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ABSTRACT

This study uses stochastic production frontier (SPF) and DEA frontier methods to estimate the impact of urban influence on the cost of production for traditional corn/soybeans farms in the Southern Seaboard (excepting Virginia and Alabama). We hypothesize that urban influence decreases the technical efficiency of these farms. Although states in this region are not entirely subject to urban influence, some parts of states in this region are highly urbanized. We find that farmers in urban-influenced locations are less technically efficient than farmers in rural locations in the region examined. During 2002-2014, stochastic production frontier and DEA frontier procedures indicate that increasing urban influence leads to a significant decrease in technical efficiency. Our statistical analysis clearly bears out the refrain in popular literature that urban proximity raises the cost for, and decreases the viability of, traditional farms. And seed treatment and pesticide use trends affecting environmental quality (due to old line herbicide applications used to counter weed resistance in GMO crops) suggest the potential for new regulations on farm practices and, hence, costs.

INTRODUCTION

The expansion of low-density nonfarm development into traditionally rural areas is affecting more and more U.S. farmland (Nehring et al., 2006). The direct effect of such development, the conversion of rural lands to housing, and other nonfarm uses is well documented (Cho et al., 2003). In more recent years, ongoing land-use changes have been further noted and analyzed (Johnston and Swallow, 2006; Irwin et al., 2009; Wu, 2006; Wu, 2008; Wu, 2009; Kuethe et al., 2011; Cromartie et al., 2015).

However, this direct conversion may be overshadowed by the secondary effects of "urban influence" on the active farmland that remains interspersed among nonfarm development. Recent studies suggest that such interspersion raises the cost of producing agricultural commodities (Nehring et al., 2006; Gardner, 1994; Lopez and Munoz, 1987; Abdalla and Kelsey, 1996; Lopez

et al., 1988). For example, Nehring et al. (2006) found that urban influence raises total variable costs per acre for traditional farms in the Heartland by more than 8% and is consistent with a 67% higher price of land per acre. Policies such as government payments, farmland preservation, and environmental impacts that affect land use cannot be properly evaluated without including the urbanization component.

In addition, interspersion may be widespread. The 6.6% of nonfederal land categorized as "developed" by the Natural Resource Conservation Service (NRCS) is estimated to "influence" a much larger proportion of U.S. farmland acres (USDA/NRCS, 1978) , perhaps as much as 17% (Barnard, 2000). Close to two-thirds of the 3,141 U.S. counties are classified as metropolitan or metro-adjacent. The number of urban-influenced acres is so large (relative to acres directly required for urban use) that vast amounts of U.S. agricultural land will operate subject to urban influence

indefinitely. Nelson (2004), in a report for the Brookings Institution, estimates that an additional 35 million acres might need to be developed by 2030. More striking, the 17% of U.S. farmland that Barnard et al. (2003) estimates is urban influenced represents 159 million acres. Even allowing for necessary commercial/industrial land, many times more acres are currently urban influenced than will be required for additional urban use within the next 30 years. Recent work by Brown and Weber (2013) suggests that urban influence continues to increase in agricultural areas.[1]

We use stochastic production frontier (SPF) procedures to estimate the impact of urban influence on the cost of production for traditional corn/soybean and high-value crop and livestock farms in the South. We hypothesize that urban influence decreases the technical efficiency (TE) of such farms (not including greenhouses, nurseries, and turf operations). For example, the entire Central Southern Seaboard is not subject to widespread urban influence, but some of its areas are. North Carolina, for example, has some of the most ubiquitous low-density urban influence in the United States (U.S. Department of Commerce, Bureau of the Census, 2017; Cromartie, 2017). Despite regional variations in urban influence, the Central Southern Seaboard has soil types, climate, and cropping patterns/rotations that are relatively homogeneous, helping us isolate the effect of urbanization.

PREVIOUS LITERATURE

Urban influence changes the cost, revenue, and operating structure of remaining active farms (Heimlich & Barnard, 1992, 1997; Kuethe et al., 2011). Most studies find that urban influence creates opportunities for farms that adapt to the urbanizing environment and imposes costs on traditional farms (Berry, 1978; Lopez, Adelaja, & Andrews, 1988; Larson, Findeis, & Smith, 2001). Many farms can adjust their operations to tap into a growing and nearby market. The availability of seasonal labor may also benefit fringe-area farming. Some operations produce for niche markets, selling directly to consumers or providing agritainment. Increased farmland values can often provide collateral to finance farm operating and capital expenses.

Several studies have found that corn and livestock producers are likely to bear added costs from (environmental) constraints on agricultural practsices and the disappearance of input suppliers and output markets (Adelaja, Miller, & Taslim, 1998; Herriges, Secchi, & Babcock, 2003; Sharma et al., 1999). Over time, traditional land-extensive enterprises generally yield to enterprises that are more land intensive and more urban compatible. Livestock operations, particularly hog and dairy operations, which haul manure daily, are especially incompatible with urban-oriented neighbors due to negative externalities, including odors, insects, and water contaminants. High-value crops such as fruits and vegetables that can be sold directly to consumers often replace field crops (Lopez, Adelaja, & Andrews, 1988). Greenhouses, nurseries, and turf farms, which cater to urban markets, proliferate. The net effect of the positive opportunities and constraints is to increase the proportion of crops relative to livestock (Lockeretz, 1986, 1989).

Much of our understanding of urban-influenced agriculture, however, is derived from studies such as those cited above, which are generally based on county- or state-level analysis; the Heimlich and Barnard (1992, 1997) and Heimlich and Anderson (2001) studies are exceptions, since they are based on farm-level data. Few studies, excepting Nehring et al. (2006) have looked at the costs and benefits of urban influence on traditional enterprises at the farm level and isolated the cost-increasing effects of urban nuisances and regulations from the revenue/profit-increasing effects of new and larger markets brought about by urban proximity. This study updates the Nehring et al. effort for three regions using 2002–2014 Agricultural Resource Management Survey (ARMS) data (see USDA/ERS, 2002–2014) and tests the hypothesis that urban influence decreases the TE of traditional crop/livestock farms in the Central Southern Seaboard.

DATA AND METHODS

Data

For our analysis we use U.S. farm-level crop/livestock data from the 2002 to 2014 U.S. Department of Agriculture (USDA) ARMS surveys related to the value of output and cost of production. ARMS is an annual USDA survey of U.S. farms (see USDA/

ERS, 2002–2014; USDA/NASS, 2002–2016) that elicits information on farm production, input, operator, and financial attributes. ARMS is not a panel but instead is a series of annual cross sections. The sample is stratified, with selection probabilities varying with farm size, location, and primary specialization, so observations must be weighted for estimation. The states covered are Georgia, North Carolina, and South Carolina in the Central Southern Seaboard.[2] The data set consists of 27,243 crop/livestock operations in the region. The farm-level data is used in an innovative way. We define three outputs (gross value of sales from noncorn output [including livestock], value of corn output, and off-farm income) and four inputs (labor, miscellaneous, capital, and a quality-adjusted land input). We use regression techniques that allow us to relate several outputs to several inputs in a single equation to develop measures of technical (best practice production techniques) and scale efficiency scores by farm. We use SPF measurement to econometrically estimate an input distance function frontier. We will test for and correct for inputs that are endogenous to the production process.

Our two urban-influence variables, described in Barnard, Wiebe, and Breneman (2003), are a continuous index and a categorical variable created from the continuous index. The index was created from an analysis of block-level group population data from the 1990 Census of Population (U.S. Department of Commerce, Bureau of the Census, 1990). Using statistical smoothing techniques within a Geographic Information System (GIS) framework, population was estimated for each cell in a 5-kilometer grid laid out across the total U.S. land area. An index number was calculated for each cell using a GIS function based on the concept of a "gravity" model of urban development. In our study, urban influence at a single grid cell location is defined as $U_{ij} = \{P_j/D_{ij}\}$, where U_{ij} is the computed index number representing the influence on cell i of the population located in cell j, P_j is the population of cell j, and D_{ij} is the distance from cell i to cell j. In order to assess the effect on cell *i* of proximity to population in multiple nearby cells, the index is aggregated across n possible locations (cells). In an aggregate form, the index used in this study for each cell is given by $UI_i = \sum_{j=1}^{n} \{P_j/D_{ij}\}$, where the index j represents grid cells within a 50-mile radius of cell i.

The continuous index increases as population increases (since population is in the numerator) and/or as distance to the population decreases (since distance is in the denominator).[3] The index number assigned for each county is the value of the index as measured at the geographic center of the county (centroid). Computed values of UI_i used in this analysis range from less than 10 to greater than 6,000, with the majority ranging from 20 to 700. The urban-influence index is modeled as an inefficiency effect in equation 2 and is used as a characteristic in the hedonic specification from which the quality-adjusted price of land is estimated.

