Management Survey (ARMS) [2001-2023]

Table S2: U.S. Federal Crop Insurance Program (FCIP)- and Meta-Frontier Efficiency Parameters for Real Agricultural Production Value in the US (2001-2023)

	Naïve frontier	Group frontier		Meta frontier	
		FCIP farms	**non-FCIP farms**	**Unmatched sample**	**Matched sample**
Female operator (binary)	0.2684*** (0.0168)	0.3253*** (0.0920)	0.1229*** (0.0260)	0.2346** (0.0937)	0.0825* (0.0432)
Operator age (years)	0.1976*** (0.0258)	0.3302*** (0.0714)	0.0689 (0.0481)	-0.3030** (0.1368)	0.0009 (0.0337)
Operator education (base < high school)					
High school	-0.2440*** (0.0187)	-0.2404*** (0.0259)	-0.1496*** (0.0238)	-0.3507*** (0.0936)	-0.1984* (0.1088)
Some college	-0.1675*** (0.0095)	-0.1812*** (0.0207)	-0.0332 (0.0313)	-0.4935*** (0.1515)	0.0365 (0.0426)
College graduate/beyond	-0.2124*** (0.0190)	-0.2038*** (0.0547)	-0.1007** (0.0416)	-0.5428*** (0.1751)	0.1087* (0.0589)
Land ownership (base =fully owned)					
Partly owned	-0.3440*** (0.0325)	-0.2448** (0.1105)	-0.4698*** (0.0393)	-0.7496** (0.2940)	-0.4193 (0.3091)
Rented	-0.3977*** (0.0313)	-0.2904* (0.1469)	-0.4872*** (0.0446)	-0.6233** (0.2959)	-0.2056 (0.2207)
Federal program participation (binary)					
Conter cyclical	0.0479*** (0.0071)	0.1126 (0.1271)	-0.0890*** (0.0233)	-0.4148*** (0.0873)	-0.2105*** (0.0530)
Ad-Hoc	0.1665*** (0.0256)	0.3602*** (0.0511)	-0.1235 (0.0959)	0.0729 (0.2237)	-0.3239** (0.1281)
Farm bill period (base=1997-2000)					
2008-2013	-0.1270*** (0.0043)	-0.0894*** (0.0070)	-0.1907*** (0.0068)	-0.0583*** (0.0175)	-0.0143 (0.0294)
2014-2017	0.0447 (0.0330)	0.0697 (39.3381)	0.0698*** (0.0201)	-0.2141 (11.4059)	-0.0491 (0.2803)
2018-2022	-0.1828*** (0.0469)	-0.1830 (40.2488)	-0.1858*** (0.0186)	-0.2529 (11.6527)	-0.1704 (0.2141)
Farm typology (base= limited resources/retirement/residential/lifestyle farm)					
Farming occupation/lower sales farm	-0.0331 (0.0305)	0.2362*** (0.0400)	-0.1595*** (0.0196)	-0.7840 (0.6290)	-0.5672 (0.4969)
Farming occupation/higher sales farm	-1.2657*** (0.0253)	-1.0302** (0.4189)	-1.4901*** (0.0621)	-37.7960 (26.2841)	-1.6221* (0.9123)
Large farm	-1.9612*** (0.0190)	-1.7822** (0.7875)	-2.1223*** (0.0439)	-87.3995* (47.6814)	-1.4831** (0.6453)
Very large farm	-2.2307*** (0.0334)	-2.0024* (1.0469)	-2.4114*** (0.0278)	-49.9687** (19.2430)	-1.5219 (0.9010)
Non-family farm	-0.5371*** (0.0549)	-0.4930 (0.5494)	-0.2721*** (0.0444)	-1.0571 (0.9524)	-0.4564 (0.6004)
Intercept	-0.5240*** (0.0507)	-1.4538 (39.8405)	0.1782 (0.1542)	-1.0990 (11.3665)	-2.7149*** (0.6975)

