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Examining the effects of federal crop insurance premium subsidies on allocative and technical inefficiency in the U.S. Cornbelt

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The findings and conclusions in this manuscript are those of the author and should not be construed to represent any official USDA or U.S. Government determination or policy.

Prepared for the 2020 AAEA annual meeting taking place in Kansas City, MO, July 26-28, 2020.

Preliminary – Please do not cite without permission.

Background

The United States agricultural sector is subject to numerous risks arising from price fluctuations, weather variability, and natural disasters. In order to mitigate losses due to these hazards the Federal government offers a highly subsidized crop insurance program designed to indemnify agricultural producers against yield losses, price fluctuations, and catastrophic loss. The program is overseen by the Federal Crop Insurance Corporation (FCIC) and is operated through a public-private arrangement whereby: Approved Insurance Providers (AIP) sell and service insurance policies; the FCIC reinsures the policies and subsidizes premiums on behalf of farmers; and the Risk Management Agency (RMA), a federal agency, establishes the actuarially fair cost of premiums for the various crop insurance programs available, determines policy terms, and regulates the AIPs.

The received literature observes that the Federal Crop Insurance program has expanded its product offerings to producers while increasing subsidy rates and as a result participation rates have soared (Belasco, Cooper and Smith 2020; Smith and Glauber 2012). Further, Coble and Barnett (2013) and Annan and Schlenker (2015) argue that, from an input demand perspective, the resulting moral hazard has producers adjusting their insurance coverage upwards in order to take advantage of the expected increase in the crop insurance indemnity and that this may encourage producers to oversubscribe for insurance coverage thus raising the cost of the federal crop insurance program. Other studies argue (e.g., Goodwin and Smith 2012; Yu, Smith and Sumner 2017; Goodwin, Vandeveer and Deal 2004) that subsidizing crop insurance premiums induces farmers to assume more risk thus resulting in changes and distortions in production practices, characterized by an alteration in the quantity and allocation of factors of production, such as acreage, fertilizers & chemicals, equipment and machinery in ways that would not have occurred had the subsidy not been available. There is additional evidence in the literature indicating that farmers may seek to obtain more coverage rather than engage in other possible adaptation strategies that could mitigate risk (Coble and Barnett 2013; Annan and Schlenker 2015).

This study will evaluate the effect of Federal Crop Insurance premium subsidies on allocative efficiency and technical efficiency, following crop insurance premium subsidies. Technical efficiency is a measure of managerial performance that captures how effective producers are at combining various inputs in order to maximize output. In this sense, any deviation from the maximal frontier is considered technically inefficient. Allocative efficiency measures the degree to which producers utilize the correct proportion of inputs given input prices or the extent to which firms operate off their least cost expansion path (Schmidt and Lovell 1979). Alternatively, allocative efficiency can be considered a component of productivity growth that measures how well producers capture economies of input substitution (O'Donnell 2018).

This paper develops an empirical framework that combines input-output variables alongside information on crop insurance coverage, and agronomic weather measures in order to establish the overall cost efficiency generated by the availability of highly subsidized crop insurance premium subsidies. The argument is that subsidized crop insurance coverage may create a distortionary effect in how producers utilize the correct proportions of inputs in order to maximize the corn production. The focus of this study will be on corn production as this received the largest portion of insurance protection. Of the approximately 300 million acres insured under the Federal Crop Insurance program in 2018, close to 75 million acres were dedicated to corn production. In the counties, and across the years analyzed in this study corn acreage planted stood at 335.2 million acres of which 290.8 million acres were covered under the Federal Crop insurance Program. Similarly, total subsidies directed towards corn planted in these counties stood at $6.25

billion with producers paying an aggregate of 10.64 billion in premiums. Meanwhile, the estimated total liabilities stood at $127.9 billion.

Empirical Strategy

The cost minimization problem that the producer faces takes on the following form:

(1) $min\ w'x$ s.t. $q = f(x, z)\exp(v - u)$

Where w, x, z and q are vectors that represent the input price, conventional input, environmental inputs, and outputs, respectively. Furthermore, v and u are a composed error term that capture statistical noise and technical inefficiency, respectively. The function $f(.)$ is an approximating function that specifies the input-output relationship. The magnitude of allocative inefficiency is captured by solving the system of first-order conditions for the cost minimizing problem above. Input allocation is considered optimal only if producers allocate inputs in such a manner that equates input price ratios to their marginal products, such that:

(2) $\frac{f_i}{f_1} = \frac{w_i}{w_1}\ \forall\, i = 2, \ldots\ldots, I$

A graphical illustration of allocative and technical inefficiency for the representative firm is provided in Figure 1 below. Suppose output q is generated using inputs x_1 and x_2 combined using proportions a, b or c. Input combination a far exceeds what is necessary to produce at level q. This is the idea behind technical inefficiency. Input combination c, is also suboptimal because for a given input x_2 relative to x_1 the deviation from the optimal condition is given by η, such that if $w_2^{\exp(\eta)} > w_2$ then x_2 is under-utilized relative to x_1. Conversely, if $w_2^{\exp(\eta)} < w_2$, then x_2 is over-utilized relative to x_1. The optimal input proportion is denoted at point b where the tangency of the isocost line and isoquant is such that $\frac{f_1}{f_2} = \frac{w_1}{w_2}$.