The continuous urban-influence index, however, does not identify which counties are rural and which are urban influenced. To do that and to create the categorical variable, we set thresholds for the continuous variable based on the level of the urban-influence index in "totally rural" census tracts (which were previously defined by Cromartie, n.d.). "Totally rural" means that the census tract does not contain any part of a town of 2,500 or more residents and that the primary commuting pattern is to sites within the census tract. Any parcel not satisfying these conditions was considered urban influenced. Those cells classified as urban influenced were subdivided into three categories labeled "near rural," "near urban," and "urban," each representing an increasing level of urban influence. More specifically, we defined counties as rural if $UI_i <= 115$, near rural if $115 < UI_i <= 155$, near urban if $155 < UI_i <= 236$, and urban if $UI_i > 236$.

Figure 1 presents the spatial distribution of the rural and urban-influenced categories by agricultural statistics district. Regional variations in the level of urban influence are important and tend to be highest in the eastern United States and on the West Coast.

Stochastic Production Frontier Models

A parametric input distance function approach is used to estimate performance measures, including returns to scale (RTS) and TE (Paul et al., 2005; Paul & Nehring., 2004). The input distance function is denoted as $D^I(X,Y,R)$, where X refers to inputs, Y to outputs, and R to other farm-efficiency determinants. For the analysis, three outputs were developed from the ARMS for crop/livestock farms: Y_{CORN} = value of corn production,
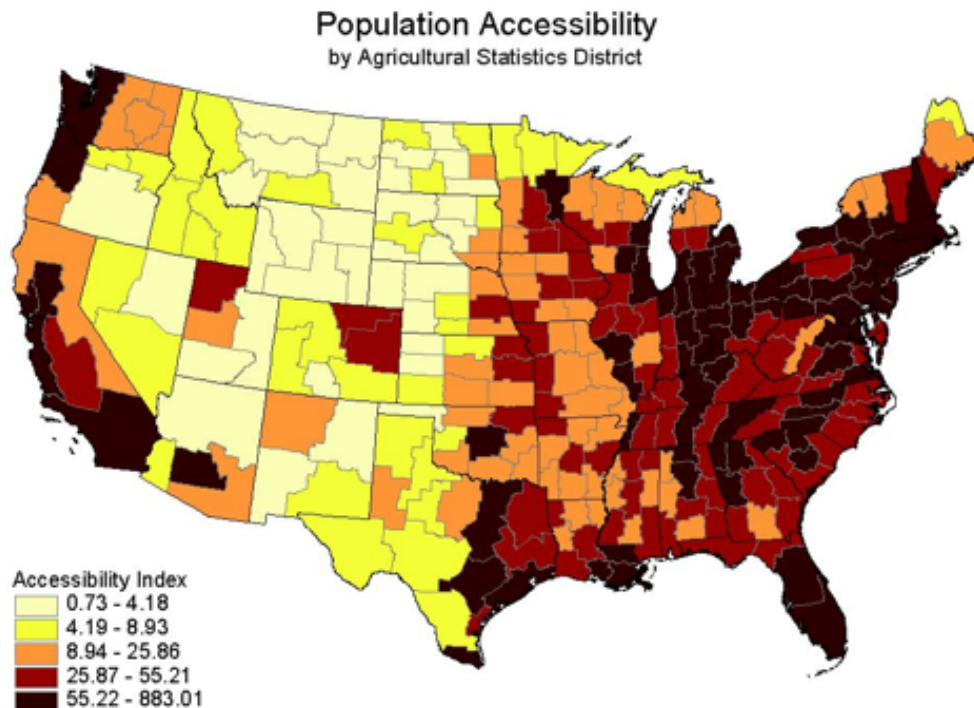
Figure 1. Population Accessibility Scores

Source: ERS estimates. The urban index used here was based on 1990 census population data and 1994–1996 USDA June area survey data. See also U.S. Department of Commerce, Bureau of the Census (2017).

$Y_{NONCORN}$ = value of noncorn production and livestock production included in the data, and Y_{OFF} = off-farm income, which is total off-farm income less unearned income. Inputs are costs of X_{LAB} = labor; X_{CAP} = capital; X_{MISC} = miscellaneous including feed, fertilizer, and fuel; and X_{QLND} = quality-adjusted land. Thus, our analysis is whole farm. The input distance function represents farms' technological structure in terms of minimum inputs required to produce given output levels, as farmers typically have more short-term control over input than output decisions (Paul & Nehring, 2004). Also, Paul et al. (2005) found output-oriented models to have limitations—a less good fit—when output composition differences are important, as is the case in the crop/livestock surveys used in this study, designed to include very small crop/livestock farms along with large crop/livestock farms to get population estimates. For ARMS applications of distance functions, see Paul and Nehring (2004) and Dorfman and Koop (2005).

To account for differences in land characteristics, state-level quality-adjusted values for the United States estimated in Ball et al. (2008) are multiplied by pasture plus nonpasture acres to construct a stock of land by farm. That is, the estimated state-level quality-adjusted price for each farm is multiplied by actual acres of pasture and nonpasture, and a service flow is computed based on a service life of 20 years and an interest rate of 6%. See Nehring et al. (2006) for a fuller description. Ignoring land heterogeneity, including urbanization effects on productivity and agronomic (i.e., water-holding capacity, organic matter, slope, etc., of land) and climatic information incorporating the differing cropping and pasture patterns used in crop/livestock production in the regions examined, would result in biased efficiency estimates (Ball et al., 1997; Ball et al., 2008; Nehring et al., 2006). Figure 2 presents one important characteristic used in the quality-adjusted land construction—soil texture—and reveals how different soil texture levels are by agricultural statistics district in states within the Central Southern Seaboard.

Estimating $D^I(\textbf{X,Y,R})$ requires imposing linear homogeneity in input levels (Färe & Primont,
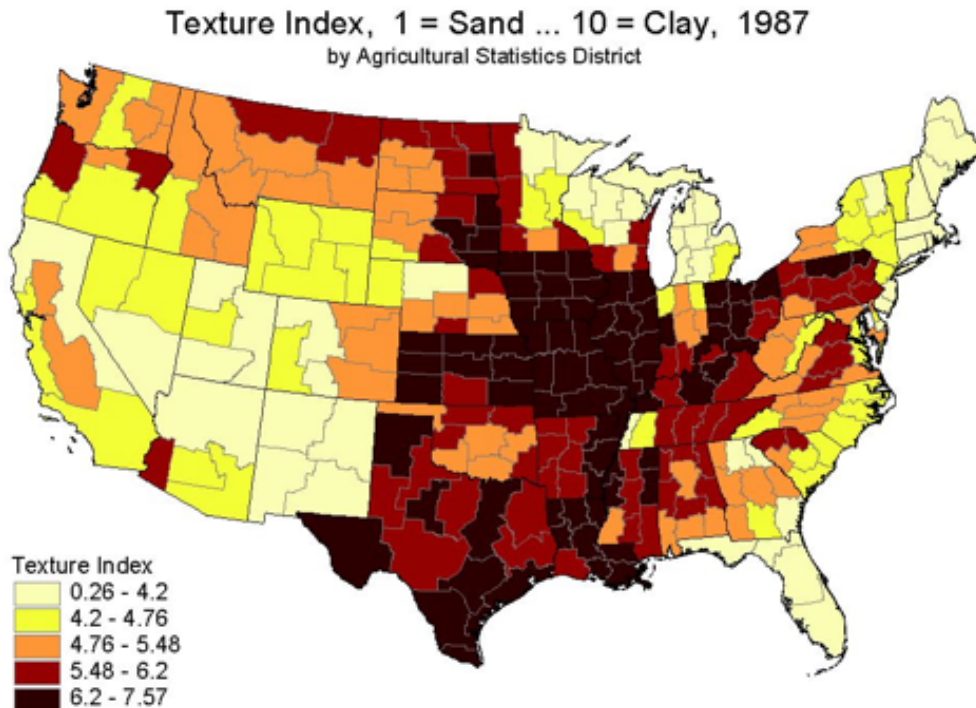
Figure 2. Texture Index, 1987

Source: USDA/NRCS (1994).