Significance levels: * p<0.10, ** p<0.05, ***p<0.01
Values in parenthesis are standard errors estimated via USDA recommended delete-a group (out of 30 groups) jackknife procedure.
Data Sources: Agricultural Resource Management Survey (ARMS) [2001-2023]

Figure S1: Covariate balance summary

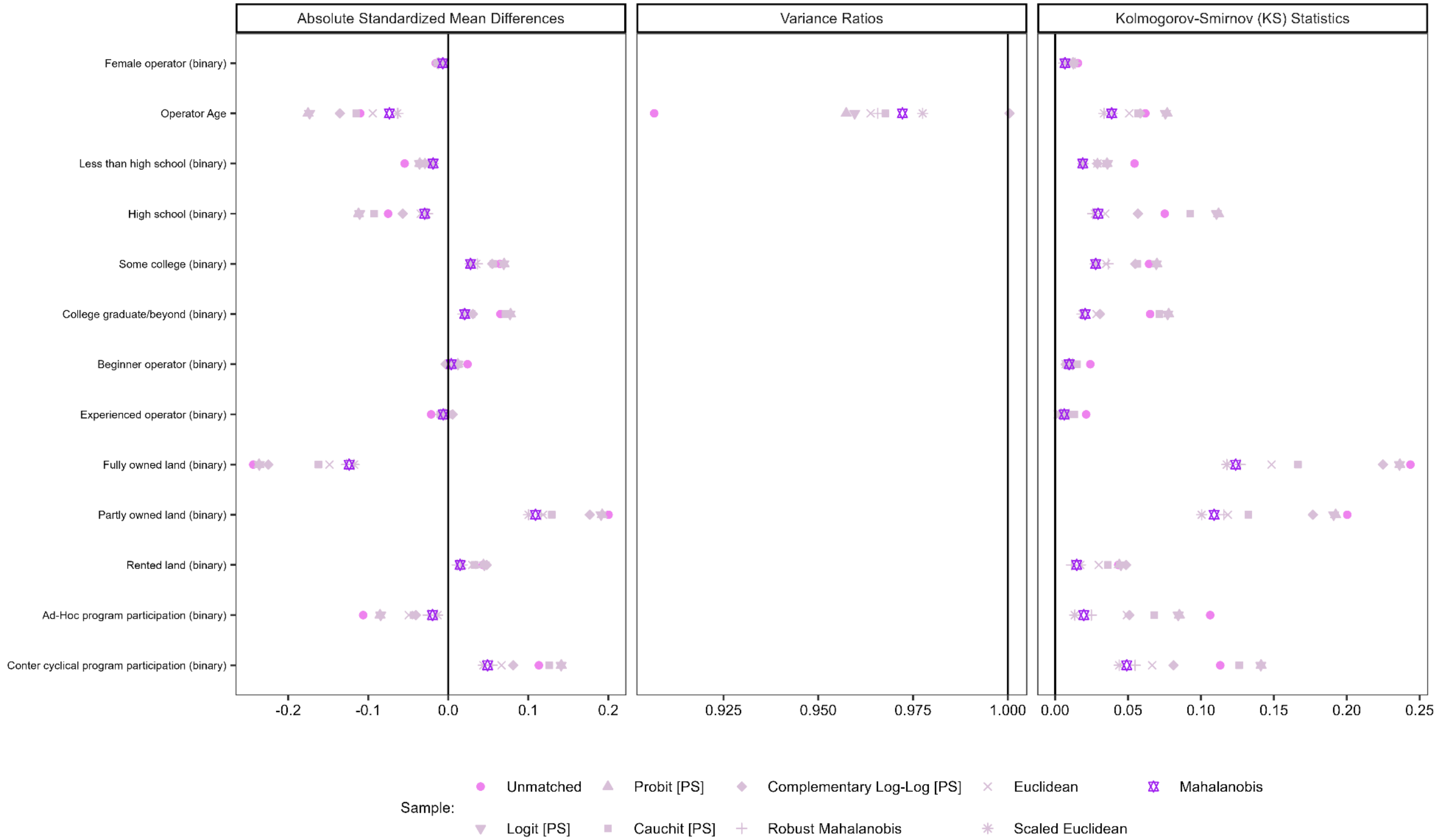

Figure S2. Temporal Dynamics of Agricultural Production Elasticities by Federal Crop Insurance Program (FCIP) Participation in the U.S. (2001-2023)