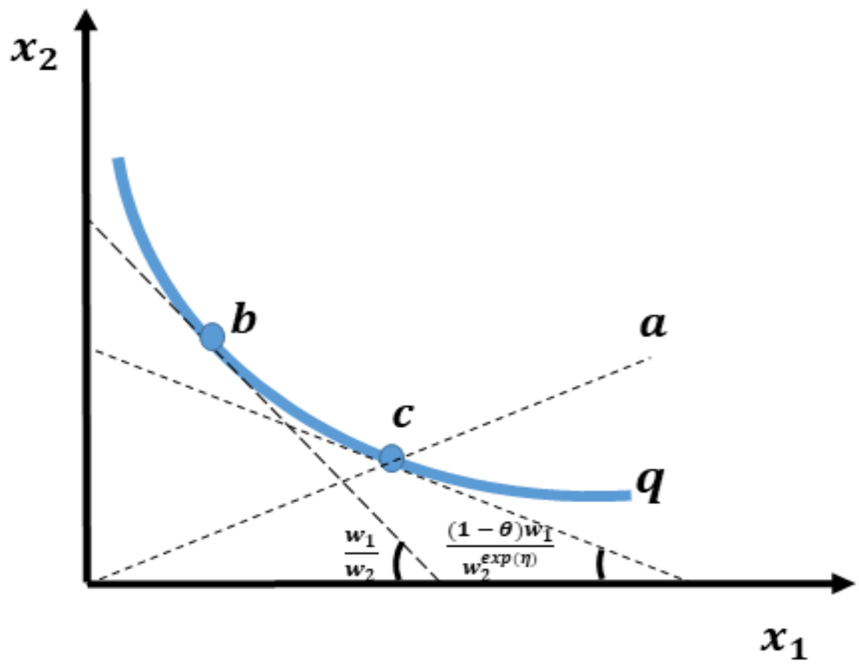


Figure 1: Graphical illustration of allocative and technical efficiency

The cost minimizing framework above can be used to generate estimates of allocative and technical efficiency. However, it is not possible to disentangle the contribution of allocative inefficiency from that of technical inefficiency because the composed error term is intractable (Kumbhakar and Lovell 2000). An alternative modeling strategy proposed by (Schmidt and Lovell 1979) reformulates the approximating function used to characterize the production technology into a primal approach. Stochastic production frontiers have implications for determining the magnitude of the distance from the frontier that firm operates, that is the level technical inefficiency. By combining this information with information on allocative efficiency, then we can shed some light on a decision making-units cost efficiency. The relationship between the input-output variables involved in the production process is rewritten as:

(3) $\ln q_{it} = f^t(x_{it}, z_{it}) + v_{it} - u_{it}$

Where $\ln q_{it}$ is the log of output, $f^t$is a function that approximates the production technology, x_{it} represents conventional inputs, z_{it} denotes characteristics of the production environment, and the subscripts i and t denote decision making-unit and period, respectively. Finally, v_{it} and u_{it} are independent random variables that capture statistical noise and technical inefficiency, respectively, with distributional properties $v_{it} \sim N\,(0, \sigma_v^2)$ and $u_{it} \sim\, N^+(0, \sigma_u^2)$. The approximating function used in this study is a Cobb-Douglas functional form expressed as:

$$(4) \quad \ln q_{it} = \phi_i + \delta_t + \sum_{m=1}^{M} \beta_m \ln x_{mit} + \sum_{j=1}^{J} \gamma_m \ln z_{jit} + v_{it} - u_{it}$$

Where ϕ_i and δ_t capture unobserved time-invariant and time-varying characteristics, $\ln q_{it}$, $\ln x_{mit}$, $\ln z_{jit}$, v_{it} and u_{it} are as defined above. Furthermore, $(\phi, \delta, \beta, \gamma)$ are parameters to be estimated. Suppose that agricultural producers purchase x_1 units of crop insurance at unit price$(1-\theta)w_1$, where $\theta \in (0,1)$ is the per unit subsidy provided by government. The system of first-order conditions for cost minimization can be estimated in a stochastic production frontier framework denoted as:

$$(5) \quad \ln \frac{\beta_m}{\beta_1} - \ln \frac{w_m}{(1-\theta)w_1} - \ln \frac{x_m}{x_1} = \eta_m, \forall\, m = 2, \dots, M$$

In the expression above, w_m, represents input prices for any other inputs, and η_m is a random error term that captures allocative inefficiency, with distributional properties $(\eta_2, .., \eta_M) \sim iid\ N(0, \Sigma)$. Values of η_m take on positive or negative values when relative input combinations are over- or under-utilized. A firm is considered to be allocatively efficient in its input use when the value η_m equals zero. Firm-specific estimates of technical inefficiency and allocative inefficiency are obtained from expression 4 and 5 above, respectively.