1995), which is accomplished through normalization (Lovell et al., 1994): $D^I(X, Y, R)/X_1 = D^I(X/X_1, Y, R) = D^I(X^*, Y, R)$. Approximating this function by a translog functional form to limit a priori restrictions on the relationships among its arguments results in:

(1a) $\ln D^I_{it}/X_{1,it} = \alpha_0 + \Sigma_m \alpha_m \ln X^*_{mit}$
$+ .5 \Sigma_m \Sigma_n \alpha_{mn} \ln X^*_{mit} \ln X^*_{nit} + \Sigma_k \beta_k \ln Y_{kit}$
$+ .5 \Sigma_k \Sigma_l \beta_{kl} \ln Y_{kit} \ln Y_{lit} + \Sigma_q \phi_q R_{qit}$
$+ .5 \Sigma_q \Sigma_r \phi_{qr} R_{qit} R_{rit} + \Sigma_k \Sigma_m \gamma_{km} \ln Y_{kit} \ln X^*_{mit}$
$+ \Sigma_q \Sigma_m \gamma_{qm} \ln R_{qit} \ln X^*_{mit} + \Sigma_k \Sigma_q \gamma_{kq} \ln Y_{kit} \ln R_{qit}$
$+ v_{it} = TL(X^*, Y, R) + v_{it}$, or

(1b) $-\ln X_{1,it} = TL(X^*, Y, R) + v_{it} - \ln D^I_{it}$
$= TL(X^*, Y, R) + v_{it} - u_{it}$,

where i denotes farm; t the time period; k,l the outputs; m,n the inputs; and q,r the R variables. We specify $X_1 = X_{QLND}$ as land, so the function is specified on a per-acre basis, consistent with much of the literature on farm production in terms of yields.

Distance from the frontier, $-\ln D^I_{it}$, is characterized as the technical inefficiency error $-u_{it}$. Equation 1b was estimated as an error components model using maximum likelihood methods. The one-sided error term u_{it}, with a half-normal distribution, is a nonnegative random variable independently distributed with truncation at zero of the $N(m_{it}, \sigma_u^2)$ distribution, where $m_{it} = R_{it}\delta$, R_{it} is a vector of farm-efficiency determinants (assumed to be the factors in the R vector) and where δ is a vector of estimable parameters. The random (white noise) error component v_{it} is assumed to be independently and identically distributed, $N(0, \sigma_v^2)$. Estimated using SPF[4] techniques, TE is characterized assuming a radial contraction of inputs to the frontier (constant input composition).

Scale economies are calculated as the combined contribution of the M outputs Y_m, or the scale elasticity $SE = -\varepsilon_{DI,Y} = -\Sigma_m \partial \ln D^I(X, Y, R)/\partial \ln Y_m = \varepsilon_{X1,Y}$. That is, the sum of the input elasticities, $\Sigma_m \partial \ln X_1/\partial \ln Y_m$, indicates the overall input-output relationship and thus RTS. The extent of scale economies is thus implied by the shortfall of SE from 1; if SE<1, inputs do not increase proportionately with output levels, implying increasing RTS. Previous studies on corn and on dairy farm efficiency using ARMS have found significant economies of size (Paul et al., 2005; Tauer &

Mishra, 2006; Mosheim & Lovell, 2009; Mayen et al., 2010).

Finally, TE "scores" are estimated as TE = $\exp(-u_{it})$. Impacts of changes in R_q on TE can also be measured by the corresponding δ coefficient in the inefficiency specification for $-u_{it}\sigma^2$. It is assumed that the inefficiency effects are independently distributed and that u_{it} arise by a truncated (at zero) half-normal distribution with mean μ_{it}, and variance σ_u^2 (see Battese & Coelli, 1995).

Input endogeneity has been a concern in the estimation of input distance functions; if found, biased estimates result. Some studies have used instrumental variables to correct the problem, while others have argued either that (1) it was not problematic in their studies because random disturbances in production processes resulted in proportional changes in the use of all inputs (Coelli & Perelman, 2000; Rodriguez-Alvarez et al., 2007) or (2) no good instrumental variables existed, thus endogeneity was not accounted for (Fleming & Lien, 2009). We estimate instruments for the two potential drivers of inefficiency, operator hours worked off-farm (ophours) and spouse hours worked off-farm (sphours).[5] For the major crop/livestock regions analyzed in this study, average annual operator hours worked off-farm during 2002–2014 amount to close to 700 hours in Georgia, North Carolina, and South Carolina in aggregate. And for the region analyzed in this study, average annual spouse hours worked off-farm during 2002–2014 were fewer than 600 in Georgia, North Carolina, and South Carolina in aggregate. The Hausman test was used to test for endogeneity. Since endogeneity was found, the predicted values for ophours and sphours are used as instruments in the SPF.

The problem of endogeneity occurs when the independent variable is correlated with the error term in a regression model. In the case of the regions analyzed in this essay, off-farm use of labor is a major source of income on many farms. Hence, it is desirable to use instrumental variables in order to predict operator and spousal labor off-farm from information that influences such decisions such as age and education (for an understanding of how instruments are used to ascertain how off-farm work decisions influence on-farm labor use, see Huffman, 1980; Huffman & El-Osta, 1997). More precisely, we employ instruments to predict

the level of operator or spousal hours off-farm, variables that do not directly influence production but do influence the labor use off-farm. For the operator, we consider population accessibility, household assets, crop production, livestock production, household well-being, and animal units as important drivers of off-farm employment. For the spouse, we consider population accessibility, household assets, crop production, and the adjusted wage as important drivers of off-farm employment. We include the predicated values of these two variables in the inefficiency effects reported in Tables 1, 2, and 3.

EMPIRICAL RESULTS

As shown in Table 1, urban-influenced farms are important in the Central Southern Seaboard, comprising 50% of all farms and accounting for almost 60% of farms and almost half of production in the region. Rural farms tend to exhibit an advantage in crop yields. Also, in the Central Southern Seaboard urban-influenced farms average about 140 acres, compared to an average close to 272 acres on rural farms. We consider this an endogenous effect of urban influence. Accordingly, assessment of the impacts of urban influence on TE must take farm size into account. Urban-influenced farms also show higher total variable costs, including higher labor, fuel, fertilizer, seed, pesticides, and machinery costs than do rural farms—all costs measured in real terms based on 2002 prices (see USDA/NASS, 2002–2016). Off-farm income is significantly higher on urban-influenced farms, as expected. Age does not tend to differ among urban-influenced and rural farms.

Stochastic Frontier

The parameter estimates for regional crop/livestock household models are reported in Table 2. Although most of the parameter estimates of the primal are not directly interpretable due to the flexible functional form (the elasticity measures are combinations of various parameters and data), the estimates of the acres and year dummies are directly interpretable. The acre dummy is defined as one if farms have acres operated of greater than 1,000 acres and as zero otherwise. The year dummy is defined as one if year is greater or equal

Table 1. Cost and Performance Ratios on Farms by Level of Urbanization, Central Southern Seaboard, 2002–2014

Item	Rural	Urban	t-statistic Urban versus Rural[a]
Number of farms	13,220	14,023	
Percent of farms	40.7	59.3	
Percent of value of production	52.9	47.1	
Proportion corn	0.04	0.02	***
Proportion soybeans	0.05	0.05	***
Labor costs per acre ($)	398.36	1,186.83	***
Fuel costs per acre ($)	15.66	17.56	—
Fertilizer costs per acre ($)	53.08	41.61	***
Capital costs per acre ($)	44.33	54.60	**
Pesticide costs per acre ($)	61.32	37.82	***
Corn yield (bushels per acre)	117.40	98.30	***
Soybean yield (bushels per acre)	31.00	29.00	**
Cotton yield in (bushels per acre)	814.50	760.30	***
Characteristics			
Price of land per acre ($)	2,698.20	4,872.60	***
Acres operated (number)	272.30	140.60	***
Prop off-farm (percent)	28.10	50.90	***
Return on assets (percent)	4.20	2.10	***
Household return (percent)	7.50	7.60	—
Operator age (years)	58.80	58.80	—
Beef cattle (number)	25.70	9.40	***
Dairy cattle (number)	3.00	4.60	***
Hogs (number)	130.10	41.20	***
Chickens (number)	24.30	175.80	***

Note: Three asterisks indicate significance at the 1% level (t = 2.576), two asterisks indicate significance at the 5% level, and one asterisk indicates significance at the 10% level. The t-statistics are based on weighting techniques described in Dubman (2000).
Source: Model results and USDA data 2002–2014 ARMS. Data based on real values using 2002 as the base. See USDA/NASS (2002–2016).

to 2008 and as zero otherwise. Hence, the input model results for the acre dummy (ACREDUM) suggest a (statistically significant) increase in productivity for farms operating at least 1,000 acres in the Central Southern Seaboard. And the dummies for the year break of 2008 or later (YEAR-DUM) suggest a statistically significant increase in productivity in later years in all three regions, implying robust yield increases over time. Also, the variables in the technical inefficiency effects are directly interpretable and are discussed below under farm employment.

