Mending the Family Tree of Acreage Choice Models*

Christophe Gouel†[1,2], Alain Carpentier[3], Fabienne Féménia[3], Obafèmi Philippe Koutchadé[3], and David Laborde[4]

[1]Université Paris-Saclay, INRAE, AgroParisTech, Paris-Saclay Applied Economics, 91120, Palaiseau, France
[2]CEPII, 20 avenue de Ségur, 75007, Paris, France
[3]SMART, INRAE, Institut Agro, 4 allée Adolphe Bobierre, 35000 Rennes, France
[4]FAO, Italy

September 8, 2026

Abstract

This paper compares three tractable specifications of acreage choice for agricultural equilibrium models: (*i*) constant elasticity of transformation (CET), as commonly used in CGE models; (*ii*) heterogeneous land with Fréchet-distributed yields, inspired by quantitative trade theory; and (*iii*) multinomial logit, derived from entropy regularization and convex management costs. Within a unified production environment, we derive land allocation, production responses, and supply elasticities, and clarify microfoundations, calibration, and empirical restrictions. A key result shows that, when calibrated on identical benchmark shares and elasticities, CET and Fréchet specifications yield identical counterfactual production responses but differ in their implications for physical acreage: the Fréchet approach preserves area balance, whereas CET generally allocates efficient land rather than hectares. We show, however, that the Fréchet mechanism imposes severe restrictions, including implausibly large acreage elasticities and negative yield-composition effects far larger than those found in the limited comparable evidence. We then estimate a nested multinomial logit model on French farm-accounting panel data, obtain acreage elasticities consistent with the literature, and use these estimates to calibrate nested logit, CET, and Fréchet specifications to match the same local output responses. Counterfactual simulations show that matching local supply elasticities is not sufficient: away from the benchmark, the Fréchet selection mechanism can generate implausibly large acreage reallocations and yield declines, while the nested logit separates acreage and intensification responses more transparently. The analysis bridges CGE, quantitative trade, positive mathematical programming, and econometric acreage models, and guides calibration choices when physical land accounting and credible yield responses matter.

Keywords: acreage choice; discrete choice; quantitative modeling; supply elasticity; yields.

JEL codes: C35, D24, D58, Q11, Q12, Q15.

*We are grateful for helpful comments and feedback from Alexandre Gohin, Pierre Mérel, and Farzad Taheripour. This work received funding from the Horizon Europe project BrightSpace (Grant Agreement No. 101060075). It is also part of project PREFALIM of the exploratory research program FairCarboN and received government funding managed by the Agence Nationale de la Recherche under the France 2030 program, reference ANR-23-PEXF-0004.

†Corresponding author

1 Introduction

Acreage-choice modeling is central to agricultural economics, underpinning our ability to estimate emissions from indirect land-use changes (Searchinger et al., 2008), evaluate the heterogeneous impacts of agricultural policies, and assess the costs of adapting to climate change (Costinot et al., 2016). Large-scale equilibrium models rely on well-established approaches, including the constant elasticity of transformation (CET) framework and modeling based on Fréchet-distributed yields; however, these approaches have substantial shortcomings, that may raise concerns about the robustness of agricultural equilibrium models in addressing pressing policy and climate-related questions.

The objective of this paper is to clarify and compare the properties of existing methods for modeling acreage choice. Its focus is on equilibrium models; within this class, it excludes programming models, which adopt distinct modeling approaches[1], but we highlight some of the connections between this literature and our focus. This paper compares three approaches. The first is the use of CET functions, which represent the standard approach in Computable General Equilibrium (CGE) models since Hertel and Tsigas (1988). The second is modeling based on Fréchet-distributed yields, an approach that has become popular in new quantitative trade models following Costinot et al. (2016). A promising third alternative is the multinomial logit framework obtained through entropy regularization. This approach was proposed by Carpentier and Letort (2014) for econometric estimation, but its application to equilibrium models has been limited (e.g., Gohin, 2020; Gohin and Matthews, 2024). This paper elucidates the calibration and properties of this approach within applied modeling. In addition to presenting analytical results, we perform a structural estimation of the multinomial logit approach using French farm-level data. We then use the resulting estimates to calibrate all three approaches in a comparable manner and evaluate their counterfactual results in a realistic setting.

Before delving further, we address a preliminary question: why do we need a specific model for acreage choice? A farmer plants the crops that maximize expected profit. Is not that sufficient to determine acreage allocation? It might be, if economists could account for all the dimensions relevant to this decision, such as crop rotation (Hennessy, 2006), the existing crop-specific capital stock, the farmer's risk aversion and risk exposure (Chavas and Holt, 1990), the productive effect of crop biodiversity (Bareille and Largier, forthcoming), or the heterogeneity of land quality. However, in practice, many of these factors are unobservable or beyond the scope of the model—whether due to the model being at the country level, static, or deterministic. The absence of these factors would lead to a trivial decision for the farmer: planting the single most profitable crop. Such a simplistic discrete choice framework fails to capture diversified acreage choices and the finite supply elasticities estimated in the data. To address this issue, economists employ modeling techniques that constrain acreage choices and enable the representation of observed crop decisions while aligning with estimated supply elasticities. By design, each technique limits acreage choice to a specific explanation and, as a result, comes with inherent constraints. It is crucial to elucidate these limitations to ensure that the modeling choices are appropriately aligned with the research question.

All acreage-choice theories rely on the idea that there are decreasing returns to specialization but differ in how these decreasing returns are implemented. The approaches based on the CET function and the Fréchet distribution both rely on the assumption that crop yields decrease with specialization because land is heterogeneous in quality, and the more a farmer specializes in one crop, the more they have to

[1] For a discussion of these models, see, e.g., Mérel and Howitt (2014)

cultivate parcels that are less suitable for that crop. This explanation draws on Ricardo's theory of rent, which posits that the best-quality land is cultivated first. A key distinction between these two approaches is that with the CET function, yields are not explicitly defined but are bundled with land into an effective land factor. In contrast, the multinomial logit approach assumes that land is of homogeneous quality and that a farmer's operations become less productive as they specialize because overall management costs increase with specialization. This explanation is based on the convexity of the cost function, an implicit assumption behind the multicrop econometric models initiated by Chambers and Just (1989). In these econometric models, the reason for convex cost functions is usually unspecified because the technology is implicit. However, the literature (Carpentier et al., 2015) discusses several justifications: the existence of crop-specific capital, the possibility of spreading workload over the year by growing different crops with staggered planting and harvesting dates, or the agronomic benefits of some crop combinations.

This work relates to three distinct research strands. First, it echoes international trade both because the modeling problem is formally analogous and because the modern Fréchet approach to acreage choice has largely been transmitted through the new quantitative trade literature. In trade, modeling import shares poses the same challenge as modeling acreages: avoiding complete specialization, which is incompatible with observed data. CGE models have traditionally addressed this issue using the Armington assumption, based on a CES function. The new Ricardian trade theory introduced by Eaton and Kortum (2002) proposed an alternative approach, relying on the assumption of Fréchet-distributed productivity for the production of a continuum of goods. Following Eaton and Kortum's route, Costinot et al. (2016) independently rediscovered and popularized a Fréchet-yield acreage model in new quantitative trade applications to agriculture; subsequent applications include Sotelo (2020) and Gouel and Laborde (2021). An agricultural antecedent, however, predates this trade-inspired strand: the use of Fréchet-distributed yields to model acreage choice was first introduced by Sands and Leimbach (2003), but this earlier contribution appears not to have been connected to the later trade-inspired literature. The analogy with trade is useful because, since Arkolakis et al. (2012), it has been well recognized in the trade literature that, when calibrated on the same trade shares and trade elasticities, trade models based on Eaton and Kortum's theory yield the same counterfactual predictions as Armington trade models. The same result applies to acreage choices: with identical calibration, a Fréchet-based theory of acreage choice produces the same counterfactual results as a CET-based theory. What is often overlooked, however, is that although both approaches yield the same counterfactual changes in values (the primary focus in trade), they have different implications for quantities.[2] In this paper, we clarify the similarities and differences between these two approaches.[3]

Second, this study aims to clarify the connections between acreage-choice modeling in equilibrium models and the econometrics of agricultural production. We analyze the empirical moments that each method can replicate, highlighting the inherent functional-form restrictions associated with the CET, Fréchet, and multinomial logit approaches. The multinomial logit approach offers a flexible specification that facilitates direct estimation. Following Koutchadé et al.'s (2018; 2021) methodology, we structurally estimate the multinomial logit model using detailed farm-level data from France. This estimation not only provides valuable behavioral parameters for calibrating the three approaches but also demonstrates

[2] Sogalla et al. (2024) is one of the rare papers touching on the quantity implications in trade models.

[3] Fujimori et al. (2014) also compared a CET specification to one similar to that derived from a Fréchet distribution, but they did not provide any theoretical foundation for the latter approach and failed to note that both approaches should be equivalent, except for the physical acreage balance (Proposition 2 in this article), a property identified in Taheripour et al. (2020).

consistency with acreage elasticities reported in the literature. Multinomial logit models have a long history in the econometric modeling of land-use choices (e.g., Chomitz and Gray, 1996; Lubowski et al., 2006; Souza-Rodrigues, 2018), often derived under the assumption of Gumbel-distributed errors in the profit function. However, this assumption presents conceptual challenges in equilibrium models, as the Gumbel distribution permits negative profit values due to its support over the entire real line. To address this, we rely on the deterministic convex-program representation of the same logit structure. In this representation, the log-sum-exp surplus function is the value of an entropy-regularized rent-maximization problem, and acreage shares are obtained as its derivatives with respect to crop-specific rents. The multinomial logit model can therefore be read either as the deterministic equivalent of stochastic rent maximization with additive extreme-value heterogeneity or as an entropy-regularized optimization problem. This dual interpretation reconnects the econometric discrete-choice tradition with structural equilibrium modeling.