We are also interested in establishing the impact of technical and allocative inefficiency on costs. Expression 4 has the convenient property that it is self-dual, thus parameter estimates, and the residuals can be substituted into a system of input demand equations for x_1 and x_m in order to derive an expenditure function. This expenditure function can then be used to establish the impact of allocative inefficiency and technical inefficiency on firms' costs (Kumbhakar and Lovell 2000).

$$\text{(6)} \quad \ln E_i = \ln r - \frac{\phi_i}{r} - \frac{1}{r}\ln\prod_{m=1}^{M}\beta_m + \sum_{m=1}^{M}\frac{\beta_m}{r}\ln w_{mi} + \frac{1}{r}\ln q - \left(\frac{v_i}{r} + \frac{u_i}{r}\right) + (A - \ln r)$$

Where $A = \frac{1}{r} + \sum_{m=2}^{M}\beta_m\,\eta_m + [\ln\beta_1 + \sum_{m=2}^{M}\beta_m\exp(-\eta_m)]$, and $r = \sum_{m=1}^{M}\beta_m$ measures the returns to scale. The term u_i/r captures cost increases due to technical inefficiency, whereas $(A - \ln r)$ captures cost increases due to allocative inefficiency. Finally, one can generate a rank ordering of cost efficiency across firms by using an expression that compares overall cost efficiency for firm i at time t with that of firm k at time s:

$$\text{(7)} \quad \frac{CE_{it}}{CE_{ks}} = \frac{AE_{it}}{AE_{ks}} \times \frac{TE_{it}}{TE_{ks}}.$$

Data

The input-output data used is derived from the U.S. Department of Agriculture quinquennial census of agriculture for the years 1997, 2002, 2007, 2012 and 2012. The data is at the county-level and comprises 1011 counties spread across 12 states in the U.S. cornbelt[1]. Figure 2 provides an illustration of the location of these counties. The input-output variables include corn bushels harvested, acres of corn planted, value of machinery and equipment, expenditures on hired and contract labor, and expenditures on intermediate materials (i.e., fertilizer, chemicals and fuel). Information on value of machinery and equipment is used to construct a measure of a capital stock variable using the perpetual inventory method. Using 1997 as the base year, the value of the capital stock at the end of each period, K_t, is a function of past investments weighted by its relative

[1] The 1011 counties are spread across Illinois, Iowa, Indiana, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin.

efficiency, s_τ, such that, $K_t = \sum_{\tau=0}^{\infty} s_\tau I_{t-\tau}$. The value s_τ is estimated using a hyperbolic efficiency function (e.g., Ball et al. 2016; Ball et al. 1999)

$$(8) \quad s_\tau = \frac{L - \tau}{L - \Omega\tau}$$

Where L is the service life of the asset, τ is the age of the equipment, and Ω is the parameter of efficiency. Following similar studies that use capital stock as one of the variables (Ball et al. 2008; Ball et al. 1999) the service life of the asset, L, and the parameter of efficiency, Ω, are set at 7 years and 0.5, respectively. The variable for labor hours is constructed by dividing aggregate labor expenditures by the corresponding state-level hourly wage rate obtained from the U.S. Bureau of Labor Statistics (BLS) Occupational Employment Statistics for farmworkers and laborers. Monetary values are converted into constant 2017 dollars using deflators based on the producer price index provided by the U.S. Department of Labor.

The data is augmented with information on crop insurance premiums and subsidies obtained from the summary of business reports generated by the Risk Management Agency of the U.S. Department of Agriculture for the years that correspond to the census of agriculture. Data on characteristics of the production environment, which include temperature and precipitation, are derived from the parameter-elevation regressions on independent slopes model (PRISM). These data are used to calculated agronomic weather measures that include growing degree days, harmful degree-days, cumulative precipitation, and vapor pressure deficit. Input price information which includes cropland values per acre, interest rate expenses, and a fertilizer and chemical price index for the corresponding census years are obtained from records maintained by the National Agricultural Statistical Service. Fuel prices in equivalent British thermal units (Btu) are obtained from the Energy Information Administration. These input prices are used to generate the primal cost function as well as the factor demand equations discussed above. Table 1 provides a summary description of the data used in this study.

Results

The parameters in the stochastic production frontier model given by equation 4 are estimated using maximum likelihood methods with the standard errors clustered at the county-level. These parameter estimates, which can be interpreted as elasticities are reported in Table 2. The β_m parameters are all positive and significantly different from zero indicating that inputs are strongly disposable. The γ_j estimates that measure the impact of observed weather variables, are also significantly different from zero indicating that marginal increases in growing degree days and precipitation lead to marginal increases in corn output. Conversely, marginal increases in harmful degree days and vapor pressure deficit lead to marginal decreases in corn output. In addition, estimates of, δ_t, and state-level fixed effects, ϕ_i, which capture unobserved time-varying and time-invariant heterogeneity, respectively, are also reported. It is also noteworthy that the maximum likelihood value for $\lambda = \sigma_u/\sigma_v$ is 2.16, thus providing evidence of substantial technical inefficiency.

Assuming that the representative decision-making unit also seeks to minimize cost, then one can estimate the extent to which any given county deviates from its least cost expansion path. Estimates of allocative efficiency are obtained by exploiting the duality of the production frontier and by utilizing the system of first-order conditions for cost minimization in equation 5. From the system of equations in 4 and 5 one can derive the input demand equations for x_m and subsequently, an expenditure function. The results for the primal cost function are provided in Table 3. A comparison of technical efficiency estimates for the stochastic production function and the primal cost function are provided in Table 4, indicating that the average county generates corn output at

68% of its maximum production potential and approximately 24.8% above its minimal cost level. An illustration of their density functions is provided in Figure 3.