Off-Farm Employment

As discussed earlier, the importance of off-farm income to economic well-being of all U.S. farmers is widely acknowledged; however, it is less clear if off-farm work is actually helping farm households improve their economic performance across farm

Table 2. Input Distance Function Parameter Estimates, Southern Seaboard, 2002–2014

Variable	Parameter	t-test	Variable	Parameter	t-test
α_0	9.865	(56.17)***	$\alpha_{XLAB,XLAB}$	−0.002	(−0.89)
α_{XLAB}	−0.270	(−19.37)***	$\alpha_{XMISC,XMISC}$	−0.020	(−10.21)***
α_{XMISC}	−0.086	(−12.18)***	$\alpha_{XCAP,XCAP}$	−0.002	(−0.95)
α_{XCAP}	−0.074	(−13.94)**	$\alpha_{XLAB,XMISC}$	−0.006	(−1.53)
$\beta_{YNONCORN}$	0.067	(2.74)**	$\alpha_{XLAB,XCAP}$	0.004	(1.45)
β_{YCORN}	−0.293	(−12.11)***	$\alpha_{XMISC,XCAP}$	−0.011	(−3.60)***
β_{YOFF}	−0.198	(−4.74)***	$\alpha_{XACRESDUM}$	0.030	(0.79)
$\beta_{YNCORN,YNC}$	0.005	(2.25)**	$\alpha_{XYEARDUM}$	0.968	(18.98)***
$\beta_{YCORN,YCORN}$	0.036	(32.51)***	$\delta_{INEFF\ EFFECTS}$	−0.611	(−1.42)
$\beta_{YOFF,YOFF}$	0.017	(6.25)**	δ_{URBAN}	0.001	(2.63)**
$\beta_{YNCORN,YCOR}$	−0.006	(−3.79)***	$\delta_{OPLABOR}$	−0.0002	(−1.50)
$\beta_{YNCORN,YOFF}$	−0.001	(−1.49)	$\delta_{SPLABOR}$	0.0008	(0.57)
$\beta_{YCORN,YOFF}$	−0.001	(−0.43)	δ_{OPAGE}	−0.011	(−2.49)
			δ_{YEAR}	0.077	(2.52)**
			$\delta_{\_v\_}$	0.613	
			Pseudo-loglikelihood	−1,705,706.8	
			Eff	0.610	
			RTS	0.322	

Notes: ***significance at the 1% level (t = 2.977), **significance at the 5% level (t = 2.145), and *significance at the 10% level (t = 1.761). Source: USDA, National Agricultural Statistics Service and Economic Research Service Agricultural and Resource Management Surveys (2002–2014). The t-statistics are based on 27,243 observations for the sample derived from three states: Georgia, North Carolina, and South Carolina. The coefficient for $\delta_{\_v}$ does not have a t-distribution and is reported with a 95% confidence interval in STATA.

sizes and types of enterprises. In this section we examine the drivers of off-farm hours worked off-farm by operator and spouse.[6]

As noted above the variables in the technical inefficiency effects are directly interpretable. We find a significant negative impact on TE as spouse hours (about 80% of the total) worked off-farm increase in the Central Southern Seaboard. And the positive and statistically significant coefficient on year suggests that TE has increased over time in the region.

Comparison of Rural and Urban-Influenced Costs of Production

Below we compare cost of production on rural and urban-influenced farms both by degree of urbanization—rural, medium, and high. We can learn more about the specific costs due to urban influence and the associated farm and operator characteristics by linking individual input characteristics to the degree of urban influence. To examine costs relative to degree of urban influence, we compare costs and performance on rural farms (UI_i <115) to medium urban-influenced farms (115<= UI_i <236) and high urban-influenced farms (UI_i >236). As shown in Table 3, land prices, as one would expect, generally follow a clear pattern as our index of urbanization increases, jumping from $2,698 per acre on rural farms in the Central Southern Seaboard to $3,862 on medium urban-influenced farms and jumping again to $5,649 per acre on high urban-influenced farms. A t-test of equal means for the rural and high-medium urban-influenced categories is conducted as shown in Table 3.

The comparisons in this table generally show lower TE as urbanization increases and lower scale

Table 3. Cost and Performance Ratios on Farms by Level of Urbanization, Central Southern Seaboard, 2002–2014

Item	Rural	Medium	High	t-statistic Medium versus Rural[a]	t-statistic High versus Rural[a]
Number of farms	13,220	9,655	4,368		
Percent of farms	40.7	36.5	22.8		
Percent of value of production	52.9	36.5	10.6		
Proportion corn	0.04	0.02	0.01	***	***
Proportion soybeans	0.05	0.05	0.02	***	***
Efficiency score	0.62	0.61	0.58	**	**
Returns to scale	0.34	0.32	0.30	*	*
Labor costs per acre ($)	398.36	1,066.82	1,206.19	***	**
Fuel costs per acre ($)	15.66	20.56	15.16	***	—
Fertilizer costs per acre ($)	53.08	41.61	25.87	***	***
Capital costs per acre ($)	44.33	58.60	48.91	**	*
Pesticide costs per acre ($)	61.32	47.82	29.70	***	***
Corn yield in bushels per acre	117.40	92.30	103.20	***	***
Soybean yield in bushels per acre	31.00	27.00	30.50	—	—
Cotton yield in bushels per acre	814.50	740.30	806.90	***	—
Characteristics					
Price of land per acre	2,698.20	3,862.20	5,649.10	***	***
Acres operated	272.30	150.60	111.80	***	***
Prop off-farm (percent)	28.10	40.90	58.40	***	***
Return on assets (percent)	4.20	3.10	1.00	***	***
Household return (percent)	7.50	7.60	7.10	—	—
Off-farm income	74.47	118.40	127.41	***	***
Operator age	58.80	58.20	59.20	—	—
Beef no	25.70	10.40	7.30	***	***
Dairy no	3.00	4.20	4.80	***	***-
Hogs no	130.10	44.20	34.20	***	***
Chickens no	24.30	115.80	214.90	***	***

Note: Three asterisks indicate significance at the 1% level, two indicate significance at the 5% level, and one indicates significance at the 10% level (t = 1.65).
The t-statistics are based on weighting techniques described in Dubman (2000).
Source: Model results and USDA data 2002–2014 ARMS.

efficiency. For example, in the Central Southern Seaboard, medium and high urban farms exhibit significantly lower TE than rural farms (see Appendix 1). Variable costs per acre generally remain high or continue to increase and, in the case of animal odors and polluted water, excess fertilizer, or old-line pesticide use, may imply increasing "bad" inputs in the environment (for a description of hog smells and pesticide contamination in the environment and the impact on urban amenities and property values in the Central Southern Seaboard, see Kellogg, 2004; Färe & Grosskopf, 2004; Färe et

al., 2005, 2006; Kim & Goldsmith, 2009; Hakim, 2016; Owen and Zeleya, 2014; Neubauer, 2016; Taylor et al., 2016; Plesha, 2016; Nehring, 2018).

We find that in general, fertilizer and pesticide use is highest in rural areas and remains quite high in many urban areas, implying that overuse of fertilizer (e.g., nitrogen fertilizer)[7] or of pesticides (such as atrazine for corn and metolachor for corn, cotton, and soybeans) that stay in the environment are potentially large environmental issues in the Central Southern Seaboard. National Agricultural Statistics Service (USDA/NASS, 1994) data indicates that fertilizer application rates remained flat between 2002 and 2014. In contrast, Osteen and Fernandez (2016) demonstrate that given weed resistance to glyphosate use in GMO corn, cotton, and soybeans, recent pesticide use data indicates that old-line herbicides show a resurgence, or an increase in application rates. We see old-line herbicide shares increasing for corn and cotton production in North Carolina and Georgia and application rates ramping up on major crops in all three states in the southern seaboard. In aggregate, the share of old-line herbicide use, measured in pounds, on all crops in the southern seaboard increased to a 35% share in 2014 compared to 28% in 2010 (for herbicide data used to calculated these shares, see Baker, 2017).