Finally, our work could help create links between the CGE literature on agricultural issues and the mathematical programming literature (e.g., Howitt, 1995; Mérel et al., 2011; Mérel and Howitt, 2014). Despite addressing similar topics, these fields have tended to overlook each other and develop distinct methods. In this article, we demonstrate how these practices are closely connected. First, the debate over whether acreage-choice specifications should rely on declining yields or increasing costs with specialization has already occurred in this literature (Mérel and Howitt, 2014). However, as noted in the survey of the positive mathematical programming (PMP) literature by Mérel and Howitt (2014), there is no firm empirical basis for choosing between these alternatives. Direct evidence on the yield-composition mechanism is sparse and only partially comparable, although available studies suggest that composition effects can be negative and are modest in magnitude (Stigler, 2020; Pates and Hendricks, 2021). We show that the theoretical properties of the Fréchet distribution instead imply much larger responses of yield to specialization. We also demonstrate how some of the methods presented in this article relate to those used in the PMP literature. The Fréchet-based approach is simply a stochastic equivalent of the deterministic assumption of yield decreasing with acreage adopted in Mérel et al. (2011). The multinomial logit approach, in turn, is the entropy analogue of quadratic PMP (Howitt, 1995): both introduce a convex regularization term that rationalizes observed diversification and prevents corner solutions, but entropy regularization delivers closed-form logit acreage shares. This analysis shows substantial similarities between the practices in equilibrium and programming models, with their acreage modeling methods existing on a continuum—from the more parsimonious approaches employed in equilibrium models for reasons of tractability and data availability, to the more detailed ones used in programming models.

The rest of this paper is organized as follows. To compare the three approaches, section 2 presents a common modeling framework for crop production with three inputs: land, a yield-enhancing input, and a land-proportional input. This framework is used for expository purposes to detail the properties of the approaches. Section 3 estimates a more realistic specification of the multinomial logit approach on farm-level data. Using calibrations based on these estimates, section 4 compares the Fréchet and logit approaches through illustrative simulations. Finally, section 5 concludes. All proofs are provided in Appendix A.

2 Common modeling framework

Let us consider a common model of crop production. The set of goods is $\{\mathcal{K}, X, M\}$, where $\mathcal{K}$ is the set of crops indexed by k, X is a yield-enhancing (land-intensification) input, and M is an input that does not affect yields. In the CET and Fréchet models, M is proportional to the land area used; in the multinomial logit model, it pays for costs associated to acreage management. A farmer chooses how to allocate a fixed land endowment to the most profitable crops.[4] The yield-enhancing input X is combined with land through a CES function. The choice of a CES function is imposed by the Fréchet model, which requires multiplicative first-order conditions for the land rents to be Fréchet distributed. In section 3, because the estimation uses the less restrictive multinomial logit model, we use a quadratic yield function for additional flexibility and tractability. For simplicity, except for land, input prices are assumed to be the same across all crops. As much as possible, notation is kept consistent across the modeling approaches.

In all three approaches, the farmer's decision can be interpreted as a two-stage process. In the first stage, for given acreage shares, the farmer chooses the intensity of the yield-enhancing input and obtains a per-crop profitability measure. In the second stage, these crop-specific profitability measures determine the allocation of land across crops according to the acreage-choice mechanism of each model.

2.1 The constant elasticity of transformation function

This modeling approach rests on the intuition that land is heterogeneous: the more a farmer devotes land to a given crop, the less productive that land becomes for that crop, because production must expand onto parcels that are less well suited to it. Rather than representing land heterogeneity directly, as in the next section, this approach uses an efficient-land factor that combines physical land with productivity, which varies with specialization.

There is a fixed endowment of efficient land, denoted $\bar{L}$. This total land endowment is assumed to be imperfectly substitutable between uses according to a CET function:

$$\bar{L} = \left(\sum_{k \in \mathcal{K}} b_k^{1/\eta} \bar{L}_k^{(\eta-1)/\eta} \right)^{\eta/(\eta-1)}, \tag{1}$$

where $\eta < 0$ is the elasticity of transformation between uses and the $b_k > 0$ are parameters governing land efficiency in its various uses.

Production, Y_k, is generated by a CES function of efficient land and a yield-enhancing input, with crop-specific substitution elasticity between inputs, $\sigma_k \geq 0$, $\sigma_k \neq 1$:[5]

$$Y_k = \left[\left(a_k^L \bar{L}_k \right)^{(\sigma_k-1)/\sigma_k} + \left(a_k^X X_k \right)^{(\sigma_k-1)/\sigma_k} \right]^{\sigma_k/(\sigma_k-1)}, \tag{2}$$

where the $a_k^x > 0$ are productivity shifters for each input x. The input that does not affect yields is proportional to land:[6]

$$M_k = \left(a_k^L / a_k^M \right) \bar{L}_k. \tag{3}$$

[4] This paper does not address the issue of land supply and focuses on the allocation of crops on a given area of land.

[5] We do not detail the equations for the case $\sigma_k = 0$, which is used only for illustration purpose in the figures presented in this section.

[6] This setting corresponds to a two-tiered production system: the first nest combines land with the land-proportional input using a Leontief technology, and the second nest combines this first nest with the yield-enhancing input.

Standard CES algebra yields the land rents R_k as a function of the other prices:

$$R_k = a_k^L \left\{ \left[P_k^{1-\sigma_k} - \left(P_X / a_k^X \right)^{1-\sigma_k} \right]^{1/(1-\sigma_k)} - P_M / a_k^M \right\}, \tag{4}$$

where P_g is the price of good g.

The farmer chooses the mix of crops by maximizing total crop returns $\sum_{k \in \mathcal{K}} R_k \bar{L}_k$ subject to equation (1), which gives the following land allocation:

$$\bar{L}_k = b_k \left(\frac{R}{R_k} \right)^{\eta} \bar{L}, \tag{5}$$

where R is an index of land rents defined as

$$R = \left(\sum_{k \in \mathcal{K}} b_k R_k^{1-\eta} \right)^{1/(1-\eta)}. \tag{6}$$

The land allocation can also be expressed as

$$\bar{s}_k = \frac{R_k \bar{L}_k}{R \bar{L}} = \frac{b_k R_k^{1-\eta}}{\sum_{l \in \mathcal{K}} b_l R_l^{1-\eta}}, \tag{7}$$

where $\bar{s}_k$ denotes the share of the value of land allocated to crop k.

The CET approach focuses on allocating efficient land, whereas researchers are often interested in physical land allocations. Thus, although it is inconsistent with the microfoundations of the CET approach, in policy analyses changes in $\bar{L}_k$ are commonly interpreted as changes in physical acreages. We now consider the consequences of this interpretation for the physical acreage balance. Suppose efficient land, $\bar{L}_k$, is interpreted as physical land, and denote by L the total physical land used across crops:

$$L = \sum_{k \in \mathcal{K}} \bar{L}_k. \tag{8}$$

Given equation (1) that characterizes the CET function, the condition $\bar{L} = L = \sum_{k \in \mathcal{K}} \bar{L}_k$ is generally not satisfied. If it holds initially, then if relative land rents stay constant it is satisfied, in which case acreage shares also stay constant. Outside this situation of little interest, we analyze below what determines compliance with physical acreage balance. First, we assume that the baseline calibration respects this condition, which using equation (7) involves the following constraint on land rents in the baseline:

$$\sum_{k \in \mathcal{K}} \bar{s}_k \frac{R}{R_k} = 1. \tag{9}$$

This ensures that the sum of demand for land equals available land, but not that the initial acreage pattern is reproduced in the baseline. Let s_k denote the initial acreage shares. They are reproduced in the baseline only if

$$\frac{R_k}{R} = \frac{\bar{s}_k}{s_k}. \tag{10}$$

The conventional practice in CGE modeling is to initialize all prices to one (Shoven and Whalley, 1984), because initial prices do not matter for the counterfactual results expressed in relative changes, which depend only on initial value terms. A standard initialization of prices to 1 ($R = R_k = 1$) implies that acreage shares are equal to land-revenue shares in the baseline ($\bar{s}_k = s_k$). This is generally not the case in observed farm accounting data, which shows that this practice should not be followed when one is interested in reproducing initial acreage patterns.

Second, assuming that equation (10) holds in the baseline (and so equation (9)), we calculate the ratio of L to $\bar{L}$ and take a first-order approximation, yielding Proposition 1.

Proposition 1. *An acreage model based on a constant elasticity of transformation function cannot track physical hectares; to a first-order approximation, the deviation between total land and land demand is given by*

$$\mathrm{d}\ln\frac{L}{\bar{L}} = \eta \sum_{k\in\mathcal{K}} (\bar{s}_k - s_k)\,\mathrm{d}\ln R_k. \tag{11}$$

Proposition 1 shows that the magnitude of the deviation increases with (*i*) the absolute value of the elasticity of transformation, η; (*ii*) the difference between the land-revenue share and the acreage share, $\bar{s}_k - s_k$; and (*iii*) the relative changes in land rents. Only relative changes matter: an increase in land rents that leaves relative rents unchanged (i.e., $\mathrm{d}\ln R_k = \mathrm{d}\ln R_l$) preserves the physical acreage balance, because equations (9) and (10) imply $\sum_{k\in\mathcal{K}}(\bar{s}_k - s_k) = 0$. Interesting counterfactual shocks are typically nonmarginal and have nonuniform effects; therefore they are likely to violate the physical acreage balance.[7]

The extent of the violation of the physical acreage balance is illustrated in figure 1 using a two-crop model, employing equations (5)–(8) and (10) directly, and abstracting from intensification (i.e., $\sigma_k = 0$).[8] At the calibration benchmark, land revenues are equal between the two crops, although acreage may differ. The elasticity of transformation, η, takes two values: -0.5 and -1, the latter being the smallest value used in GTAP-AEZ (Hertel et al., 2009). The land rent of the first crop is held constant, while the land rent of the second crop is varied along the x-axis. The y-axis represents the percentage violation of the physical acreage balance ($L/\bar{L} - 1$).

Figure 1 confirms the intuitions drawn from the first-order approximation: deviations increase with the difference between revenue and acreage shares, with relative land rents, and with the absolute value of the elasticity of transformation. For large initial differences between revenue and acreage shares, the violation of the physical acreage balance can become substantial. The violation is minimal for $s_2 = 0.6$, as this is the situation where $\bar{s}_k - s_k$ is closest to zero throughout the simulations (since $\bar{s}_k$ increases faster with R_k than s_k).

