Appendix for: Let Them Eat Switchgrass? Modeling the Displacement of Existing Food Crops By New Bioenergy Feedstocks

Soren Anderson Chenguang Wang Jinhua Zhao

A Derivation and illustration of conceptual model

As in the main text, profits conditional on crop choice are given by:

$$\pi_j = p_j \mu_j f(\lambda_j z + x) + \theta_j - rx \tag{1}$$

The first-order condition with respect to the variable input is given by:

$$\frac{\partial \pi_j}{\partial x} = p_j \mu_j f'(\lambda_j z + x) - r = 0. \tag{2}$$

Solving for total inputs gives:

$$\lambda_j z + x^* = f'^{-1}\left(\frac{r}{p_j \mu_j}\right), \tag{3}$$

where $x^* > 0$ is the optimal use of the variable input; the inequality implicitly assumes that marginal revenue product at $x = 0$ exceeds variable costs r. Yield at the optimum is then given by:

$$y_j^* = f\left(f'^{-1}\left(\frac{r}{p_j \mu_j}\right)\right). \tag{4}$$

As can be seen from equations (3) and (4), total inputs and yields at the optimum are independent of the fixed input, depending instead on input and output prices the crop-specific parameter. At the optimum, variable inputs are given by:

$$x^{*} = f'^{-1}\left(\frac{r}{p_j \mu_j}\right) - \lambda_j z, \tag{5}$$

which follows directly from equation (3). Thus, profits at the optimum are given by plugging (4) and (5) back into (1) above:

$$\pi_j^{*} = p_j \mu_j f\left(f'^{-1}\left(\frac{r}{p_j \mu_j}\right)\right) + \theta_j - r\left(f'^{-1}\left(\frac{r}{p_j \mu_j}\right) - \lambda_j z\right). \tag{6}$$

As presented in the main text, this expression simplifies to:

$$\pi_j^{*} = p_j \mu_j f\left(f'^{-1}\left(\frac{r}{p_j \mu_j}\right)\right) + \theta_j - r f'^{-1}\left(\frac{r}{p_j \mu_j}\right) + r \lambda_j z.$$

When prices are the same everywhere, the first three terms collapse to a crop effect. The fourth term depends both on crop-specific parameters (λ_j) and location (via z). In our econometric model, we capture the first three terms with crop dummies, while the fourth term is captured by our interactions of crop attributes with county characteristics.

Figure 1 illustrates our model graphically. The horizontal axis measures the index of fixed and variable inputs, while the vertical axis measures price. Optimal inputs are given by the intersection of the downward-sloping marginal revenue product curve with the horizontal marginal cost curve. At the optimum, revenue (the first term in equation A) is given by area $A + B + C$, variable cost assuming zero fixed inputs (the third term in equation A) is given by area $B + C$, and the value of the fixed input endowment (the fourth term in equation A) is given by area B; the fixed production cost (the second term in equation A) is omitted, since it does not affect input demand conditional on crop choice. Intuitively, the fixed input endowment subtracts from what the landowner would otherwise have spent on