It is noteworthy that returns on assets tend to be lower on medium-high urban-influence farms compared to rural farms in the southern seaboard. It is also noteworthy that returns on assets tend to be lower on medium-high urban-influence farms compared to rural farms in the Central Southern Seaboard.
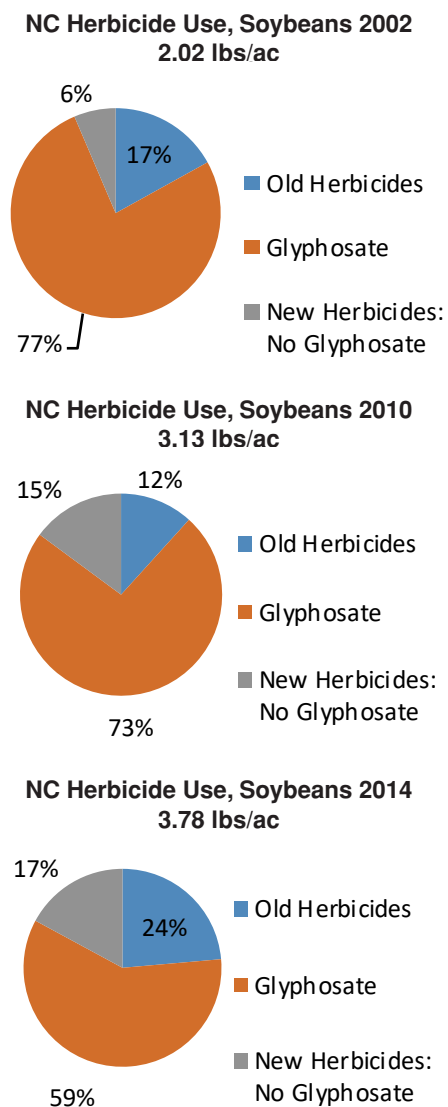
Old-Line Herbicide Pesticide Use in Georgia, North Carolina, and South Carolina

We see old-line herbicide shares increasing for corn and cotton production in North Carolina and Georgia and application rates ramping up on major crops in all three states in the southern seaboard. The aggregate share of old-line herbicide use, measured in pounds of active ingredient, on all crops in the region increased to a 35% share in 2014 compared to 28% in 2010.

Old-line herbicides commonly used in U.S. crop production include 2,4-D, atrazine, acetachlor, dicamba, linuron, metolachlor, MSMA,

pendamethlain, prometryn, simazine, and trifluralin (for a complete list, see Osteen & Fernandez, 2016). New-line herbicides commonly used in U.S. crop production include acifluorfen, clethodim, flumoxizin, imazaquin, glufosinate, imazaquin, mesotrinone, nicosulfruon, pyrithiobac-sodium, rimsulfuron, and thifensulferon (for a more complete list, Osteen and Fernandez, 2016).
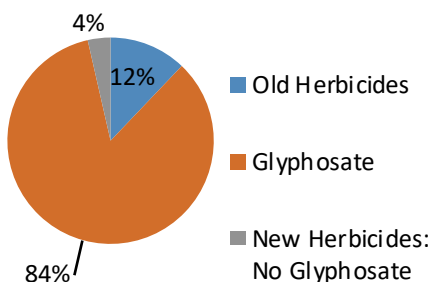
We see below that for soybean production in North Carolina, the glyphosate share of herbicide use, measured in pounds, has decreased in recent years- while the old- and new-line shares both increased. And herbicide use rates per acre rose modestly, boosted by increased rates for glyphosate and metolachlor.

NC Herbicide Use, Soybeans 2002
2.02 lbs/ac

6% · 17% · 77%

- Old Herbicides
- Glyphosate
- New Herbicides: No Glyphosate

NC Herbicide Use, Soybeans 2010
3.13 lbs/ac

15% · 12% · 73%

- Old Herbicides
- Glyphosate
- New Herbicides: No Glyphosate

NC Herbicide Use, Soybeans 2014
3.78 lbs/ac

17% · 24% · 59%

- Old Herbicides
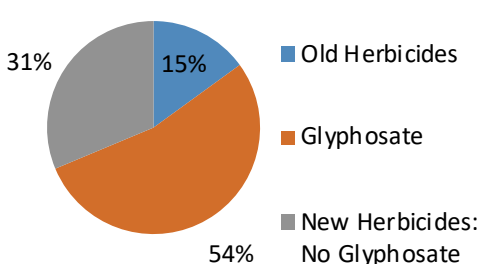- Glyphosate
- New Herbicides: No Glyphosate

Source: USDA/NASS (2002–2016); Baker (2017).

The glyphosate share of herbicide use on soybeans, measured in treatment acres, has also decreased in recent years, while both the old-line and new-line shares have increased—roughly one-third shares each for glyphosate and the old and new lines in 2014.
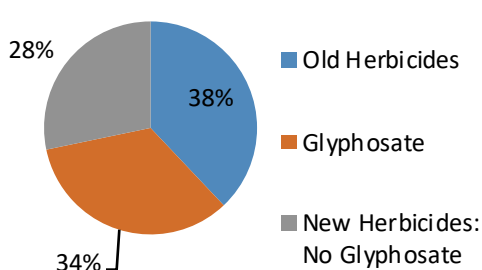
We see below that for cotton production in Georgia, the glyphosate and old-line shares of herbicide use, measured in pounds, both increased in recent years, while the new-line share decreased. In addition, herbicide use rate per acre was up sharply, boosted by increased rates for glyphosate and metolachlor.

NC Herbicide Use, Soybeans 2002
Treatment Acres

4%
12%
84%

- Old Herbicides
- Glyphosate
- New Herbicides: No Glyphosate

GA Herbicide Use, Cotton 2002
2.09 lbs/ac

11%
36%
53%

- Old Herbicides
- Glyphosate
- New Herbicides: No Glyphosate

NC Herbicide Use, Soybeans 2010
Treatment Acres

31%
15%
54%

- Old Herbicides
- Glyphosate
- New Herbicides: No Glyphosate
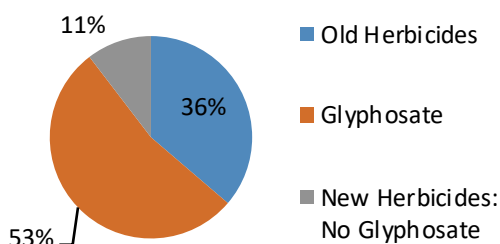
GA Herbicide Use, Cotton 2010
3.03 lbs/ac

24%
39%
37%

- Old Herbicides
- Glyphosate
- New Herbicides: No Glyphosate

NC Herbicide Use, Soybeans 2014
Treatment Acres

28%
38%
34%

- Old Herbicides
- Glyphosate
- New Herbicides: No Glyphosate

Source: USDA/NASS (2002–2016); https://www.nass.usda.gov/Quick_Stats.

GA Herbicide Use, Cotton 2014
3.99 lbs/ac

15%
40%
45%

- Old Herbicides
- Glyphosate
- New Herbicides: No Glyphosate

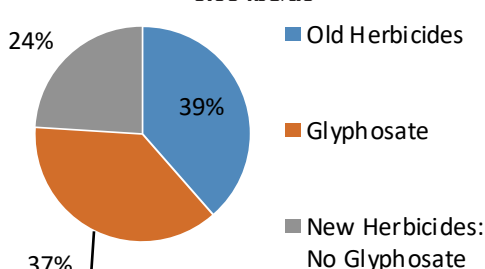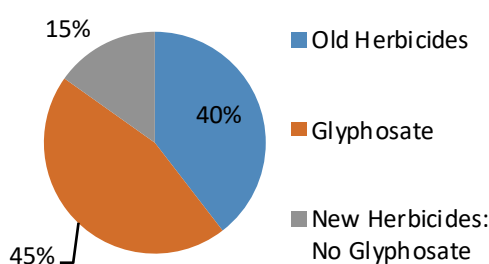Source: USDA/NASS (2002–2016); Baker (2017).

The glyphosate share of herbicide use on soybeans, measured in treatment acres, has also decreased in recent years, while both the old-line and new-line shares have increased—roughly one-third shares each for glyphosate and the old and new lines in 2014.

The glyphosate and old-line and new-line shares of herbicide use on cotton in Georgia, measured in treatment acres, held steady in recent years—led by old-line use followed by glyphosate and then new-line use, in order of importance.

GA Herbicide Use, Cotton 2003
Treatment Acres

- Old Herbicides — 37%
- Glyphosate — 55%
- New Herbicides: No Glyphosate — 8%

GA Herbicide Use, Cotton 2010
Treatment Acres

- Old Herbicides — 46%
- Glyphosate — 36%
- New Herbicides: No Glyphosate — 18%

GA Herbicide Use, Cotton 2015
Treatment Acres

- Old Herbicides — 44%
- Glyphosate — 37%
- New Herbicides: No Glyphosate — 19%

Source: USDA/NASS (2002–2016); https://www.nass.usda.gov/Quick_Stats.

We see below that for cotton production in South Carolina, the glyphosate and new-line shares of herbicide use, measured in pounds, both decreased in recent years, while the old-line share increased smartly. Herbicide use rate per acre was up sharply in recent years, boosted by increased rates for glyphosate and metolachlor and trifluralin.