As indicated above, the direction and scale of allocative inefficiency is given by the value, η_m, which may take on the positive, negative or zero values characterizing over-utilization, under-utilization or efficient use of any given pair of inputs. A summary of the estimates is provided in Table 5. The mean value for η_{25} and η_{45}, representing the allocative efficiency for the pair of inputs capital and subsidies, and intermediate materials and subsidies, respectively, are both negative revealing that capital and intermediate materials are under-used relative to premium subsidies. Conversely, mean allocative efficiency estimates, η_{15} and η_{35}, representing the input pairs corn acres and subsidies, and labor and subsidies, respectively, are positive indicating that on average corn acres planted and labor hours are over-used relative to the premium subsidies. A graphical illustration of the density functions is provided in Figure 4. We can also establish the impact of technical efficiency and allocative efficiency on overall costs. This is done by comparing the expenditure function as given in equation 6, with and without technical, and allocative inefficiency. A summary of the results is provided in Table 6. The results reveal that, on average, costs are increased by 42.3% in the presence of technical inefficiency and by 5.2% when counties deviate from their least-cost combination.

Finally, we consider cost efficiency, which is a measure of how well producers have minimized costs when output and the production environment are predetermined, and inputs are chosen freely (O'Donnell 2018). Cost efficiency is calculated as the product of technical and allocative efficiency. A summary of the cost efficiency is provided in Table 7. These results reveal that cost efficiency for the average corn producing county was 45.9%. We also construct a measure of cost efficiency index that compares the cost efficiency of county i at time t relative to county k

at time s following equation 7. A rank ordering of cost efficiency is relevant to inform economic policy in order to target public policy. Using Adams county, IL in 1997 as the reference vector we can compare every other county in the data set in order to generate a relative ranking. An illustration of this cost efficiency index is provided in Figure 7.

Concluding Remarks

This study analyzes cost efficiency, which is defined as technical efficiency: a measure of how well producers combine various inputs in order to maximize corn production; and allocative efficiency, which measures the degree to which producers utilize the correct proportion of inputs given input prices. Using the duality of the stochastic production frontier, a primal cost model is evaluated in order to generate estimates of technical and allocative efficiency. These estimates of technical and allocative efficiency provide vital information for evaluating: (1) how effective producers are at combining various inputs in order to maximize corn production; and (2) the over- and under-utilization of various inputs relative to premium subsidies provided under the Federal Crop Insurance program, and in turn how these two concepts impact overall costs.

The findings reveal that corn acreage under the Federal Crop Insurance program increased over the years providing evidence of increased participation rates by producers. Secondly, a comparison of the proportions of conventional inputs (i.e., land, labor, capital, and intermediate materials) used relative to premium subsidies provide evidence of deviation from the least-cost expansion path. Capital and intermediate materials were under-utilized relative to premium subsidies, conversely acreage under corn and labor were over-utilized relative to premium subsidies. Third, the relative under- and over-utilization of inputs had implications for overall costs, resulting on average to a 5.2% increase in overall costs. Finally, we find that in general, counties produced corn at 75% of their maximum potential. This deviation from the maximal frontier had the effect of raising overall costs for the average county by 42.3%.

Table 1: Descriptive statistics of variables used in estimation

Variable	Observations	Mean	Std. Dev.	Min	Max
Corn harvested (bushels)	4838.00	9,830,005.00	10,200,000.00	2,756.00	74,700,000.00
<u>Conventional inputs</u>					
Corn acres planted	4837.00	69,295.48	61,505.78	31.00	396,552.00
Capital ($)	4840.00	128,000,000.00	95,200,000.00	2,487,000.00	822,000,000.00
Labor (hours)	4812.00	534,378.40	549,723.30	3,263.16	7,670,282.00
Fertilizer expenditures ($)	4840.00	9,739,775.00	9,072,815.00	32,000.00	80,800,000.00
Chemical expenditures ($)	4835.00	6,195,176.00	5,522,376.00	5,000.00	42,200,000.00
Fuel and lube expenditures ($)	4840.00	4,931,627.00	3,763,421.00	88,000.00	37,900,000.00
Corn acres insured	4840.00	60,079.97	55682.57	9.00	351,302.00
Insurance liabilities ($)	4840.00	26,400,000.00	34,800,000.00	310.00	277,000,000.00
Insurance premiums ($)	4840.00	2,199,055.00	2,682,895.00	84.00	29,100,000.00
Insurance subsidies ($)	4840.00	1,290,567.00	1,644,913.00	56.00	18,800,000.00
Insurance indemnity ($)	4840.00	2,827,947.00	8,114,861.00	-1402.00	140,000,000.00
<u>Agronomic weather variables</u>					
Growing degree days	4840.00	2981.26	483.52	1,571.70	4,636.30
Growing degree days (April-May)	4840.00	548.32	190.61	66.45	1144.35
Growing degree days (June-July)	4840.00	1,306.38	157.57	807.40	1,676.35
Harmful degree days	4840.00	48.33	24.95	0.00	121.00
Harmful degree days (April-May)	4840.00	3.01	3.76	0.00	24.00
Harmful degree days (June-July)	4840.00	27.73	12.94	0.00	58.00
Precipitation (inches)	4840.00	20.23	6.10	3.56	46.86
Precipitation (April-May)	4840.00	7.54	3.57	0.71	24.89
Precipitation (June-July)	4840.00	6.49	3.10	0.58	29.99