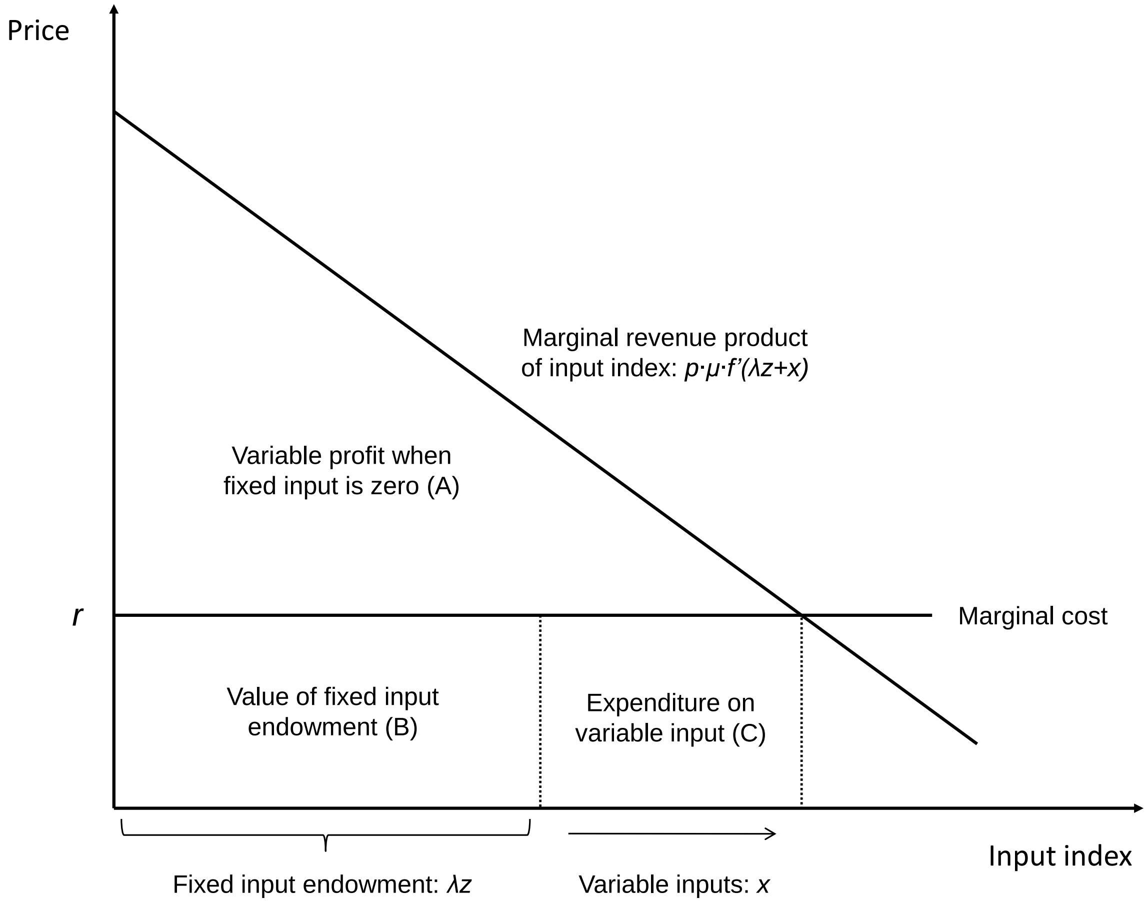

Figure 1: Illustration of conceptual model

Note: Figure illustrates profit maximization conditional on crop choice. See text for details.

variable inputs. Thus, the fixed input endowment increases profits according to the size of the endowment itself (given by z), scaled by marginal product of the fixed input relative to the variable input (given by λ_j), and weighted by the marginal cost of the variable input (given by r).

B Crop attribute sources

Our measures of water-use efficiency come from a variety of published sources. These studies report water-use efficiency measures for corn and soybeans (Yu, Wang, and Zhuang, 2004), corn and wheat (Fang, Ma, Yu, Ahuja, Malone, and Hoogenboom, 2010), chickpeas, peas, wheat, rapeseed, flaxseed, and mustard (Gan, Campbell, Liu, Basnyat, and McDonald, 2009), corn, sorghum, wheat, alfalfa, and cotton (Pessarakli, 1999), peas, sorghum, wheat, and sunflower (Steduto and Albrizio, 2005), beans, wheat, barley, flaxseed, sunflower, corn, soybeans, and sugarbeet (Bauder and Ennen, 1981), sorghum and switchgrass (Cogburn, Cogburn), barley, corn, oats, sorghum, wheat, and potatoes (Yoo, Pence, Hasegawa, and Mickelbart, 2009), tomatoes (Lei, Yunzhou, Fengchao, Changhai, Chao, Yuxin, Mengyu, and Baodi, 2009), rye (Cox, Parr, and Plant, 1988), peanuts (Wright, Hubick, and Farquhar, 1988), safflower (Dordas and Sioulas, 2008), sugar beet (Rinaldi and Vonella, 2004), miscanthus (Clifton-Brown and Lewandowski, 2000), miscanthus, corn, soybeans, wheat, and switchgrass (Vanloocke, Twine, Zeri, Arundale, and Bernacchi, 2010), and tobacco (Cakir and Cebi, 2010).