SC Herbicide Use, Cotton 2002
3.28 lbs/ac

- Old Herbicides — 20%
- Glyphosate — 54%
- New Herbicides: No Glyphosate — 26%

SC Herbicide Use, Cotton 2010
5.13 lbs/ac

- Old Herbicides — 25%
- Glyphosate — 62%
- New Herbicides: No Glyphosate — 13%

SC Herbicide Use, Cotton 2015
4.47 lbs/ac

- Old Herbicides — 42%
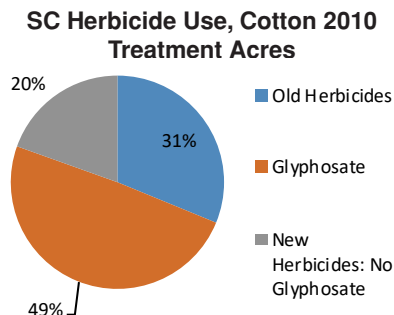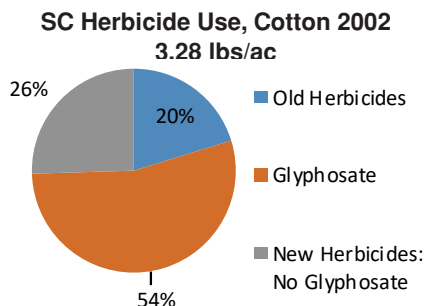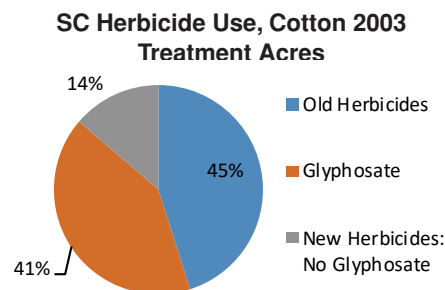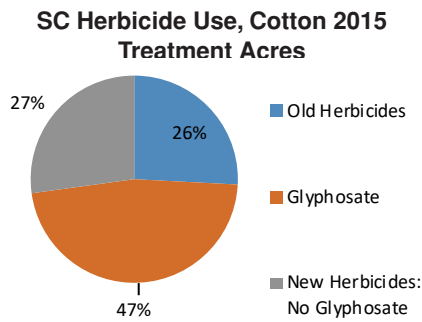- Glyphosate — 55%
- New Herbicides: No Glyphosate — 3%

Source: USDA/NASS (2002–2016); Baker (2017).

Again as in Georgia cotton production, the glyphosate and old-line and new-line shares of herbicide use on cotton in South Carolina, measured in treatment acres, held steady in recent years, led by old-line use followed by glyphosate, with new-line use showing a small share, in order of importance.

SC Herbicide Use, Cotton 2003
Treatment Acres

- Old Herbicides — 45%
- Glyphosate — 41%
- New Herbicides: No Glyphosate — 14%

SC Herbicide Use, Cotton 2010
Treatment Acres

- Old Herbicides — 31%
- Glyphosate — 49%
- New Herbicides: No Glyphosate — 20%

SC Herbicide Use, Cotton 2015
Treatment Acres

Source: USDA/NASS (2002–2016); https://www.nass.usda.gov /Quick_Stats.

SUMMARY AND CONCLUSIONS

Popular press and numerous studies relying on aggregate data suggest that the interspersion of agricultural and urban-related activities raises the cost of producing agricultural commodities in urban-influenced areas. Examining USDA farm-level survey data on costs, we find that urban influence significantly raised variable costs per acre for traditional farms in the Central Southern Seaboard during 2002–2014. Urban-influenced farms are also less technically efficient than rural farms in the region.

Using SPF analysis, we find that urbanization leads to a decrease in TE. For 2002–2014, an increase in urban influence leads to significantly lower TE for traditional farms. Traditional corn/soybean/livestock farms are at a competitive disadvantage in urban-influenced areas, as reflected in lower TE, lower productivity, and lower returns on assets.

Future research examining-high performance urban-influence farms (farms with TE scores above the median for all urban influenced farms), as in the Nehring et al. (2006) presentation, may provide information on how such farms have controlled costs. Nehring et al., for example, found that such high-performance urban farms in the Heartland tend to de-emphasize livestock activities, do not rely extensively on off-farm income, and are larger and more grain-oriented than less successful urban-influenced farms.

The potential impact of urbanization on rural agriculture is not of minor importance. The urban-influenced farms that we analyzed represent about 60% of all farms in the Central Southern Seaboard and about 40% of the value of

production in the region during 2002–2014. Current Census data indicate clusters of fast-growth rural counties sprinkled throughout the Central Southern Seaboard, suggesting that urban influence on agriculture will grow in the future. To properly measure farm-level economic activity, given this phenomenon, requires an analysis of agricultural production that recognizes the role of nonagricultural demand for land and realizes that farms face differing levels of urban pressure.

NOTES

1. The number of urban-influenced acres is so large (relative to acres directly required for urban use) that it is likely that vast amounts of U.S. agricultural land will operate subject to urban influence indefinitely. Close to two-thirds of the 3,141 counties were classified as metropolitan or metro-adjacent in USDA/ERS (2004). Barnard et al. (2003) estimated that 17 percent of U.S. farmland is urban influenced, representing 189 million acres. Nelson (2004), in a report for the Brookings Institution, estimated that an additional 35 million acres might need to be developed by 2030. Work by Cromartie (2017) indicates, based on 2013 census data, that urbanization influence trends remained strong in recent years.

2. The ERS resource region "Southern Seaboard" includes parts of 11 states. Our sample for this report includes Central Southern Seaboard farms from three of 3 states, Georgia, North Carolina, and South Carolina, which in 2014 accounted for close to 60 percent of the value of all farm production in the southern seaboard. In the remainder of this report, we use the term "southern seaboard" to refer to farms in those three states.

3. In Shi, Phipps, and Colyer (1997) and in Hardie, Narayan, and Gardner (2001), distance is accounted for using D^2. In our analysis we use D rather than D^2, based on information in Song (1996) that the reciprocal of distance, the most commonly used weight in gravity-type measures, is statistically equivalent to any of eight other measures.

4. We used STATA Version 12 commands for the SPF estimation.

5. For the major crop/livestock regions analyzed in this study, average annual operator hours worked off-farm during 2002–2014 amounted to close to 700 hours in the southern seaboard. And, for the region analyzed in this study, average annual spouse hours worked off-farm during 2002–2014 were and to less than 600 in the southern seaboard.

6. The instrumental variable results indicate that for operator hours, household assets (–) and household

well-being (+) are important drivers of off-farm employment. The time dummies indicate significant declines in 2008 and 2010. The instrumental variable results indicate that for the spouse hours, household assets (–) and the adjusted wage (+) are important drivers of off-farm employment. The time dummies indicate significant increases in 2005, 2008 and 2010.

7. Available NASS data on per acre nitrogen application rates by state indicate far higher rates in the Central Southern Seaboard than in the major more rural cotton growing state, Texas (85 and 117 pounds per acre in Georgia and North Carolina, respectively, compared to 77 pounds in Texas in 2017), and in a major more rural corn growing state, Iowa (187 pounds per acre in Georgia compared to 150 pounds in Iowa) (USDA/NASS, 2002–2016). Following Kellogg et al. (2000), we use the ARMS data for 2002–2014 to calculate for the Central Southern Seaboard excess nitrogen per harvested acre levels of 36 and 33 pounds for medium and high levels of urbanization, respectively, only slightly below the estimated level of 40 pounds in rural areas. And for pesticides available, ARMS data on pesticide use per acre reveals that the use of $41 per acre in the Central Southern Seaboard in 2002–2014 is close to 40% higher than that used in the Heartland for the same time period (see Nehring et al., 2016). Further, the old-line/new-line presentation by crop shown later in this essay indicates that the share of old-line herbicides used has increased sharply in recent years in the Central Southern Seaboard.

REFERENCES

Abdalla, C. W., & Kelsey, T. W. (1996). Breaking the impasse: Helping communities cope with change at the rural-urban interface. *Journal of Soil and Water Conservation*, 462–466.

Adelaja, A. O., Miller, T., & Taslim, M. (1998). Land values, market forces, and declining dairy herd size: Evidence from an urban-influenced region. *Agricultural and Resource Economics Review, 27,* 63–71.

Baker, N. T. (2017). *Estimated annual agricultural pesticide use by crop group for states of the conterminous United States, 1992–2015*. U.S. Geological Survey data release, https://doi.org/10.5066/F7NP22KM

Ball, V. E., Butault, J.-P., Nehring, R., & Somwaru, A. (1997). Agricultural productivity revisited. *American Journal of Agricultural Economics, 79,* 1045–1063.

Ball, V. E., Lindamood, W., Nehring, R., & Mesonada, C. S. J. (2008). Capital as a factor of production in OECD Agriculture: Measurement and data. *Applied Economics, 40* (October), 1253–1277.