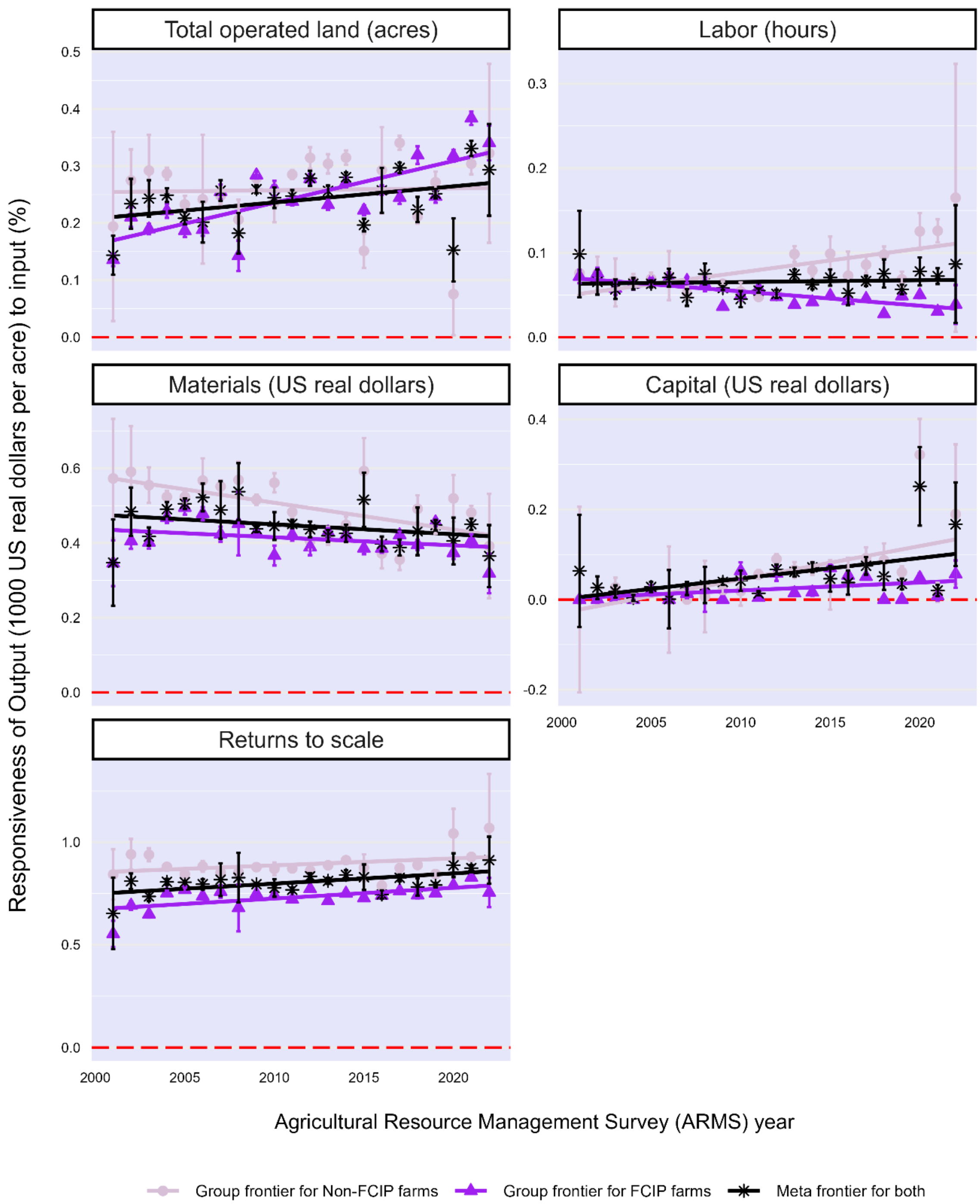

Figure S3. Robustness checks

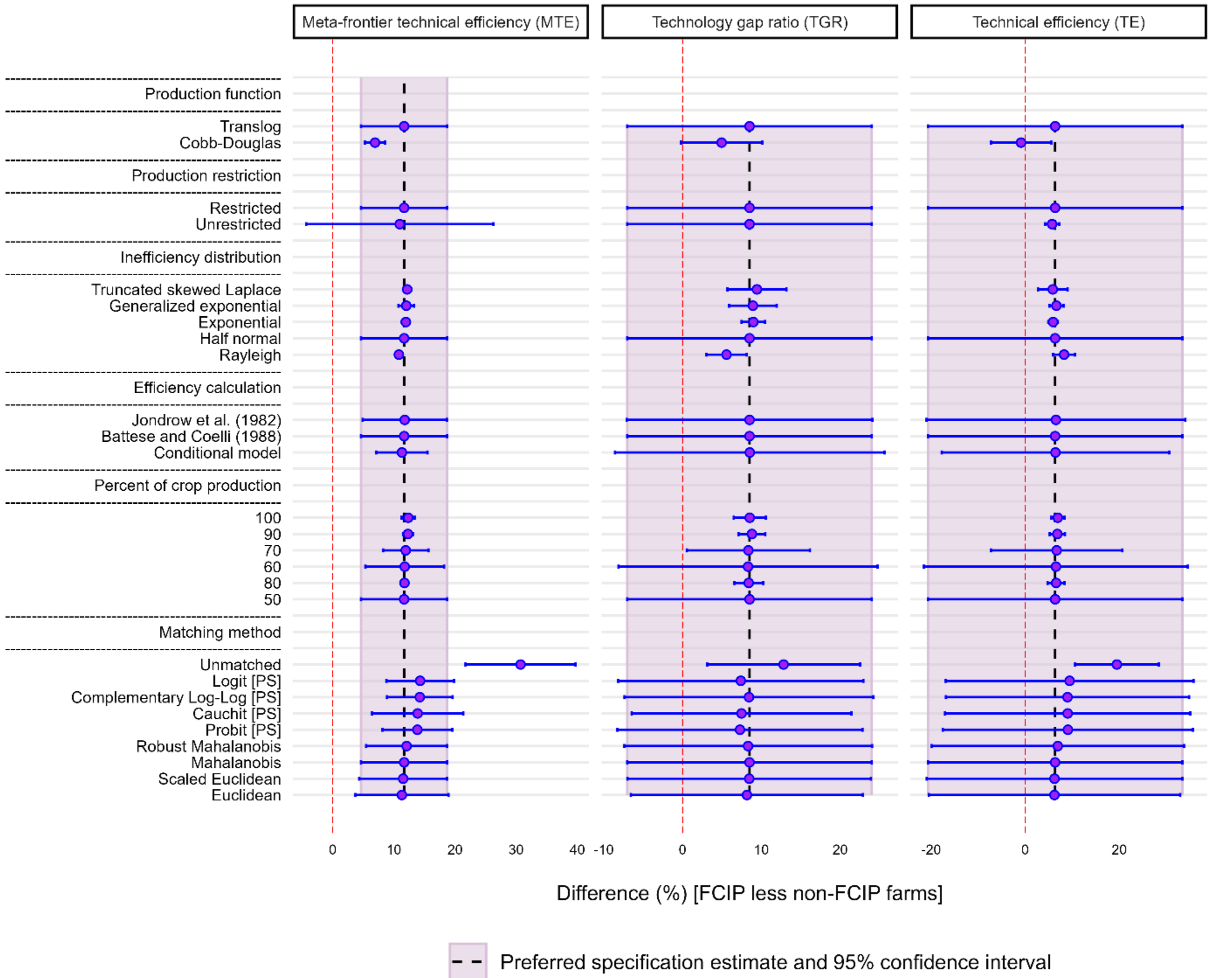

Figure S4. Spatial Dynamics in Agricultural Insurance Driven Differences in Farm Level Real Production Value in the U.S. (2001-2023)