Discrepancies are likely to be pronounced in settings where land-revenue shares differ substantially from acreage shares. Such a situation arises, for instance, when analyzing substitution between pastures and cropland: pastures tend to have low land rents but constitute a high proportion of physical acreage. One argument for using the CET is that it accounts for the observed heterogeneity of land, acknowledging

[7] This property of the CET has long been recognized in the CGE community and addressed through various fixes. Because they all lack microfoundations, we do not discuss them here. See Horridge (2021) for an exposition.

[8] This is purely for expositional simplicity: results are in fact unaffected by this assumption, since the analysis concerns the extensive margin, not the input-intensity margin governed by σ_k.

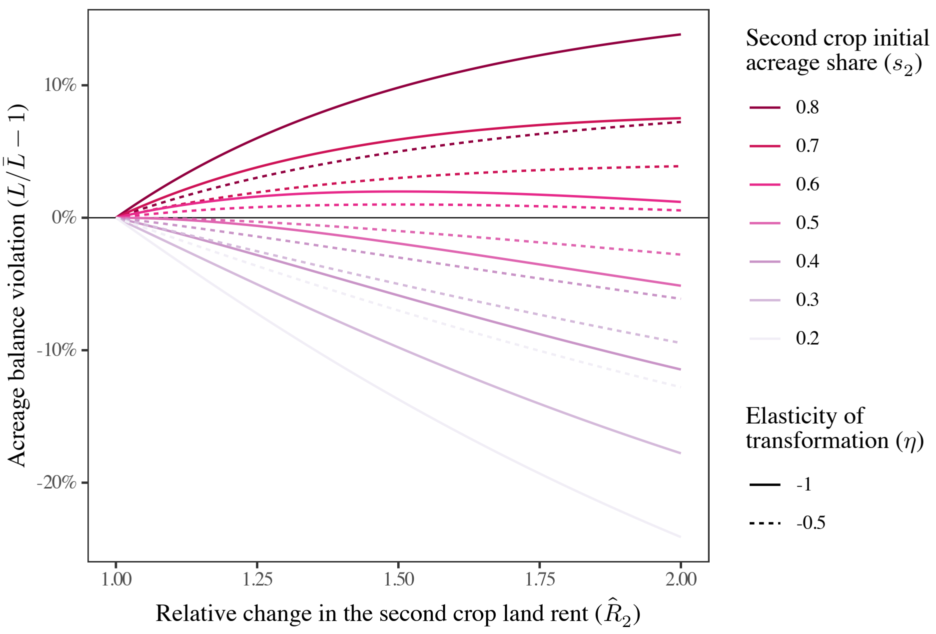

Figure 1: Physical acreage-balance violation in a two-crop CET model. Initial land-revenue shares are equal ($\bar{s}_1 = \bar{s}_2 = 0.5$); the land rent for the first crop is constant; and there is no intensification ($\sigma_k = 0$).

that different crops are associated with different land rents. Our results indicate that these are precisely the settings where discrepancies are more likely to occur.

From the above first-order conditions, we can also derive production as a function of prices:

$$Y_k = a_k^L b_k^{1/(1-\eta)} \left[1 - \left(\frac{P_X/P_k}{a_k^X}\right)^{1-\sigma_k}\right]^{\sigma_k/(1-\sigma_k)} \bar{s}_k^{\eta/(\eta-1)} \bar{L}. \tag{12}$$

Elasticities. From the previous equations, we calculate the own-price supply elasticity:

$$\frac{\partial \ln Y_k}{\partial \ln P_k} = \underbrace{-\eta \frac{1-\bar{s}_k}{\vartheta_k^L}}_{\text{Acreage and yield composition}} \underbrace{+\sigma_k \frac{\vartheta_k^X}{1-\vartheta_k^X}}_{\text{Intensification}}, \tag{13}$$

where $\vartheta_k^X \equiv P_X X_k/(P_k Y_k)$ is the cost share of input X, and ϑ_k^L is the cost share of land. The own-price supply elasticity is composed of two terms: the acreage and yield composition elasticity, which is governed by η, and the intensification elasticity, which is governed by σ_k. Because the CET function cannot track physical acreage, it cannot explicitly represent yields either. It is possible to isolate a yield intensification elasticity, but we ignore the size of the yield composition elasticity.

Calibration. To identify the minimum set of information required to calibrate the model, we express the key equations in deviations from the baseline, with $\hat{x} = x'/x$ denoting the ratio of the counterfactual value x' to the baseline value x, allowing prices and land productivity to change. The model can be summarized by three equations related to production, land-rent shares, and land rents (implicit within the price index equation):

$$\hat{Y}_k = \hat{a}_k^L \left\{ \left[1 - \vartheta_k^X \left(\frac{\hat{P}_X}{\hat{P}_k} \right)^{1-\sigma_k} \right] \Big/ \left(1 - \vartheta_k^X \right) \right\}^{\sigma_k/(1-\sigma_k)} \hat{\bar{s}}_k^{\eta/(\eta-1)}, \tag{14}$$

$$\hat{\bar{s}}_k = \frac{\hat{R}_k^{1-\eta}}{\sum_{l\in\mathcal{K}} \bar{s}_l \hat{R}_l^{1-\eta}}, \tag{15}$$

$$\hat{P}_k = \left[\left(1 - \vartheta_k^X\right)^{\sigma_k} \left(\vartheta_k^L \hat{R}_k / \hat{a}_k^L + \vartheta_k^M \hat{P}_M \right)^{1-\sigma_k} + \vartheta_k^X \left(\hat{P}_X\right)^{1-\sigma_k} \right]^{1/(1-\sigma_k)}, \tag{16}$$

where ϑ_k^M is the cost share of input M. These equations clarify that the counterfactual simulations depend solely on two observables, the initial cost shares ϑ_k^x and land-rent shares $\bar{s}_k$, and two behavioral parameters, η and σ_k.

2.2 Fréchet-distributed yields

This modeling approach is similar to the previous one in that it assumes land is heterogeneous in quality. However, a key difference is that this heterogeneity is explicitly represented by assuming that yields follow a Fréchet distribution.

There is a fixed endowment of land with a total area of L. The land is composed of a continuum of parcels indexed by $\omega \in [0, 1]$, and parcel quality is heterogeneous. If parcel ω is planted with crop k, yield is given by

$$y_k(\omega) = \left\{ \left[a_k^L \epsilon_k(\omega) \right]^{(\sigma_k-1)/\sigma_k} + \left[a_k^X x_k(\omega) \right]^{(\sigma_k-1)/\sigma_k} \right\}^{\sigma_k/(\sigma_k-1)}, \tag{17}$$

where $x_k(\omega)$ denotes yield-enhancing input demand per hectare, and the parcel quality heterogeneity is related to $\epsilon_k(\omega) > 0$, which parameterizes the potential yield of crop k. We assume that $\epsilon_k(\omega)$ is i.i.d. and follows a Fréchet distribution with shape parameter $\theta > 1$ and scale parameter $\gamma > 0$:

$$\Pr\left(\epsilon_k(\omega) \le e\right) = \exp\left[-\left(e/\gamma\right)^{-\theta} \right] \quad \forall e \in \mathbb{R}_{>0}. \tag{18}$$

$\gamma \equiv \left[\Gamma\left(1 - 1/\theta\right)\right]^{-1}$ is a scaling parameter introduced such that $\mathrm{E}[\epsilon_k(\omega)] = 1$, and $\Gamma(\cdot)$ is the Gamma function.[9] θ measures the dispersion of yields: a higher θ indicates more homogeneity and a lower θ more heterogeneity.

If crop k is planted on ω, its land rent is given by

$$R_k(\omega) = \epsilon_k(\omega) R_k, \tag{19}$$

which is Fréchet distributed with shape parameter θ and scale parameter γR_k, where R_k is defined by equation (4). This parcel-level land rent comprises two components: a deterministic component, R_k, which gives the land rent for a parcel with $\epsilon_k(\omega) = 1$ and follows the same formula as in the CET model; and a stochastic component, $\epsilon_k(\omega)$.

[9] The use of an extreme value distribution, such as the Fréchet distribution, is necessary to obtain analytical expressions with more than two crops. For a choice between two crops, any distribution function with positive support can be used, as shown in Lichtenberg (1989) and Martinet (2013).

A profit-maximizing farmer will plant the most profitable crop on each parcel and thus faces a discrete choice problem. The probability that crop k is the most profitable on parcel ω is defined as

$$s_k = \Pr\left(k \in \underset{l \in \mathcal{K}}{\arg\max}\, R_l(\omega)\right). \tag{20}$$

Since there is a continuum of parcels with identically distributed productivity shocks, it follows that s_k is also the share of land allocated to k. From the properties of Fréchet-distributed variables, we derive the following expression for s_k[10]

$$s_k = \frac{R_k^\theta}{\sum_{l \in \mathcal{K}} R_l^\theta}. \tag{21}$$

Therefore, acreage demand for crop k is given by $L_k = s_k L$. The parameter θ captures the acreage elasticity with respect to land rent. A higher θ, which corresponds to more homogeneous land, implies that acreages are more sensitive to land rents.

From equation (21), we can introduce the total land rent conditional on crop choice as a power sum of the unconditional land rents:

$$R = \left(\sum_{k \in \mathcal{K}} R_k^\theta\right)^{1/\theta}. \tag{22}$$

Given the properties of the Fréchet distribution, the land rents conditional on the crops being chosen are all equal to the total land rent of the farmer's land:

$$\dot{R}_k = \mathrm{E}\left[R_k(\omega) \,\middle|\, k \in \underset{l \in \mathcal{K}}{\arg\max}\, R_l(\omega)\right] = R. \tag{23}$$

Total production is obtained by integrating parcel-level production over all parcels. However, not all parcels are planted with the crop; only a share, s_k, is planted. On the planted parcels, the yield distribution differs from the unconditional yield distribution because these parcels are selected for this crop due to higher profitability compared to other crops, which skews the distribution to the right. Total production is therefore given as the product of acreage (acreage share times land endowment) and mean yield conditional on the crop being chosen:

$$Y_k = L s_k a_k^L \left[1 - \left(\frac{P_X/P_k}{a_k^X}\right)^{1-\sigma_k}\right]^{\sigma_k/(1-\sigma_k)} \dot{\epsilon}_k, \tag{24}$$

where $\dot{\epsilon}_k = \mathrm{E}\left[\epsilon_k(\omega) \middle| k \in \arg\max_{l \in \mathcal{K}} R_l(\omega)\right]$ is conditional mean productivity. Using equations (19) and (23), we have $\dot{\epsilon}_k = R/R_k = s_k^{-1/\theta}$, and

$$Y_k = L s_k^{(\theta-1)/\theta} a_k^L \left[1 - \left(\frac{P_X/P_k}{a_k^X}\right)^{1-\sigma_k}\right]^{\sigma_k/(1-\sigma_k)}. \tag{25}$$

[10] See Appendix B for the standard properties of Fréchet-distributed random variables, which are used to derive the equations in this Section.