Barnard, C. H. (2000). Urbanization affects a large share of farmland. *Rural Conditions and Trends, 10,* 57–63.

Barnard, C. H., Wiebe, K., & Breneman, V. (2003). Urban influence: Effects on U.S. farmland markets and value. In C. Moss & A. Schmitz (Eds.), *Government policy and farmland markets: The maintenance of farmer wealth* (pp. 319–341). Ames: Iowa State University Press.

Battese, G. E., & Coelli, T. J. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics, 20,* 325–332.

Berry, D. (1978). Effects of urbanization on agricultural activities. *Growth and Change, 9,* 2–8.

Brown, J. P., & Weber, J. G. (2013). *The off-farm occupations of U.S. farm operators and their spouses*, Economic Research Report, U.S. Department of Agriculture, EIB-117, September.

Cho, S-H, Wu, J. J., & Boggess, W. G. (2003). Measuring interations among urbanization, land use regulations, and public finance. *American Journal of Agricultural Economics, 85*, 988–999.

Coelli, T., & Perelman, S. (2000). Technical efficiency of European railways: A distance function approach. *Applied Economics, 32,* 1967–1976.

Cromartie, J. (2001). Data: Rural-urban commuting area code. U.S. Department of Agriculture, Economic Research Service. Retrieved July 26, 2001, from http://www.ers.usda.gov/emphases/rural/data/ruca/

Cromartie, J. (2017). Rural America at a glance. Economic Research Report No. (EIB-182), November.

Cromartie, J., von Reichert, C., & Arthun, R. (2015). Factors affecting former residents' returning to rural communities. Economic Research Report No. (ERR-185), 37 pp., May.

Dorfman, J. H., & Koop, G. (2005). Current developments in productivity and efficiency measurement. *Journal of Econometrics, 126*(2) (June), 233–240.

Dubman, R. W. (2000). *Variance estimation with USDA's farm costs and returns surveys and agricultural resource management study surveys*. Washington, DC: U.S. Department of Agriculture, Economic Research Service Staff Paper AGES 00-01.

Färe, R., & Grosskopf, S. (2004). Modeling undesirable factors in efficiency evaluation: Comment. *European Journal of Operational Research, 157*, 242–245.

Färe, R., Grosskopf, S., & Lovell, C. A. K. (1994). *Production frontiers*. Cambridge, UK: Cambridge University Press.

Färe, R., Grosskopf, S., Noh, D-W., & Weber, W. (2005). Characteristics of a polluting technology: Theory and practice. *Journal of Econometrics, 126*, 469–492.

Färe, R., Grosskopf, S., & Weber, W. (2006). Shadow prices and pollution costs in U.S. agriculture. *Ecological Economics, 56* , 89–103.

Färe, R., & Primont, D. (1995). *Multi-output production and duality: Theory and applications*. Boston: Kluwer Academic Publishers.

Fleming, E., & Lien, G. (2009). Synergies, scope economies, and scale diseconomies on farms in Norway. *Acta Agriculturae Scandinavica, Section C—Food Economics, 6*(1), 21–31.

Gardner, B. L. (1994). Commercial agriculture in metropolitan areas: Economics and regulation issues. *Agricultural and Economics Review, 15*, 100–109.

Hakim, D. (2016, October 30). Doubts about promised bounty of genetically modified crops. *New York Times*.

Hardie, I. W., Narayan, T. A., & Gardner, B. L. (2001). The joint influence of agricultural and nonfarm factors on real estate values: An application to the Mid-Atlantic region. *American Journal of Agricultural Economics, 83*, 120–132.

Heimlich, R. E., & Anderson, W. D. (2001). *Development at the urban fringe and beyond: Impacts on agriculture and rural land*. Washington, DC: U.S. Department of Agriculture, Economic Research Service, Agricultural Economic Report No. 803.

Heimlich, R. E., & Barnard, C. H. (1992). Agricultural adaptation to urbanization: Farm types in northeast metropolitan areas. *Northeastern Journal of Agricultural and Resource Economics, 21*, 50–60.

Heimlich, R. E., & Barnard, C. H. (1997). Agricultural adaptation to urbanization: Farm types and agricultural sustainability in U.S. metropolitan areas. In I. Audirac (Ed.), *Rural sustainable development in America* (pp. 283–303). New York: Wiley.

Herriges, J. A., Secchi, S., & Babcock, B. A. (2003). Living with hogs in Iowa: The impact of livestock facilities on rural residential property values. Working Paper 03-WP 342, Center for Agricultural and Rural Development, Ames, Iowa.

Huffman, W. E. (1980). Farm and off-farm work decisions: The role of human capital. *Review of Economics and Statistics, 62*, 14–23.

Huffman, W. E., & El-Osta, H. (1997). Off-farm work participation, off-farm labor supply and on-farm labor demand of U.S. farm operators. Department of Economics, Staff Paper No. 290, Iowa State University.

Irwin, E., Newburn, D. A., Bell, K. P., Bockstael, N. E., Partridge, M., & Wu, J. (2009). The economics of urban-rural space. *Annual Review of Resource Economics*, *1*(1), 435–462.

Johnston, R., & Swallow, S. K. (Eds.). (2006). *Economics and contemporary land use policy development and conservation at the rural-urban fringe*. Washington, DC: Resources for the Future.

Kellogg, R. (2004). *Environmental indicators of pesticide leaching and runoff from farm fields* . Washington, DC: U.S. Department of Agriculture, NRCS.

Kellogg, R. L., Lander, C. H., Moffitt, D. C., & Gollehon, N. (2000). Manure nutrients relative to the capacity of cropland and pastureland to assimilate nutrients: Spatial and temporal trends for the United States. U.S. Department of Agriculture, Natural Resources Conservation Service. Publication No. nps00-0579, December.

Kim, J., & Goldsmith, P. (2009). A spatial hedonic approach to assess the impact of swine production on residential property values. *Environmental Resource Economics, 42*, 509–534.

Kuethe, H., Ifft, J., & Morehart, M. (2011). *The influence of urban areas on farmland values*. Washington, DC: U.S. Department of Agriculture, Economic Research Service, Choices, Second Quarter.

Larson, J. M., Findeis, J. L., & Smith, S. M. (2001). Agricultural adaptation to urbanization in southeastern Pennsylvania. *Agricultural and Resource Economics Review, 30*, 32–43.

Lockeretz, W. (1986). Trends in farming near cities. *Journal of Soil and Water Conservation, 41*, 256–262.

Lockeretz, W. (1989). Secondary effects on midwestern agriculture on metropolitan development and decreases in farmland. *Land Economics, 65*, 205–216.

Lopez, R. A., Adelaja, A. O., & Andrews, M. S. (1988). The effects of suburbanization on agriculture. *American Journal of Agricultural Economics, 70*, 346–358.

Lopez, R. A., & Munoz, A. O. (1987). Supply response in the northeastern fresh tomato market. *Northeastern Journal of Agricultural and Resource Economics, 16*, 35–43.

Lovell, C. A. K., Richardson, S., Travers, P., & Wood, L. L. (1994). Resources and functioning: A new view of inequality in Australia. In W. Eichhorn (Ed.), *Models and measurement of welfare and inequality* (pp. 787–807). Berlin: Springer-Verlag.

Mayen, C. D., Balagtas, J. V., & Alexander, C. E. (2010). Technology adoption and technical efficiency: Organic and conventional dairy farms in the United States. *American Journal of Agricultural Economics, 92*(1) (January), 181–195.

Mosheim, R., & Lovell, C. A. K. (2009). Scale economies and inefficiency in U.S. dairy farms. *American Journal of Agricultural Economics, 91*(3), 777–794.

Nehring, R. (forthcoming). Pest management. In D. Hellerstein & M. Ribaudo (Eds.), *Agricultural resources and environmental indicators*. Washington, DC: Economic Research Service, U.S. Department of Agriculture.

Nehring, R., Barnard, C., Banker, D., & Breneman, V. (2006). Urban influence on costs of production in the Heartland. *American Journal Agricultural Economics, 88*(4) (November), 930–946.

Nehring, R., Erickson, K., Harris, M., Hallahan, C., & Katchova, A. (2016). Impacts of urbanization on costs of production and land use in the Heartland, southern seaboard, and Prairie Gateway: A Farm-Level Analysis. Paper presented at the annual meeting of the Agricultural and Applied Economics Association, Boston, July 31–August 2.