Our measures of radiation-use efficiency come mainly from Sadras and Calderini (2009), which compiles this information from a variety of sources. Other studies report radiation-use efficiency for beans and chickpeas (Kiniry, Jones, O'toole, Blanchet, Cabelguenne, and Spanel, 1989), tobacco (Ceotto and Castelli, 2002), and tomatoes (Gent, 2008).

We compile data on crop attributes potatoes, safflower, sugar beet, and tobacco from a large number of published and unpublished sources. These citations will be added soon.

C Quasi-likelihood estimation approach

Following Papke and Wooldridge (1996, 2008) and Mullahy (2010), we develop a quasi-likelihood approach for modeling county-level crop shares that does not require us to drop zero values or add small acreage values prior to calculating crop shares.[1] This approach begins with a functional form assumption for the expected share of crop j in county c:

$$\mathbb{E}\left[s_{cj}|x, z_c; \alpha, \gamma, \delta\right] = G_j(x, z_c; \alpha, \gamma, \delta) = \frac{\exp(\beta_j(x;\alpha)' z_c + \gamma_j + \delta(z_c))}{1 + \sum_{k=1}^{K} \exp(\beta_k(x;\alpha)' z_c + \gamma_k + \delta(z_c))}, \quad (7)$$

for crops $j = 1, \ldots, K$, and,

$$\mathbb{E}\left[s_{c0}|x, z_c, \alpha, \gamma, \delta\right] = G_0(x, z_c \alpha, \gamma, \delta) = \frac{1}{1 + \sum_{k=1}^{K} \exp(\beta_k(x;\alpha)' z_c + \gamma_k + \delta(z_c))}, \quad (8)$$

for the base crop $j = 0$, where x and z_c are vectors of observed crop attributes and county characteristics, γ is a vector of crop fixed effects, $\delta(\cdot)$ is a function of county characteristics, and $\beta_j(x; \alpha)$ is a linear function of crop attributes x, with parameter vector α, as shown in the main text.

Following Mullahy (2010), we assume that the quasi-likelihood takes the form of a categorical distribution (the multinomial generalization of the Bernoulli distribution), which leads to the following quasi-likelihood function:

$$QL(\alpha, \gamma, \delta) = \prod_{c=1}^{N} \prod_{j=0}^{K} G_j^{s_{cj}}, \quad (9)$$

and thus the following quasi log-likelihood function:

$$\ln(QL(\alpha, \gamma, \delta)) = \sum_{c=1}^{N} \sum_{j=0}^{K} s_{cj} \ln G_j, \quad (10)$$

where s_{cj} is the observed share of crop j in county c. Note that this is simply the log-likelihood function for a conditional logit model in which the 1s and 0s of the bivariate

[1] In their seminal paper, Papke and Wooldridge (1996) develop a quasi-likelihood approach for modeling univariate fractional outcome variables that potentially exhibit corner solutions (i.e., 0s and 1s), which they use to model employee participation rates in 401k pension plans. Papke and Wooldridge (2008) extend this approach to a panel-data context, modeling student pass rates on standardized tests. Mullahy (2010) extends this approach to the case of a multivariate fractional outcome variable, modeling the distribution of household financial assets across different asset categories.

discrete-choice outcome variable have been replaced with the fractional outcomes (the s_{cj}) of our crop shares model. Following Papke and Wooldridge (1996, 2008) and Mullahy (2010), maximizing this function with respect to the parameter vector (α, γ, δ) yields the quasi-maximum likelihood estimator (QMLE) for (α, γ, δ). This estimator will be consistent for expected crop shares, provided the identification assumption given in equations (7) and (8) is correct. Mullahy (2010) shows that the conventional likelihood-based standard errors will always be too large, however, since fractional data necessarily exhibit under-dispersion relative to their multinomial discrete counterparts. Thus, use of robust standard errors is necessary for valid inference.[2]

While the model described in equations (7)–(10) is similar to our main specification, there are several notable differences. First, the main specification assumes additive error terms (the ξs) after taking logs, while the model here implicitly assumes additive errors in levels. Thus, linear estimation of the main specification is based on setting the logged residuals to be uncorrelated with the explanatory variables, yielding expected shares in logs, while nonlinear estimation here is based on setting the level residuals to be uncorrelated with the explanatory variables, yielding expected shares in levels. Second, the county effects (the δs) in the main specification are absorbed through fixed effects estimation, which is equivalent to including county dummies. Neither approach is appropriate here, given our nonlinear model. Thus, we use the Mundlak (1978) device of modeling the county fixed effect as a linear function of the county averages of our observed explanatory variables.[3] Third, whereas the empirical model for our main specification aligns very closely with a structural model

[2] In his empirical application for financial asset shares, Mullahy (2010) finds that conventional ML standard errors are 1.1–2.4 times too large.