Since $s_k^{-1/\theta} > 1$, the expected conditional yields exceed the expected unconditional yields. The more land that is devoted to a crop (the higher s_k), the lower the land quality and the yield, and expected unconditional yield provides the lower bound. The conditional yields adjust to equalize the conditional land rents across uses.

This rent equalization may seem paradoxical: although land is heterogeneous, the endogenous selection of crops leaves conditional land rents equal across uses, exactly as if land were homogeneous. In fact, equation (23) implies that acreage shares equal revenue shares, $s_k = \bar{s}_k$ (because the definition of $\bar{s}_k$ is $\dot{R}_k s_k / R$), an equality that typically holds in models with homogeneous land.

Figure 2 illustrates the adjustments of conditional yields using the example of a farmer who can plant maize and soybeans without using any input other than land (i.e., $a_k^X = a_k^M = \sigma_k = 0$). The expected unconditional yields are 7 and 2 tons per hectare, respectively. The shape parameter of the distributions, θ, is 2. Prices are set at 120 dollars per ton for maize and 400 dollars per ton for soybeans. The unconditional density functions are represented by solid lines, with the expected unconditional yields marked by vertical segments. For this parameter combination, equation (21) implies that the farmer allocates 48% of land to soybeans. The yield distributions conditional on the crops being planted are shifted to the right due to the endogenous selection of the most profitable crop for each parcel, which excludes the lowest-yield parcels. As a result, the expected conditional yields increase to 9.7 tons per hectare for maize and 2.9 tons per hectare for soybeans.

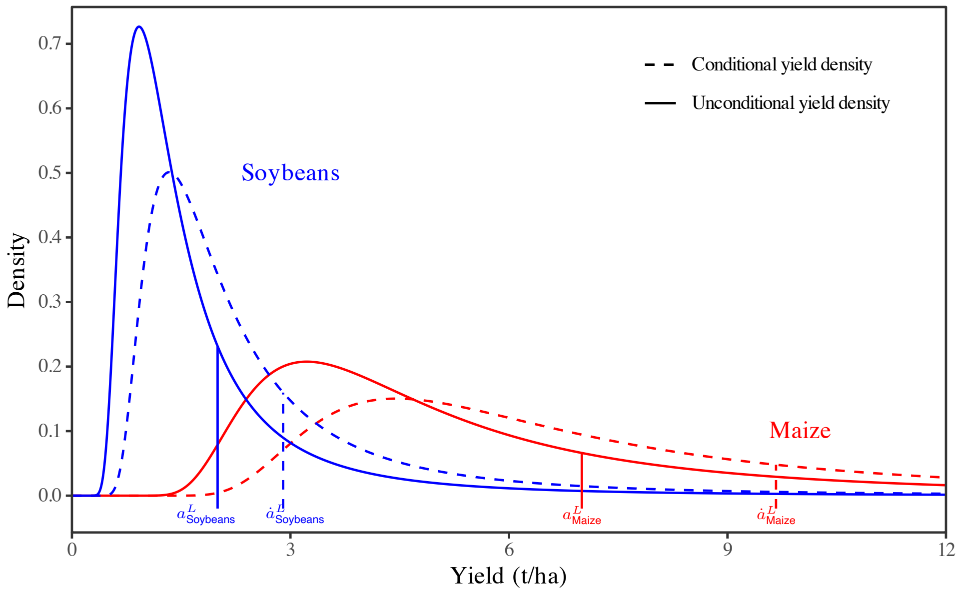

Figure 2: Conditional and unconditional yield distributions under Fréchet productivity. Expected unconditional yields are 2 tons per hectare for soybeans and 7 tons per hectare for maize; prices are US$400 per ton for soybeans and US$120 per ton for maize; $\theta = 2$; $a_k^X = a_k^M = 0$, and $\sigma_k = 0$.

Figure 2 also highlights a limitation of this approach. When unconditional land rents, R_k, become highly disparate, the crop with the highest rents occupies the majority of the land, causing its expected conditional yield to converge toward its expected unconditional value. Conversely, the crop with the lowest rents is only planted on parcels with the highest yields. Given the heavy right tail of the Fréchet distribution, this can push the expected conditional yield to unrealistically high values.

Elasticities. From equation (25), we can derive the own-price supply elasticity:

$$\frac{\partial \ln Y_k}{\partial \ln P_k} = \underbrace{\theta \frac{1-s_k}{\vartheta_k^L}}_{\text{Acreage}} + \underbrace{\left(\underbrace{-\frac{1-s_k}{\vartheta_k^L}}_{\text{Composition}} + \underbrace{\sigma_k \frac{\vartheta_k^X}{1-\vartheta_k^X}}_{\text{Intensification}} \right)}_{\text{Yield}}. \tag{26}$$

This formula shows that θ parameterizes the acreage elasticity but plays no role in the yield-composition elasticity, which is only determined by equilibrium values: the acreage share and the cost share of land. Since the acreage and yield-composition elasticities are both proportional to $(1-s_k)/\vartheta_k^L$, in the supply elasticity (outside intensification), the composition effect partially offsets the acreage effect, and the total elasticity is proportional to $\theta - 1 > 0$.

This modeling approach imposes strong constraints on both the acreage and yield-intensification elasticities. Since a Fréchet-distributed random variable has a finite mean only if $\theta > 1$ (see Appendix B), low acreage elasticities cannot be represented with this approach. For example, consider the conditions required to obtain an acreage elasticity below one. This requires $\theta < \vartheta_k^L(1-s_k)^{-1}$, which for most commodities will be incompatible with the constraint that $\theta > 1$. We can go one step further: this upper limit is itself above 1 only if $\vartheta_k^L + s_k > 1$—or in words, if the sum of the cost share of land and the acreage share exceeds one. Since typical cost shares of land are approximately 0.1–0.4 (Fuglie et al., 2024), this implies that it will not be possible to calibrate acreage elasticities below 1, except for crops that dominate the acreages. Since elasticity estimates below 1 are common in the literature (Carpentier and Letort, 2012, 2014; Li et al., 2019; Miao et al., 2016), this constraint is likely to lead to large discrepancies between calibrated and estimated elasticities.

The yield elasticity has an indeterminate sign because it is composed of two terms: an intensification effect, which is positive, and a composition effect, which is negative. Figure A1 represents the yield-composition elasticity as a function of s_k and ϑ_k^L. It shows that, except when acreage and land-cost shares are both high, the Fréchet specification implies a large negative composition elasticity. The literature provides little direct evidence against which to assess this mechanism. Stigler (2020, working paper) provides suggestive field-level evidence that aggregation can attenuate estimated yield-price responses. For corn, the preferred yield-price elasticity is about 0.18 in field-level regressions but close to zero after aggregation to pseudo-county averages, whereas the corresponding difference for soybeans is small. The paper attributes these patterns to changes in the mix of fields and cropping sequences, including both marginal-land entry and the loss of rotation benefits. It does not, however, directly estimate a composition elasticity comparable to equation (26). Even the implied field-to-county coefficient difference for corn is much smaller than many of the composition effects generated by the Fréchet specification for empirically plausible values of s_k and ϑ_k^L.

Calibration. As in the CET model, calibration uses deviations from the benchmark. The model can be defined by three equations related to production, land shares, and land rents:

$$\hat{Y}_k = \hat{a}_k^L \left\{ \left[1 - \vartheta_k^X \left(\frac{\hat{P}_X}{\hat{P}_k} \right)^{1-\sigma_k} \right] / \left(1 - \vartheta_k^X \right) \right\}^{\sigma_k/(1-\sigma_k)} \hat{s}_k^{(\theta-1)/\theta}, \tag{27}$$

$$\hat{s}_k = \frac{\hat{R}_k^\theta}{\sum_{l\in\mathcal{K}} s_l \hat{R}_l^\theta}, \tag{28}$$

with equation (16) characterizing the land rents. Thus, calibration requires the initial cost shares and acreage shares s_k, and the parameters θ and σ_k.

In this model, acreage and land-rent shares are equal, $s_k = \bar{s}_k$. Therefore, the model admits two theoretically compatible calibrations: one calibrated on acreage shares and the other calibrated on land-rent shares.

Dual and primal representations. We can define the landowner's profit function as the expectation, with respect to the distribution of land productivity shocks, of the land-rent function:

$$\Pi^F(\mathbf{R}) = \mathrm{E}\left[\max_{k\in\mathcal{K}} R_k \epsilon_k(\omega) \right] L, \tag{29}$$

which, from the above properties of the Fréchet distribution, is equal to $\Pi^F(\mathbf{R}) = RL$. Under the Daly–Zachary–Williams (DZW) theorem,[11] the profit function Π^F is differentiable with respect to the unconditional land rents R_k and its gradient is the vector of efficient acreages:

$$\frac{\partial \Pi^F(\mathbf{R})}{\partial R_k} = L_k \left(\frac{L_k}{L} \right)^{-1/\theta} = L s_k^{(\theta-1)/\theta} = L_k \dot{\epsilon}_k. \tag{30}$$

The gradient is not the vector of physical acreages, because R_k is not the rent of a physical hectare in general, but the rent of an hectare with unit productivity shock, $\epsilon_k(\omega) = 1$. The gradient instead equals the vector of efficiency-weighted acreages, where the weight $\dot{\epsilon}_k$ reflects the productivity selection effect.