Vapor pressure deficit (min) (hPa)	4840.00	1.38	0.66	0.20	5.01
Vapor pressure deficit (max) (hPa)	4840.00	19.46	4.65	6.60	38.94
Prices					
Cropland values ($/acre)	4840.00	2,906.20	1,893.86	427.00	7,440.00
Interest expenses ($)	4819.00	5,261,515.00	3,566,202.00	92,000.00	35,900,000.00
Wage rate ($/hour)	4840.00	10.29	2.35	6.55	17.59
Fertilizer index	4840.00	97.44	17.46	82.10	128.20
Chemical index	4840.00	68.19	31.16	32.80	106.50
Fuel prices (equiv $/btu)	4840.00	2.30	1.29	0.79	3.85

Table 2: Parameter estimates of stochastic production frontier

	Parameter/Variable	Coefficient	Robust Std. Error
β_1	Corn acres	0.3990***	0.0160
β_2	Labor hours	0.1225***	0.0220
β_3	Capital	0.0784**	0.0405
β_4	Materials	0.4174***	0.0405
β_5	Premium subsidies	0.3088***	0.0132
γ_1	Growing degree days	0.3979***	0.1119
γ_2	Harmful degree days (Jun-Jul)	-0.0997***	0.0145
γ_3	Precipitation (April-May)	0.0211**	0.0160
γ_4	Vapor pressure deficit (Max)	-0.0083***	0.0038
γ_5	Vapor pressure deficit (Min)	-0.0661***	0.0181
δ_1	1997	1.7346***	0.0925
δ_2	2002	0.9799***	0.0873
δ_3	2007	1.0735***	0.0822
δ_4	2012	0.9473***	0.0858
δ_5	2017	0.8691***	0.0869
ϕ_1	Illinois	0.1947***	0.0577
ϕ_2	Indiana	0.2494***	0.0590
ϕ_3	Iowa	0.2496***	0.0507
ϕ_4	Kansas	-0.1022	0.0624
ϕ_5	Michigan	0.0498	0.0631
ϕ_6	Minnesota	0.0967	0.0604
ϕ_7	Missouri	-0.0555	0.0616
ϕ_8	Nebraska	0.2786***	0.0556
ϕ_9	North Dakota	-0.8559***	0.0751
ϕ_{10}	Ohio	0.2232***	0.0562
ϕ_{11}	South Dakota	-0.3385***	0.0664
σ_v		0.2630***	0.0161
σ_u		0.5677***	0.0248
σ^2		0.3915***	0.0251
λ		2.1582***	0.0358

***, **, * ==> Significant at 1%, 5%, 10% level.

Table 3: Primal cost estimates

	Parameter/Variable	Coefficient	Std. Error
β_0	Constant	-0.099	0.156
β_1	Corn acres	0.720***	0.014
β_2	Capital	1.228***	0.025
β_3	Labor hours	0.027***	0.001
β_4	Materials	0.157***	0.002
β_5	Premium subsidies	0.002***	0.000
γ_1	Growing degree days	-0.484***	0.194
γ_2	Harmful degree days (Jun-Jul)	-0.056***	0.029
γ_3	Precipitation (April-May)	0.027	0.033
γ_4	Vapor pressure deficit (Max)	-0.004	0.006
γ_5	Vapor pressure deficit (Min)	-0.109***	0.032
δ_1	1997	0.875***	0.048
δ_2	2002	-0.228***	0.039
δ_3	2007	0.389***	0.042
δ_4	2012	0.630***	0.045
ϕ_1	Illinois	0.421***	0.073
ϕ_2	Indiana	0.722***	0.070
ϕ_3	Iowa	0.215***	0.067
ϕ_4	Kansas	0.456***	0.078
ϕ_5	Michigan	0.292***	0.068
ϕ_6	Minnesota	0.084	0.069
ϕ_7	Missouri	0.457***	0.078
ϕ_8	Nebraska	0.771***	0.071
ϕ_9	North Dakota	-0.794***	0.078
ϕ_{10}	Ohio	0.347***	0.068
ϕ_{11}	South Dakota	0.241***	0.075
σ_u		-1.887	0.699
σ_v		-0.483	0.081

Table 4: Summary of technical efficiency

	Parameter/Variable	Mean	Std. Dev.	Min	Max
$\bar{u}_{it}^{p}$	TE - Production frontier model	0.680	0.149	0.264	0.973
$\bar{u}_{it}^{c}$	TE - Primal cost model	0.752	0.045	0.359	0.900

Table 5: Summary of allocative efficiency

	Parameter/Variable	Mean	Std. Dev.	Min	Max
η_{15}	Corn acres/Subsidies	2.656	2.366	-15.193	18.260
η_{25}	Capital/Subsidies	-1.613	2.363	-18.259	4.354
η_{35}	Labor/Subsidies	6.595	2.119	-9.322	15.495
η_{45}	Intermediate/Subsidies	-0.822	1.973	-14.843	7.959

Table 6: Summary of allocative and technical inefficiency impact on costs

Parameter/Variable	Mean	Std. Dev.	Min	Max
Technical inefficiency on total cost	0.423	0.030	0.183	0.525
Allocative inefficiency on total cost	0.052	0.002	0.006	0.059