[3] We also could have applied the Chamberlain (1980) device, which in our case would be to model the county effect as a linear function of the explanatory variables for *all* crops in a given county. However, since most of our explanatory variables are crop attributes interacted with county characteristics, and since the crop attributes are the same for every county, the two approaches are nearly equivalent in our application. The only difference derives from our pH variables, which are not simple interactions between the crop attribute (pH tolerance) and the county characteristic (average soil pH). In a linear model, pooled OLS using the Chamberlain (1980) approach is equivalent to the Mundlak (1978) approach (which in turn equals the usual fixed effects estimator). While the two approaches in general are not equivalent for a nonlinear model, they are nearly so in our application, and would be exactly equivalent were it not for the pH variables.

of profit maximization, facilitating simulations for the adoption of new crops, the model here is not well-suited to simulations that involve changes in the choice set. On balance, we therefore prefer our main approach and its structural interpretation, given that we are attempting to model the addition of new crops to the choice set.

While our QMLE approach closely follows that in Mullahy (2010), the approaches are not identical. He assumes a true multinomial logit specification in which the explanatory variables differ only across cross-sectional units (not outcome categories) and in which there is a unique parameter measuring the effect of every explanatory variable on every possible outcome. In our context, this would amount to replacing our observable crop attributes with a set of crop dummies and estimating a unique coefficient for every county soil and climate characteristic interacted with every crop dummy. In contrast, we assume a conditional logit specification in which the explanatory variables differ both across the cross-sectional units and across the share outcomes. Given that we model crop-specific coefficients as a linear function of crop attributes, however, our approach amounts to imposing a set of linear restrictions on the parameters of his more general model. That is, his approach would estimate a separate β_j for each crop, while our approach models the β_js as a linear function of crop attributes. Thus, the difference is only superficial, and all of the consistency results and many of the specification tests described in Mullahy (2010) would carry through, assuming the parameter restrictions we impose are valid. While the multinomial logit model is more flexible, and likely better for some applications, such as predicting how patterns of adoption for existing crops might respond to climate change, our approach is both necessary and appropriate for modeling the adoption of new crops that do not yet exist in the historical data.

We program our estimator in Stata using Stata's built-in ML package, which facilitates user-written maximum likelihood routines. Our code is available upon request.

D Nested logit derivation and estimation

Following the derivation of the main empirical model, let

$$V_{icjn} = \beta_{jn} z_c + \gamma_{jn} + \delta_c + \xi_{cjn} + \epsilon_{icjn} \tag{11}$$

be the expected profit on parcel i in county c from planting crop j from nest n. If we assume that the idiosyncratic error term ϵ_{icjn} is drawn from a generalized extreme value distribution (i.e., nested logit), then the share of crop j in nest n in county c is given by:

$$S_{cjn} = \frac{\left(\sum_{k \in n} \exp\left(\frac{V_{ckn}}{(1-\rho)\sigma}\right)\right)^{1-\rho}}{1 + \sum_m \left(\sum_{k \in m} \exp\left(\frac{V_{ckm}}{(1-\rho)\sigma}\right)\right)^{1-\rho}} \cdot \frac{\exp\left(\frac{V_{cjn}}{(1-\rho)\sigma}\right)}{\sum_{k \in n} \exp\left(\frac{V_{ckn}}{(1-\rho)\sigma}\right)}, \tag{12}$$

while share of the base crop 0 (assumed to occupy its own nest) in county c is given by:

$$S_0 = \frac{1}{1 + \sum_m \left(\sum_{k \in m} \exp\left(\frac{V_{ckm}}{(1-\rho)\sigma}\right)\right)^{1-\rho}}, \tag{13}$$