The primal form corresponding to this dual profit function is

$$\max_{\mathbf{s}\in\Delta} L \sum_{k\in\mathcal{K}} R_k s_k^{(\theta-1)/\theta}, \tag{31}$$

where $\Delta = \{\mathbf{s} \geq 0 : \sum_{k\in\mathcal{K}} s_k = 1\}$. So, the equations obtained under the Fréchet-distributed-yield assumption can be obtained from a deterministic problem where yields evolve with specialization proportionally to $s_k^{-1/\theta}$.

Relationship with positive mathematical programming. This primal form makes the connection with positive mathematical programming transparent. In the land-only case, where $R_k = P_k a_k^L$, equation (31)

[11]The theorem is typically stated for an additive random-utility/logit problem. The present multiplicative problem has the same choice rule after the monotone transformation $r_k = \log R_k$: $\arg\max_k R_k \epsilon_k(\omega) = \arg\max_k \{r_k + \eta_k(\omega)\}$, with $\eta_k = \log \epsilon_k$. For Fréchet shocks with shape parameter θ, η_k is Gumbel (with scale $1/\theta$, up to the normalization used above), so the DZW theorem applies to the logit inclusive value in r. Since Π^F is the exponential of this inclusive value (times L and the normalization constant), its derivatives with respect to R_k follow by the chain rule.

is almost the same as equation (1) in Mérel et al. (2011), who study the calibration of PMP problems, particularly those in which yields are power functions of acreage, which corresponds to the primal deterministic form of the Fréchet approach.[12]

There are two key differences between the two approaches. First, the PMP literature often allows crop-specific rates of decreasing returns to scale by using different exponents on s_k rather than the common exponent $(\theta - 1)/\theta$, which enlarges the set of feasible calibrations that can be represented. Under the Fréchet assumption, achieving that same flexibility would require allowing for correlated yields, which we do in the following section, but at the cost of greater mathematical complexity.

Second, the two approaches rest on different microfoundations. The Fréchet model is based on a parcel-level discrete-choice problem with a specific distribution for yields and becomes tractable by integrating over a continuum of parcels. The PMP model is deterministic and directly postulates a functional form linking yields to acreages. Despite these different foundations, we have seen that they can be connected to the same primal problem and lead to the same equilibrium conditions.[13] This primal deterministic counterpart is also useful in the next section, where it helps motivate a logit solution without relying directly on a distributional assumption.

2.3 Multinomial logit

For this approach, we assume that land is of homogeneous quality, but we prevent complete specialization by introducing an acreage management function whose cost increases with specialization. We assume that the input that does not affect yields is used to pay for this acreage management. Production per hectare is given by

$$y_k = Y_k/L_k = \left[\left(a_k^L\right)^{(\sigma_k - 1)/\sigma_k} + \left(a_k^X x_k\right)^{(\sigma_k - 1)/\sigma_k} \right]^{\sigma_k/(\sigma_k - 1)}, \tag{32}$$

where y_k denotes yields, and $x_k = X_k/L_k$ denotes yield-enhancing input demand per hectare.

The per-hectare profit of a farmer is defined over all crops by

$$\pi = \sum_{k \in \mathcal{K}} s_k \left(P_k y_k - P_X x_k\right) - P_M f(\mathbf{s}), \tag{33}$$

where $f(\mathbf{s})$ is a convex management-cost function measured in units of input M. Here, we follow Carpentier and Letort (2014) by assuming that this function includes an entropy term. This assumption leads to a parsimonious system of multinomial logit acreage-share equations that closely resembles the preceding approaches.[14] We define the management function as

$$f(\mathbf{s}) = \sum_{k \in \mathcal{K}} c_k s_k + \alpha^{-1} \sum_{k \in \mathcal{K}} s_k \ln s_k, \tag{34}$$

where the $c_k > 0$ are parameters that allow the model to reproduce the initial acreage shares and $\alpha > 0$ is

[12] The PMP approach discussed here is also identical to the approach based on the CRETH function proposed by Horridge (2021) for equilibrium models.

[13] It is also trivial to show that a yield composition elasticity formula similar to that of equation (26) can be found for the PMP approach of Mérel et al. (2011) and the CRETH of Horridge (2021).

[14] An alternative would be to assume a quadratic management function (Carpentier and Letort, 2012), a common assumption in the PMP literature (Howitt, 1995).

a behavioral parameter that governs the acreage elasticity.

The entropy term has the following properties: it is negative, convex in the acreage shares, maximal at 0 when one share equals 1, and minimal when all shares are equal ($s_k = 1/|\mathcal{K}|$). These properties ensure that acreage shares remain strictly positive, thereby preventing full specialization. The higher the value of α, the lower the weight of the entropy term, causing the model to favor specialization in the most profitable crop.

Define crop-specific real profits—profits deflated by P_M and net of the linear management-cost terms—as $\varpi_k = (P_k y_k - P_X x_k - P_M c_k)/P_M$. For given $(\varpi_k)_{k\in\mathcal{K}}$, the acreage decision in (33) is an entropy-regularized allocation over the simplex Δ. It is useful to record not only the optimal acreage shares but also the maximized value of this allocation problem. The standard log-sum-exp formula gives

$$\varpi = \max_{s\in\Delta}\left\{\sum_{k\in\mathcal{K}} s_k\varpi_k - \alpha^{-1}\sum_{k\in\mathcal{K}} s_k \ln s_k\right\} = \alpha^{-1}\ln\sum_{k\in\mathcal{K}}\exp(\alpha\varpi_k). \tag{35}$$

The scalar ϖ is the logit inclusive value, or surplus, associated with acreage allocation. This value-function representation is also the deterministic counterpart of a stochastic rent-maximization problem with additive type I extreme-value heterogeneity (Galichon, 2026), up to the usual location constant. Thus, the same equations can be interpreted either as a random rent-maximization model or as an entropy-regularized deterministic profit-maximization problem.

The acreage shares themselves follow directly from maximizing the profit function (33) subject to $\sum_{k\in\mathcal{K}} s_k = 1$, yielding the multinomial logit acreage share equation

$$s_k = \frac{\exp(\alpha\varpi_k)}{\sum_{l\in\mathcal{K}}\exp(\alpha\varpi_l)}. \tag{36}$$

From the definition of ϖ, we can simplify equation (36) to

$$s_k = \exp\left[\alpha\left(\varpi_k - \varpi\right)\right]. \tag{37}$$

Maximizing the per-crop profit gives input demand:

$$x_k = y_k\left(\frac{P_k}{P_X}\right)^{\sigma_k}\left(a_k^X\right)^{\sigma_k-1}. \tag{38}$$

This allows yields to be expressed as a function of prices:

$$y_k = a_k^L\left[1-\left(\frac{P_X/P_k}{a_k^X}\right)^{1-\sigma_k}\right]^{\sigma_k/(1-\sigma_k)}. \tag{39}$$

We can express production as a function of prices only:

$$Y_k = L s_k a_k^L\left[1-\left(\frac{P_X/P_k}{a_k^X}\right)^{1-\sigma_k}\right]^{\sigma_k/(1-\sigma_k)}, \tag{40}$$

but for this we need an expression for ϖ_k as a function of prices:

$$\varpi_k = \frac{a_k^L}{P_M}\left[P_k^{1-\sigma_k} - \left(P_X/a_k^X\right)^{1-\sigma_k}\right]^{1/(1-\sigma_k)} - c_k. \tag{41}$$

This approach has markedly different properties from the preceding approaches. Input M is not a standard crop-level Leontief input in the production technology; it pays for a management function over the whole acreage vector. The linear term can be represented crop by crop through c_k, but the entropy term is tied to the acreage allocation itself. This characteristic is reminiscent of the use of management functions in PMP, where the focus is on the gross margin and where, apart from the inputs that are explicitly modeled, it is not generally possible to allocate all remaining inputs (e.g., labor and capital) to individual crops. The difference is the regularizer: quadratic PMP uses a quadratic penalty, whereas the multinomial logit uses the entropy penalty.

Elasticities. From the above, we can calculate the own-price supply elasticities:

$$\frac{\partial \ln Y_k}{\partial \ln P_k} = \underbrace{\alpha \frac{P_k y_k}{P_M}(1-s_k)}_{\text{Acreage}} + \underbrace{\sigma_k \frac{\vartheta_k^X}{1-\vartheta_k^X}}_{\text{Intensification}}. \tag{42}$$

This approach neatly distinguishes the acreage from the yield elasticity: the former is governed by the management-cost parameter α, while the latter is governed by the CES substitution elasticity σ_k for a given benchmark cost share ϑ_k^X.

Calibration. Contrary to the other approaches, the multinomial logit is calibrated in levels rather than in deviations from the benchmark, because of its exponential and additive structure; initial prices, when needed, are assumed to be observed but are typically normalized to unity. The surplus and the crop-specific real profits are recovered from the land rents and the initial acreages,

$$\varpi = \pi/P_M, \tag{43}$$

$$\varpi_k = \varpi + \alpha^{-1}\ln s_k. \tag{44}$$

Given the substitution elasticity σ_k, the CES shifters follow from the benchmark input–output ratio as

$$a_k^X = \frac{P_X}{P_k}\left(\vartheta_k^X\right)^{-1/(1-\sigma_k)} \text{ and } a_k^L = y_k\left(1-\vartheta_k^X\right)^{-\sigma_k/(1-\sigma_k)}. \tag{45}$$

Finally, the management-cost shifters are calibrated as

$$c_k = \left(P_k y_k - P_X x_k\right)/P_M - \varpi_k, \tag{46}$$

which reproduce both the acreage shares (contained in the ϖ_k) and the total expenditure on input M. Because acreage shares sum to one, the remaining degree of freedom allows the model to match the initial value of $P_M M$. Thus, calibration requires the initial land rents π,[15] acreage shares s_k, per-hectare

[15] In reality, since from equation (37), only the difference between ϖ_k and ϖ matters, it is possible to assume any land rent value for calibration.

revenues $P_k y_k$, input cost shares ϑ_k^X, and the parameters α and σ_k.

2.4 Comparison of the three modeling approaches

We can now compare these three approaches for modeling acreage choices.