Table 7: Summary of cost efficiency

Variable	Mean	Std. Dev.	Min	Max
Cost Efficiency	0.459	0.166	0.034	0.899

Figure 2: Counties represented in study

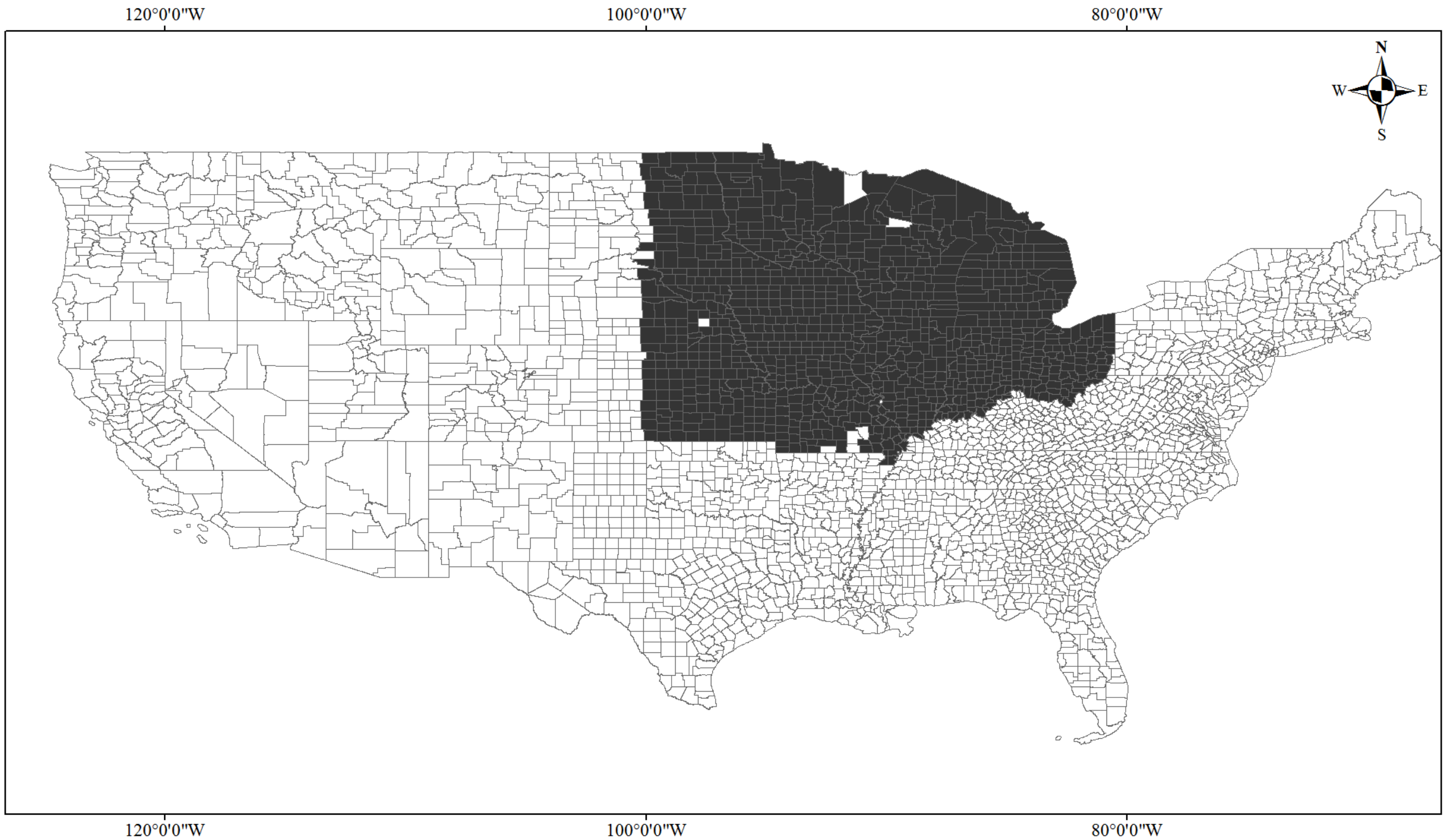


Figure 3: Estimates of technical efficiency for: a) stochastic production frontier, and; b) primal cost function