Nelson, A. C. (2004). *Toward a new metropolis: The opportunity to rebuild America*. Washington, DC: Brookings Institution Center on Urban and Metropolitan Policy. Available at https://www.brookings.edu/wp-content/uploads/2016/06/20041213_RebuildAmerica.pdf

Neubauer, R. (2016). Something smells: Hog farming waste management in North Carolina. Available at http://studentorgs.law.unc.edu/documents/elp/2016/r_neubauer.pdf

Osteen, C. D., & Fernandez, J. (2016). Herbicide use trends: A backgrounder. *Choices,* 4th Quarter, http://www.choicesmagazine.org/choices-magazine/theme-articles/herbicide/herbicide-use-trends-a-backgrounder

Owen, M. D., & Zeleya, I. A. (2014). Herbicide-resistant crops and weed resistance. *Pest Management Science, 61*, 1–11.

Paul, C. J. M., & Nehring, R. (2004). Product diversification, production systems, and economic performance in U.S. agricultural production. *Journal of Econometrics, 126*(2) (June), 525–548.

Paul, C. J. M., Nehring, R., Banker, D., & Somwaru, A. (2005). Scale economies and efficiency in U.S. agriculture: Are traditional farms history? *Journal of Productivity Analysis, 22*, 185–205.

Plesha, N. (2016). *Incorporating "bads" and "goods" in the measurement of agricultural productivity*. Dissertation, University of Connecticut, Department of Natural Resources Stores.

Rodriguez-Alvarez A., del Rosal, I., & Banos-Pino, J. (2007). The cost of strikes in the Spanish mining sector: Modelling an undesirable input with a distance function. *Journal of Productivity Analysis, 27*, 73–83.

Sharma, K. R., Leung, P., & Zaleski, H. M. (1999). Technical, allocative and economic efficiencies in swine production in Hawaii: A comparison of parametric and nonparametric approaches. *Agricultural Economics, 20*, 23–35.

Shi, Y. J., Phipps, T. T., & Colyer, D. (1997). Agricultural land values under urbanizing influences. *Land Economics, 71*, 53–67.

Song, S. (1996). Some tests of alternative accessibility measures: A population density approach. *Land Economics, 72*, 474–482.

Tauer, L. W., & Mishra, A. K. (2006). Can the small dairy farm remain competitive in U.S. agriculture? *Food Policy*, *31*, 458–468.

Taylor, L., Phaneuf, D., & Liu, X. (2016). Disentangling the property value impacts of environmental contamination from locally undesirable land uses: Implications for measuring post-cleanup stigma. *Journal of Urban Economics*, *93*, 85–98.

U.S. Department of Agriculture, Economic Research Service [USDA/ERS]. (2002–2014). Agricultural Resource Management Survey, Phase III and Farm Costs and Returns Surveys.

U.S. Department of Agriculture, Economic Research Service [USDA/ERS]. (2004). http://www.ers.usda.gov/briefing/rurality/ruralurbcon/

U.S. Department of Agriculture, National Agricultural Statistics Service [USDA/NASS]. (2002–2016) *Agricultural prices,* Washington, DC, July.

U.S. Department of Agriculture, Natural Resources Conservation Service [USDA/NRCS]. (1978). *Land resource regions and major land resource areas of the United States*. Agricultural Handbook #296. Washington, DC.

U.S. Department of Agriculture, Natural Resources Conservation Service [USDA/NRCS] National Soil Survey Center. (1994). S*tate Soil Geographic (STATSGO) Data Base*. Miscellaneous Publication No. 1492, Washington, DC, December.

U.S. Department of Commerce, Bureau of the Census. (1990). *1990 Census of Population and Housing Guide* A (1990 CPH-R-1B, Part B, Glossary, p. 9). Washington, DC.

U.S. Department of Commerce, Bureau of the Census. (2017). Population and housing unit estimates. https://www.census.gov/programs-surveys/popest.html

Williamson, J. M., & Stutzman, S. (2017). Tax policy and farm capital investment: Section 179 expensing and bonus depreciation. *Agricultural Finance Review, 77*(4) (November), 4–21.

Wu, J. (2006). Environmental amenities, urban sprawl, and community characteristics. *Journal of Environmental Economics and Management, 52*, 527–547.

Wu, J. (2008). Land use changes economic, social and environmental impacts. Transatlantic Land Use Conference Policy Brief No. 1, Farm Foundation. *Choices*, 1–10.

Wu, J. (2009). Optimal land development with endogenous environmental amenities. *American Journal of Agricultural Economics, 90*, 232–248.

APPENDIX I

Many researchers have also used data envelopment analysis (DEA) techniques to estimate performance measures to satisfactorily validate the parametric input distance function approach followed in this essay that presents performance measures by group (see, e.g., Paul & Nehring, 2004). Following the pseudopanel approach used in Paul and Nehring (2004) and Paul et al. (2005) (thus output and input observations on crop farms are reasonably homogeneous, enabling feasible DEA solutions), the DEA approach for the ARMS data set used can provide a deterministic frontier that identifies legitimate performance measures by group. Following Färe et al. (1994), we take an input perspective as used in the input distance function presentation in this essay that calls for modeling an input requirement set. Let $L(y)$ denote this set comprised of the vector of inputs $x = (x_1, \ldots, x_N) \in R_+^N$ used to produce outputs $y = (y_1, \ldots, y_M) \in R_+^M$. For observations $k = 1, \ldots, K$ this input requirement set can be constructed using DEA or activity analysis as follows:

$$L(y \mid C, S) = \{(x_1, \ldots, x_N):$$
$$\sum_{k=1}^{K} z_k y_{km} \geq y_m, m = 1, \ldots, M,$$
$$\sum_{k=1}^{K} z_k x_{kn} \leq x_n, n = 1, \ldots, N, \quad (1)$$
$$z_k \geq 0, k = 1, \ldots, K\}$$

where the z_k variables are intensity variables used to build this technology. The above technology is characterized by constant returns to scale (C) and free disposability (S). Free disposability is represented by the inequality signs in the output and input constraints above. The scale of technology can be modified by changing the restrictions on the intensity variables as follows:

$z_k \geq 0$ models constant returns to scale (C),

$\sum_{k=1}^{K} z_k = 1, z_k \geq 0$ models variable returns to scale (V),

$\sum_{k=1}^{K} z_k \leq 1, z_k \geq 0$ models non increasing returns to scale (N), $\quad (2)$

$k = 1, \ldots, K$

Technical efficiency measures the distance between a particular observation and the technology frontier. Figure 1 presents an illustration. Technology is represented by $L(y)$, which is bounded by the technology frontier or efficiency frontier. There are two observations represented by points A and B. Point A is considered technically efficient due to its location on the frontier of $L(y)$, while point B is considered technically inefficient. The inefficiency of point B can be calculated by taking the ration of OA/OB. This is the Farrell input-saving measure of technical efficiency, defined as

$$F_k(y, x \mid C, S) = \min\{\lambda : \lambda x \in L(y \mid C, S)\}.$$

We ran the input distance function, using 214 pseudopanel observations (for a description of pseudo panels using ARMS, see Paul & Nehring, 2004; Williamson & Stutzman, 2017) on rural farms (48.3% of farm-level observations) and 208 pseudopanel observations on urban farms (51.7% of farm-level observations) and found that the technical efficiency score for rural farms was 0.604 compared to 0.567 on urban farms, supporting the parametric results on technical efficiency in this essay, showing higher technical efficiency on rural farms—statistically significant at a 5% level of significance. We found scale efficiency on rural farms of 0.600 to be virtually equivalent to scale efficiency on urban farms of 0.591; the parametric rural and urban scale efficiency scores were also virtually equivalent.

GLOSSARY

off-farm income: Off-farm income earned by a household.

old-line/new line: During the herbicide growth period from the 1960s to the early 1980s, major herbicide classes were amides, anilines, carbamates, phenoxys, and triazines. Those classes encompass what are today called old-line herbicides. During the 1980s and 1990s, ALS inhibitors, and to a lesser extent Acetyl-CoA carboxylase (ACCase) and Protoporphyrinogen oxidase (PPO) inhibitors, became widely used and are referred to as new-line herbicides.

opage: Age of the principal farm operator.

ophours: Hours that the operator usually worked off of the farm/ranch for pay or to operate an off-farm business.

POPACC (Population Accessibility). An index of the urban influence to which a farm is subject

in the county in which it is located. The continuous index increases as population increases and/or as distance to the population decreases. The index number assigned for each county is the value of the index as measured at the geographic center of the county.

price of land per acre: Land owned except vines/orchard/nursery/woody crop trees estimated market value plus all land and buildings rented from others estimated market value divided by land in farms.

sphours: Hours that the operator's spouse usually worked off of the farm/ranch for pay or to operate an off-farm business.

treatment acres: A treatment acre is one acre treated with a herbicide multiplied by average number of applications per acre. This measure emphasizes the relative proportion of area treated with pesticides, accounting for multiple treatments and herbicides per acre.