Comparing CET and Fréchet. We consider two sources of shocks: prices and land productivity with shocks expressed in deviation from baseline as $\hat{P}_k$ and $\hat{a}_k^L$. Proposition 2 shows that, despite their different microfoundations, the two approaches, when calibrated identically, deliver the same counterfactual predictions except for land demand, which differs.

Proposition 2. *Calibrated on the same initial shares of land rents $\bar{s}_k$ and for behavioral parameters such that $\theta = 1 - \eta$, the acreage models based on the Fréchet distribution function and on the CET function deliver the same counterfactual changes for production but different counterfactual changes for land demand.*

The comparison can also be expressed in terms of the profit functions for land allocation. In the CET model, the profit function is $\Pi^C(\mathbf{R}) = R\bar{L}$, so Hotelling's lemma gives the demand for efficient land, $\partial\Pi^C(\mathbf{R})/\partial R_k = \bar{L}_k$. In the Fréchet model, efficient land is derived from the DZW theorem in equation (30). This object plays the same dual role in both models. Under the assumptions of Proposition 2, and normalizing $\bar{L} = L$, we have $\bar{L}_k = L_k s_k^{-1/\theta}$. One implication of this result and Proposition 2 is that the Fréchet approach can be seen as a way to explicitly decompose CET efficient land into physical acreage and yield components. Since their counterfactual predictions for production are the same, switching a model from an approach based on a CET function to an approach based on the Fréchet distribution will lead to the same market equilibrium while producing consistent acreage results.

Proposition 2 is not original. The equality of production across the CET and Fréchet approaches was already noted by Taheripour et al. (2020) and is reminiscent of Arkolakis et al. (2012)'s result that Armington and Eaton–Kortum trade models yield the same counterfactual changes in trade values and welfare.

Comparing the multinomial logit to the other approaches. The comparison of the multinomial logit with the CET and Fréchet approaches is less direct than the comparison between the latter two, because it relies on a different mechanism to prevent complete specialization: homogeneous land with convex management costs, or equivalently additive stochastic rent heterogeneity, rather than heterogeneous land quality. This difference is reflected in the structure of the supply elasticities: in the CET and the Fréchet models, the non-intensification component of the own-price elasticity is $-\eta(1 - \bar{s}_k)/\vartheta_k^L$, modulated by the inverse cost share of land, whereas in the multinomial logit it is $\alpha P_k y_k(1 - s_k)/P_M$, modulated by per-hectare crop revenue.

Despite these differences, the supply elasticities can be matched under specific conditions.

Proposition 3. *Assume that the three models use the same CES yield technology and are evaluated at a common benchmark with acreage shares s_k, yields y_k, and land cost shares ϑ_k^L. Suppose that the observed land cost per hectare is common across crops, so that there exists a scalar R satisfying $\vartheta_k^L = R/(P_k y_k)$ for all k. Locally around this benchmark, the supply elasticities of the multinomial logit model coincide with those of the CET and Fréchet models when $\theta - 1 = -\eta = \alpha R/P_M$.*

The equivalence rests on two conditions. The first is the equality of observed per-hectare land costs, which implies the CET–Fréchet equivalence (Proposition 2) and ensures that $1/\vartheta_k^L$ is proportional to $P_k y_k$, so that the crop-specific weights in the elasticity formulas coincide. In the CET model, this condition can be represented as equality of the crop-specific rents R_k. In the Fréchet model, the primitive rent indices R_k generally differ across crops to reproduce acreage shares; the relevant R in the proposition is the common observed land return per hectare generated by the selection mechanism. When observed per-hectare land costs differ across crops, the two weights diverge: the multinomial logit elasticity is driven by per-hectare crop revenue while the CET/Fréchet elasticity is driven by the inverse land cost share.

The second condition is a parameter normalization linking α to θ (or η). Because $P_k y_k$ cancels from the equivalence condition, a single scalar relationship $\alpha = (\theta - 1)P_M/R$ suffices for all crops simultaneously. This also clarifies the nature of α. Unlike θ and η, it is not dimensionless. We can define $\tilde{\alpha} \equiv \alpha R/P_M$, a dimensionless parameter directly comparable to θ and η.

This result is only a local equivalence. Proposition 2 is stronger because, once calibrated, it implies that the CET and Fréchet approaches share the same exact counterfactual system for production. Proposition 3, by contrast, only matches the own-price elasticities at the calibration point. For nonmarginal shocks, the models generally diverge because their nonlinear structures differ: acreage shares in the CET and Fréchet approaches are power functions of land rents, whereas in the multinomial logit they are exponential functions of real profits. Equal elasticities at the benchmark therefore do not imply identical counterfactual paths. Moreover, even when total supply elasticities are matched, their decomposition differs sharply. In the Fréchet model, the acreage response is larger because it is partly offset by a negative yield-composition effect; in the multinomial logit, the yield response is purely an intensification response and the acreage response is governed by convex management costs. Hence, two calibrations can generate the same own-price supply elasticity while implying very different adjustments in hectares and yields, a distinction that matters whenever the objective is to analyze physical acreage changes rather than only output responses.

3 Estimations

This section estimates a farm-level and more flexible version of the multinomial logit model. We consider two yield-enhancing inputs, replace the CES yield function with a quadratic function to obtain linear first-order conditions and more flexibility with two inputs, and replace the simple entropic term with nested terms to obtain a nested multinomial logit (NMNL) setup. Moving to a nested specification is important for both estimation and simulation. In the one-level models studied above, acreage elasticities are scaled by crop-specific objects such as per-hectare revenues in the multinomial logit and land cost shares in the CET/Fréchet approaches; because these observables can differ substantially across crops, a single top-level parameter may generate implausibly dispersed elasticities. Nesting provides additional parameters that allow substitution patterns to vary across crop groups and thus offers tighter control over the implied elasticity structure.

A second reason to introduce nests is that one-level acreage systems impose strong restrictions on cross-price elasticities: the multinomial logit exhibits the familiar independence of irrelevant alternatives property, and the one-level CET and Fréchet approaches are similarly constrained because all crops compete in a single substitution nest. By introducing the agronomically meaningful nests illustrated in figure 3, we can allow closer substitutes to respond more strongly to one another while preserving tractability. That same nested structure can then be carried through to the simulation models, providing a natural bridge between the econometric specification and the equilibrium applications.

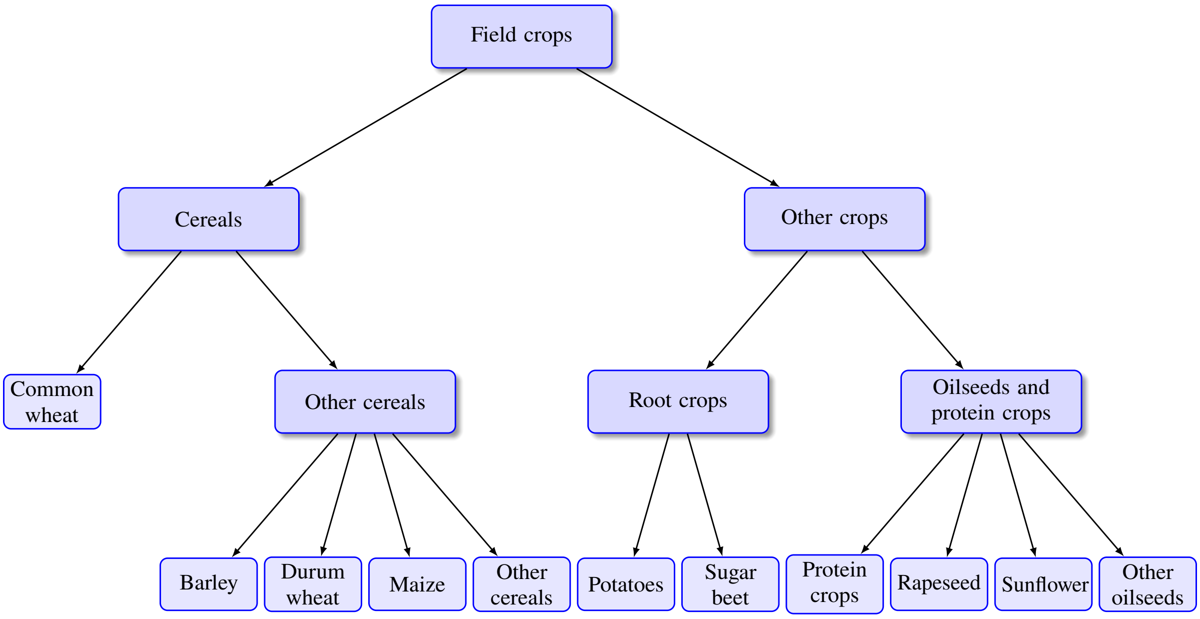

Figure 3: Crop nesting structure used for estimation and simulation.

3.1 Nested multinomial logit specification

To move from the simple multinomial logit of section 2.3 to the nested structure used for estimation, let node 1 denote the root of the tree represented in figure 3, $\mathcal{N}$ the set of non-root nodes, $\mathcal{K} \subset \mathcal{N}$ the set of crops (the leaf nodes), and $\mathcal{I} \equiv \{1\} \cup (\mathcal{N} \setminus \mathcal{K})$ the set of internal nodes, including the root. Let $p(n)$ denote the parent of non-root node n, and let $C(n)$ denote the children of node n. For each node $n \in \{1\} \cup \mathcal{N}$, let s_n denote its acreage share, so that $s_1 = 1$ and $\sum_{c \in C(n)} s_c = s_n$ for every $n \in \mathcal{I}$. We assume a nested management function,

$$f(\mathbf{s}) = \sum_{k \in \mathcal{K}} c_k s_k + \sum_{n \in \mathcal{I}} \alpha_n^{-1} \sum_{c \in C(n)} s_c \ln\left(\frac{s_c}{s_n}\right), \tag{47}$$

where $\alpha_n > 0$ and governs substitution among the children of node $n \in \mathcal{I}$. The management function is a weighted sum of convex functions, so positivity of the α_n is sufficient for convexity of the nested management function: no ordering of these parameters across levels is required. At a boundary point where $s_n = 0$, feasibility implies that every child of n also has zero share, and the node contribution is defined by continuity to be zero.