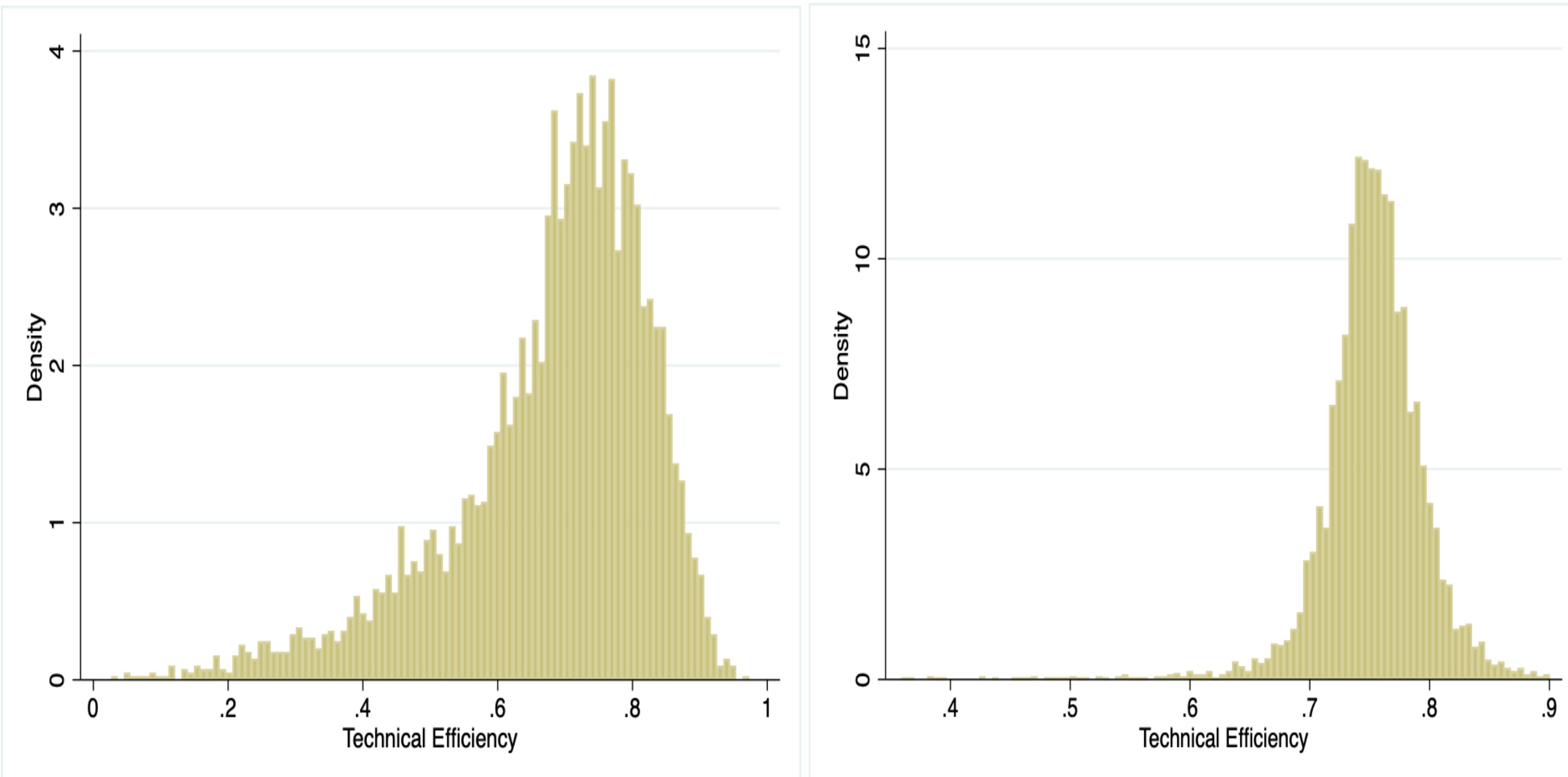


Figure 4: Input allocative efficiency

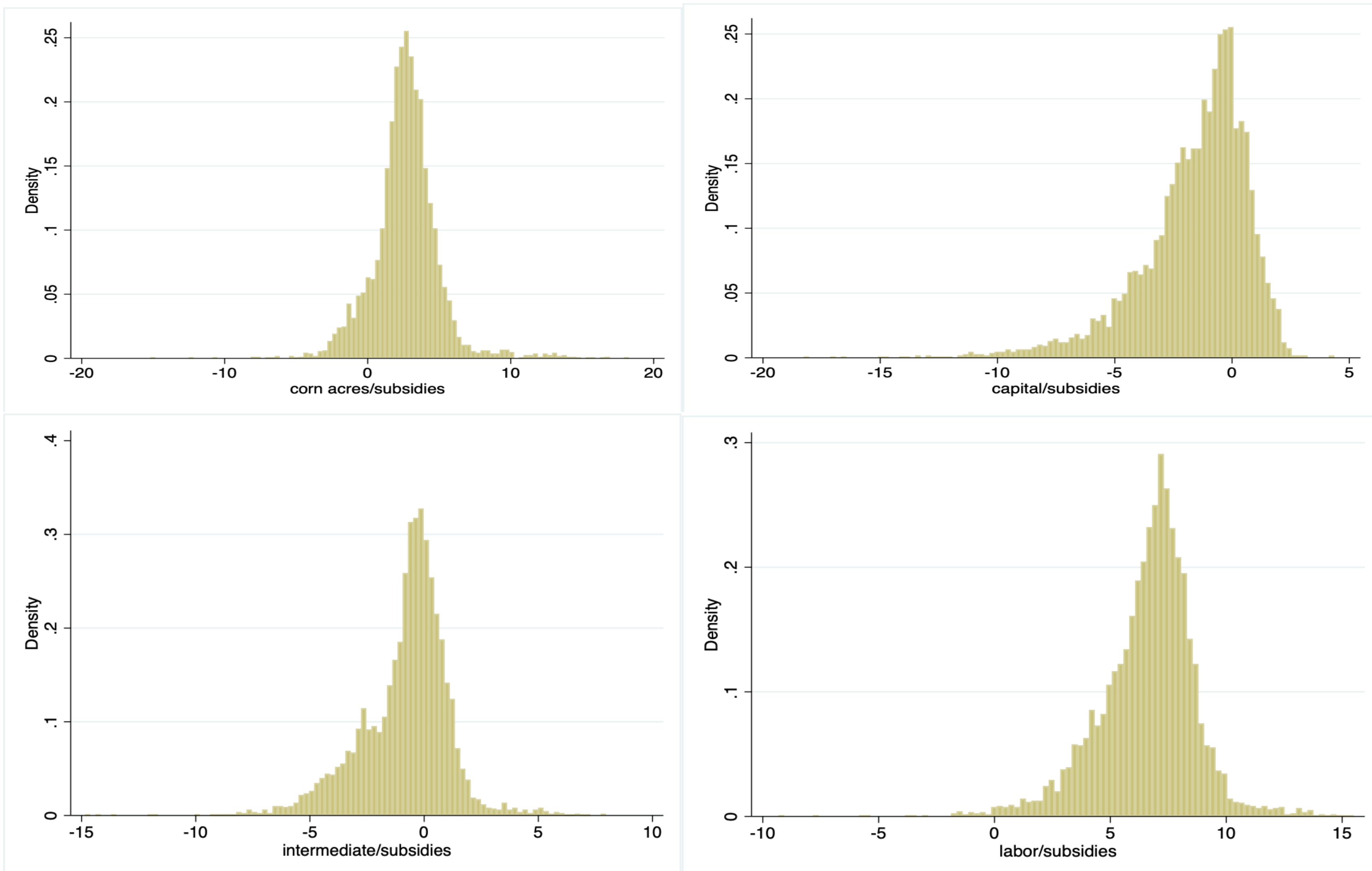
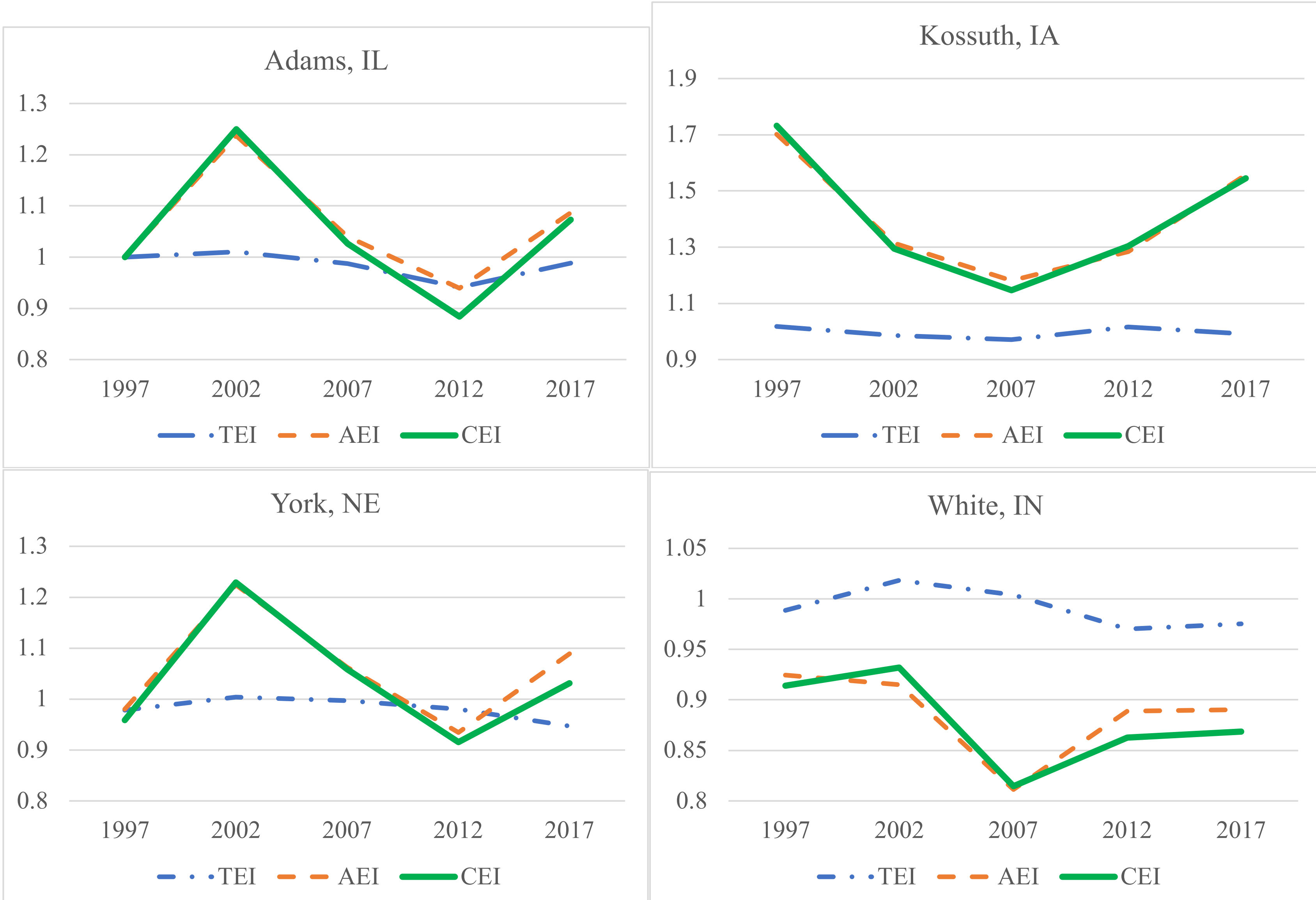


Figure 5: Illustration of cost efficiency index (CEI), technical efficiency index (TEI) and allocative efficiency index (AEI)



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