where we have normalized expected profits for the base category to be zero in each county. As above in the main text, σ scales the variance of the idiosyncratic error term ϵ_{icjn}, while now $\rho \in (-1, 1)$ is the correlation of idiosyncratic error terms in the same nest; the correlation of error terms in different nests is zero by the assumption of independence across nests. The first term in (12) above is the county share devoted to nest n, while the second term is the share of nest n devoted to crop j, conditional on being in nest n. When $\rho > 0$, the within-nest error terms are positively correlated. When $\rho = 0$, we get the original multinomial logit model. As $\rho \to 1$, the within-nest errors are perfectly correlated, and we should be modeling choice at nest level.[4]

[4]Note that we have assumed that the within-nest correlation of the idiosyncratic errors ρ is the same for every nest; it is possible to relax this assumption, though we do not do so here.

Dividing crop shares by the base crop's share and then taking logs yields:

$$\ln S_{cjn} - \ln S_{c0} = \frac{V_{cjn}}{(1-\rho)\sigma} - \rho \ln \sum_{k \in n} \exp\left(\frac{V_{ckn}}{(1-\rho)\sigma}\right), \tag{14}$$

while dividing crop shares by the share of its nest and then taking logs yields:

$$\ln S_{cjn} - \ln S_{cn} = \frac{V_{cjn}}{(1-\rho)\sigma} - \ln \sum_{k \in n} \exp\left(\frac{V_{ckn}}{(1-\rho)\sigma}\right), \tag{15}$$

where $S_{cn} = \sum_{k \in n} S_{ckn}$ is the county share for the crop's nest.

Using (15) to solve for $\ln \sum_{k \in n} \exp\left(\frac{V_{ckn}}{(1-\rho)\sigma}\right)$, substituting into (14), and then rearranging yields:

$$\ln S_{cjn} - \ln S_{c0} = \frac{1}{(1-\rho)\sigma} V_{cjn} + \frac{\rho}{1-\rho} \ln S_{c0} + \frac{\rho}{1-\rho} \ln S_{cn}. \tag{16}$$

Substituting the expression for V_{cjn} back in then yields the estimating equation:

$$\ln S_{cjn} - \ln S_{c0} = \tilde{\beta}_{jn} z_c + \tilde{\gamma}_{jn} + \tilde{\delta}_c + \frac{\rho}{1-\rho} \ln S_{c0} + \frac{\rho}{1-\rho} \ln S_{cn} + \tilde{\xi}_{cjn}, \tag{17}$$

where the tildes now indicate normalization by $1/[(1-\rho)\sigma]$.

This derivation closely follows that in Berry (1994), which shows how to estimate the nested logit and other discrete-choice models using aggregate shares data. The key difference is that he rearranges the estimating equation so that the $\frac{\rho}{1-\rho} \ln S_{c0} + \frac{\rho}{1-\rho} \ln S_{cn}$ terms above are replaced with $\rho \ln(S_{cjn}/\ln S_{cn})$ and the tildes reflect normalization by σ only. The two approaches are theoretically equivalent, given our inclusion of county fixed effects as controls, and our approach led to more robust coefficient estimates for ρ.

We estimate this model by including the logged nest share as an additional right-hand side explanatory variable in our baseline regression. As above, the terms involving the logged share of the base crop category are perfectly collinear with the county dummies and therefore drop out. That is, we can safely ignore the $\rho/(1-\rho) \ln S_{c0}$ term on the right-hand side, as it is captured by the county dummies. Note that the coefficient on the logged nest share

$\ln S_{cn}$ will be zero under the null hypothesis that the idiosyncratic errors are independent both within and across nests.

The identification challenge is that the nest's logged share $\ln S_{cn}$ is mechanically correlated with the model's residual term $\tilde{\xi}_{cjn}$. Thus, consistent estimation requires instruments for the nest's share. As described in the main text, we use the log of the predicted nest share. As described in the main text, we calculate predicted nest shares using our baseline regression results for the multinomial logit model (taking care to exclude the estimated county-level residuals from this calculation). In effect, we instrument for a nest's share with a weighted average of the nests's crop attributes interacted with county soil and climate characteristics, where the weights are chosen based on the importance of these interactions in explaining crop shares in our baseline model.

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