Although it is not required for convexity of the nested entropy, we impose in the estimation $\alpha_{p(n),i} \leq \alpha_{n,i}$ for every $n \in \mathcal{N} \setminus \mathcal{K}$. This ordering guarantees that substitution is weakly stronger within nests than across them—the pattern motivating the nesting—and is the Daly–Zachary–McFadden condition for consistency with the random-utility interpretation of the nested logit (Daly and Zachary, 1978; McFadden, 1978). Importantly for our purpose, it allows a cross-approach calibration in section 4.1, because a similar ordering is required for a valid nested max-stable Fréchet distribution.

As in the simple multinomial logit case, the relevant object of choice is the node- or crop-specific real profit. For crop k, we again use ϖ_k. The nested structure is summarized by recursively defined composite real profits:[16]

$$\varpi_n = \alpha_n^{-1} \ln \left(\sum_{c \in C(n)} \exp\left(\alpha_n \varpi_c\right) \right) \qquad \forall n \in \mathcal{I}, \tag{48}$$

with $\varpi_1 = \varpi$ denoting the top-level composite. The first-order conditions then imply that acreage shares can be computed recursively over the tree as

$$s_c = \exp\left[\alpha_n \left(\varpi_c - \varpi_n\right)\right] s_n \qquad \forall n \in \mathcal{I}, \forall c \in C(n). \tag{49}$$

For example, the share of a crop such as common wheat is obtained by recursively multiplying the root share by the relevant within-node logit terms along the path to that crop.

This nested specification relaxes the restrictive cross-elasticity structure of the simple multinomial logit by allowing substitution to be stronger within agronomically close groups than across distant groups. It also remains fully consistent with the deterministic entropy-regularization interpretation used in section 2.3, which is useful for the subsequent calibration of the simulation model. In the empirical specification, this nested acreage system is combined with a quadratic yield function, following Koutchadé et al. (2021), so that both acreage and yield responses can be identified from farm-level variation.

3.2 Data

The econometric estimation uses specialized crop farms from the European Commission's French Farm Accountancy Data Network (FADN) observations for 2016–21, yielding a rotating panel of 4,264 observations from 908 farms, observed over an average of four years. The observations are drawn from the 2015–21 raw data; 2015 is retained only for lagged output-price regressors, which cover 2015–20. French regions exhibit substantial heterogeneity in pedoclimatic conditions, so not all crops depicted in figure 3 can be grown across the entire national territory. To account for this spatial heterogeneity, we partition the sample into four main agro-climatic zones and estimate our endogenous regime-switching crop choice model separately within each zone. As illustrated in figure A2, farms in one zone have access to the full set of crops considered in the analysis; in the other zones, some crops are grown by very few or no farms in our sample, consistent with unfavorable pedoclimatic conditions or the absence of a local processing/marketing outlet, and are therefore excluded from the choice set available to farms in those regions.

FADN provides farm-level, but not crop-level, input expenditures, which are required to estimate our model. We therefore allocate crop protection and fertilizer expenditures to the crops produced by each farmer using the `winputall` R package, which implements the input allocation method described in Koutchadé et al. (2024). Summary statistics, accounting for the representativeness of each farm in our sample through FADN weights, are reported in table A1.

Output prices are readily obtained at the farm level in FADN data, as the ratio of output values to quantities, but the data contain no information on input prices or input quantities. We thus use the input

[16] In the discrete choice literature, the log-sum-exp aggregate ϖ_n is known as the *inclusive value* of nest n (McFadden, 1978).

price indices published by the French Ministry of Agriculture (IPAMPA, base 1 in 2020) and assume that input prices are the same for all farms in France.[17] These indices allow us to express input quantities in constant 2020 euros. Because input prices are common to all farms and crops in a given year, the identifying variation for input-price effects comes exclusively from their time-series variation over the 2016–21 period, rather than from cross-sectional or crop-level differences.

3.3 Econometric model

The estimated econometric model is similar to the microeconometric multicrop model with endogenous regime switching presented in Koutchadé et al. (2021), with one important difference: here, we consider two inputs rather than one, $j \in \mathcal{J} \equiv \{\text{pesticides}, \text{fertilizers}\}$. Derived from a quadratic production function, the model consists of yield, input-use, and acreage-choice equations (50)–(53) for each crop k produced by farmer i in period t, as well as a "production regime choice" equation (54) that determines, in each period, the set of crops the farmer chooses to produce from the feasible set $\mathcal{R}$. Appendix F derives the structural farm-level model underlying this econometric specification.

$$y_{k,it} = \beta^y_{k,i} + \left(\boldsymbol{\delta}^y_{k,0}\right)^\top \mathbf{z}_{k,it} - 0.5 P^{-2}_{k,it} \left(\mathbf{P}_{X,t}\right)^\top \boldsymbol{\Gamma}_{k,i} \mathbf{P}_{X,t} + \varepsilon^y_{k,it}, \tag{50}$$

$$\mathbf{x}_{k,it} = \boldsymbol{\beta}^x_{k,i} + \left(\boldsymbol{\Delta}^x_{k,0}\right)^\top \mathbf{z}_{k,it} - P^{-1}_{k,it} \boldsymbol{\Gamma}_{k,i} \mathbf{P}_{X,t} + \boldsymbol{\varepsilon}^x_{k,it}, \tag{51}$$

$$s_{c,it}(r) = \exp\left[\alpha_{n,i}\left(\varpi_{c,it}(r) - \varpi_{n,it}(r)\right)\right] s_{n,it}(r), \quad n \in \mathcal{I},\ c \in C_r(n), \tag{52}$$

$$\varpi_{n,it}(r) = \alpha^{-1}_{n,i} \ln\left(\sum_{c \in C_r(n)} \exp\left(\alpha_{n,i}\varpi_{c,it}(r)\right)\right), \quad n \in \mathcal{I}, \tag{53}$$

$$\Pr\left(r_{it} = r\right) = \frac{\exp\left[\varsigma_i\left(\varpi_{1,it}(r) - \sum_{k \in \mathcal{K}^+(r)} \beta^r_{k,i}\right)\right]}{\sum_{r' \in \mathcal{R}} \exp\left[\varsigma_i\left(\varpi_{1,it}(r') - \sum_{k \in \mathcal{K}^+(r')} \beta^{r'}_{k,i}\right)\right]}, \tag{54}$$

where $\mathbf{P}_{X,t}$ is the vector of input prices at time t, $P_{k,it}$ denotes the output price expected at the time production choices for year t are made. These expected prices are proxied empirically by the previous-year output prices, $\mathbf{z}_{k,it}$ is a set of control variables (time dummies, farm size measured by farm capital) introduced in the yield and input use equations (50) and (51), $\mathcal{K}^+(r)$ is the set of crops grown under regime r, $C_r(n)$ is the set of children active under regime r, $s_{1,it}(r) = 1$, and $s_{k,it} = s_{k,it}(r_{it})$ for observed acreage shares. The crop-level profit $\varpi_{k,it}$ is not regime-specific; when it appears inside the recursion, $\varpi_{k,it}(r) \equiv \varpi_{k,it}$ for crop leaves active under r. The regime fixed cost $\beta^r_{k,i}$ is expressed in real units, consistently with $\varpi_{1,it}(r)$.

The per-hectare real profit for crop k is equal to

$$\varpi_{k,it} = \left[\mathrm{E}\left(P_{k,it} y_{k,it}\right) - \mathbf{P}^\top_{X,t}\,\mathrm{E}\left(\mathbf{x}_{k,it}\right)\right]/P_M - \beta^s_{k,it}, \tag{55}$$

where

$$\beta^s_{k,it} = \beta^s_{k,i} + \left(\boldsymbol{\delta}^s_{k,0}\right)^\top \mathbf{z}_{k,it} + \varepsilon^s_{k,it}. \tag{56}$$

[17] As in section 2, input prices are also assumed to be the same across all crops.

Most model parameters are assumed to be farm-specific and randomly distributed across the population of farmers in order to capture unobserved heterogeneity in farmers' behavior. Empirically, we assume that the set of (transformed) random parameters $\boldsymbol{\zeta} \equiv \left(\ln(\boldsymbol{\beta}^{y}), \ln(\boldsymbol{\beta}^{x}), g(\boldsymbol{\Gamma}), \boldsymbol{\beta}^{s}, \boldsymbol{\alpha}, \ln(\varsigma), \boldsymbol{\beta}^{r}\right)$ follows a normal distribution, $\mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Theta}^{\zeta})$.[18] We also assume that the error-term vectors $\boldsymbol{\varepsilon}^{xy} \equiv (\boldsymbol{\varepsilon}^{y}, \boldsymbol{\varepsilon}^{x})$ and $\boldsymbol{\varepsilon}^{s}$ are normally distributed, with $\boldsymbol{\varepsilon}^{xy} \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Theta}^{xy})$ and $\boldsymbol{\varepsilon}^{s} \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Theta}^{s})$. The matrices $\boldsymbol{\Theta}^{\zeta}$, $\boldsymbol{\Theta}^{xy}$, and $\boldsymbol{\Theta}^{s}$ are unrestricted variance-covariance matrices, and we assume that $\boldsymbol{\zeta}$, $\boldsymbol{\varepsilon}^{xy}$, and $\boldsymbol{\varepsilon}^{s}$ are mutually independent.[19]

The model is therefore fully parametric, which allows us to estimate it using maximum likelihood. More precisely, we use a Stochastic Approximation Expectation Maximization algorithm (Delyon et al., 1999), as in Koutchadé et al. (2018, 2021).

Empirically, this paper extends Koutchadé et al. (2021) along two dimensions. First, rather than focusing on a geographically limited and pedoclimatically homogeneous area, we estimate the model for the whole of France while accounting for heterogeneity across pedoclimatic regions, with similar regions aggregated into common zones. Second, instead of using a single aggregate input, we distinguish between two variable inputs in arable crop production—pesticides and fertilizers. Although this distinction substantially increases the dimensionality of the parameter matrix to be estimated, it allows for a richer representation of farmers' production decisions.

3.4 Selected estimation results

Given the paper's objectives, we restrict the exposition here to market-level own-price elasticities. The model is estimated on panel data, but the elasticities are calculated for the year 2021. Elasticities are first calculated at the farm level. The acreage elasticities are then aggregated using either acreage-share or output-share weights, while yield elasticities are aggregated with output-share weights, with FADN sampling weights used to aggregate farms to the regional level. We then aggregate them to the national level using the corresponding regional weights. Appendix G details these computations: the farm-level formulas are integrated over the posterior distribution of the farm-specific parameters, and the reported elasticities are the price responses of the resulting aggregate French acreage and production. Table 1 presents the estimated own-price acreage and yield elasticities. The appendix reports the full estimated output-weighted cross-price acreage-elasticity matrix in table A2.

The acreage elasticity estimates are aligned with the literature. The U.S. corn-soybean system has been studied extensively. Recent estimates include 0.29 for corn and 0.26 for soybeans in Hendricks et al. (2014, long-run), 0.45 for corn and 0.65 for soybeans in Miao et al. (2016), 0.39 for corn and 0.26 for soybeans in Kim and Moschini (2018, long-run), 0.21 for corn in Li et al. (2019), and 0.57 for the national acreage-weighted long-run rotational response of corn in Pates and Hendricks (2021). The estimate for France's dominant crop, common wheat, at 0.33, is similar.

The literature on yield elasticities is less extensive, but our estimates are much lower than most published values (e.g., Carpentier and Letort, 2012; Miao et al., 2016). As noted in section 3.2, input prices vary only over time in our data, and they moved little over the estimation period,[20] so the intensification

[18] Assuming log-normal distributions ensures the positivity of β^{y}, β^{x}, and ς. The ordering condition $\alpha_{p(n),i} \leq \alpha_{n,i}$ is imposed by reparameterization: the log-normally distributed vector $\boldsymbol{\alpha}$ actually contains strictly positive increments α^{0}, from which the nesting parameters are built recursively as $\alpha_{n,i} = \alpha^{0}_{n,i} + \alpha_{p(n),i}$, with $\alpha_{1,i} = \alpha^{0}_{1,i}$ at the root. Finally, $g(\cdot)$ is a Cholesky-type transformation that ensures both the positive definiteness of the $\boldsymbol{\Gamma}$ matrix and the positivity of its off-diagonal elements, thereby guaranteeing complementarity between the two inputs considered here: fertilizers and pesticides.

[19] See the last paragraph of Appendix F for a discussion of these assumptions.

[20] This is especially striking for fertilizer prices, which usually vary more than pesticide prices.

Table 1: Estimated own-price acreage and yield elasticities.

	Acreage				Yield	
	Acreage-weighted		Output-weighted		Output-weighted	
	Estimate	SE	Estimate	SE	Estimate	SE
Barley	0.47	0.02	0.46	0.01	0.02	0.00
Common wheat	0.33	0.01	0.33	0.01	0.02	0.00
Durum wheat	0.84	0.17	0.73	0.19	0.03	0.00
Maize	0.88	0.10	0.74	0.09	0.02	0.01
Other cereals	1.11	0.34	1.09	0.21	0.01	0.00
Other oilseeds	0.98	0.42	0.63	0.08	0.03	0.00
Potatoes	1.41	0.17	1.52	0.13	0.00	0.00
Protein crops	0.53	0.07	0.40	0.02	0.01	0.00
Rapeseed	0.55	0.05	0.53	0.06	0.02	0.01
Sugar beet	0.61	0.08	0.57	0.02	0.02	0.00
Sunflower	0.56	0.05	0.50	0.02	0.01	0.00

Notes: Calculated for France in 2021.

response is identified over a narrow range of price variation and should not be extrapolated to large input-price shocks.

Farm-level elasticities can be aggregated using acreage or output weights. Weighting acreage elasticities by acreage recovers the physical acreage elasticity, while weighting by quantities recovers the acreage elasticity plus a composition elasticity. Indeed, if yields are heterogeneous across farms, average yields will change with acreage, independently of the yield-intensification margin. The difference between the quantity-weighted and acreage-weighted acreage elasticities therefore gives a yield-composition elasticity that is an empirical counterpart to the Fréchet term presented in equation (26). The objects are not identical: our measure captures heterogeneity between farms, whereas the Fréchet elasticity captures parcel-level selection and therefore also includes intra-farm heterogeneity.

To our knowledge, the closest comparable measure is provided by Pates and Hendricks (2021). They estimate a field-level U.S. corn-choice model, although the price-response coefficients are estimated by land-resource and soil group and the quantity weights use county-level yields. Their national long-run rotational estimates are 0.574 when weighted by acreage and 0.541 when weighted by quantity. The difference, -0.033, can be interpreted as a county-yield-based composition elasticity: its negative sign indicates that the corn acreage response is relatively larger among fields located in lower-yield counties. The paper does not report statistical inference for this implied difference.

Our estimates provide a similar qualitative picture. The composition effect is negative for most crops and generally small, although it is positive for potatoes. Because the covariance between the two weighting-based estimates is not available, we do not assess the statistical significance of their difference. Both our estimates and the difference implied by Pates and Hendricks (2021) are much smaller in magnitude than the composition elasticities imposed by the calibrated Fréchet model.

4 Simulations

4.1 Calibration

This section calibrates the three approaches introduced in section 2 to the preceding estimates and compares their responses in illustrative simulations. We calibrate the NMNL approach on the estimates and use the nested extension of Proposition 3, stated in Proposition 5 in Appendix E, to calibrate nested CET and Fréchet approaches so they replicate the same calibrated elasticities.[21] All approaches adopt the nesting structure presented in figure 3.

For the calibration of the NMNL, we distinguish two types of moments: the initial supply situation and the behavior around this situation, namely the price elasticities. The model exactly reproduces the initial allocation and the yield-price elasticity; the initial situation consists of the following information: acreages s_k, per-hectare real revenues $P_k y_k / P_M$, and budget shares of yield-enhancing inputs ϑ_k^X. However, regarding the acreage elasticities, the econometric model is more flexible than the simulation model, so the estimated behavior cannot be exactly reproduced.

This calibration is best understood as matching aggregate empirical moments, not as an exact aggregation of the econometric model. The farm-level estimation uses a flexible quadratic yield specification to estimate acreage and yield responses, whereas the simulation models use CES yield functions to keep the CET, Fréchet, and NMNL frameworks comparable. The functional-form mismatch is secondary: neither quadratic nor CES technologies generally aggregate exactly from heterogeneous farms or parcels to the market level. The Fréchet model has a clearer micro-to-macro interpretation, since its aggregate equations are obtained by integrating parcel-level choices under a specific distribution of land heterogeneity; parcel-level logit land-use models have a similar structure. This elegance, however, relies on strong assumptions about the distribution and independence of heterogeneity terms. We therefore use the estimated elasticities as empirical targets for the aggregate model, rather than treating them as the exact macro counterpart of the farm-level technology. Since we want to obtain market-level elasticities, we use the output-weighted elasticities as calibration targets.

To formalize the calibration procedure, let $\boldsymbol{\varphi}$ denote the vector of cross-price acreage elasticities that we want the simulation model to target and $\boldsymbol{\alpha}$ the vector of structural parameters to be calibrated. The model is calibrated by minimizing the weighted distance between the elasticities $\boldsymbol{\varphi}^{\text{est}}$, obtained from the preceding structural estimation, and the elasticities from the simulation model $\boldsymbol{\varphi}(\boldsymbol{\alpha})$, which are functions of the model's structural parameters $\boldsymbol{\alpha}$. For the calibration to be valid in the nested Fréchet case, we retain the ordering $0 < \alpha_{p(n)} \leq \alpha_n$ for every $n \in \mathcal{N} \setminus \mathcal{K}$. Denoting this feasible set by $\mathcal{A}$, the calibration formula is

$$\boldsymbol{\alpha}^{\text{cal}} = \underset{\boldsymbol{\alpha} \in \mathcal{A}}{\arg\min} \left[\boldsymbol{\varphi}^{\text{est}} - \boldsymbol{\varphi}(\boldsymbol{\alpha})\right]^\top \mathbf{W} \left[\boldsymbol{\varphi}^{\text{est}} - \boldsymbol{\varphi}(\boldsymbol{\alpha})\right], \tag{57}$$

where $\mathbf{W}$ is a symmetric, nonnegative-definite weighting matrix, constructed as the inverse of the covariance matrix of the estimates $\boldsymbol{\varphi}^{\text{est}}$.

The nested CET and Fréchet models are then calibrated from the calibrated NMNL parameters using Proposition 5. With R denoting the common benchmark per-hectare land cost, the nested CET and Fréchet transformation parameters at each internal node $n \in \mathcal{I}$ are set so as to match the same local

[21] See Appendices B.3 and C for the exposition of the nested Fréchet and CET approaches.

supply-elasticity matrix:

$$\theta_n^{\mathrm{cal}} - 1 = -\eta_n^{\mathrm{cal}} = \alpha_n^{\mathrm{cal}} R/P_M = \tilde{\alpha}_n^{\mathrm{cal}}. \tag{58}$$

With this calibration, the nested Fréchet reproduces the same output elasticities as the two other approaches. However, its acreage elasticities differ from those of the NMNL approach. Given the properties of the Fréchet approach exposed in section 2.2—in particular that it can generate acreage elasticities below one only under extreme conditions—it would not have been possible to calibrate its acreage elasticities directly.

Calibrating the three models so they replicate identical output elasticities requires information on average land rents, R. Because land rents are not usually available in farm accounting data, we construct them from other information available in FADN data. We calculate land rent as a residual using a value-added decomposition approach at the regional level. The calculation proceeds in five steps. First, for each region and year we estimate a reference wage rate as the weighted average hourly wage of hired labor, using only farms that report positive hired labor hours and wages paid. Second, we compute total labor remuneration for each farm by multiplying total labor input by this regional reference wage, thereby imputing a cost for both hired and family labor at the same rate. Third, we set capital remuneration equal to 3% of net capital assets, reflecting an opportunity cost of capital. Fourth, we aggregate output value, intermediate consumption, labor remuneration, capital remuneration, and subsidies at the regional level using FADN farm weights. Finally, we calculate regional land rent as the residual of output plus subsidies after subtracting intermediate consumption and labor and capital remuneration; this residual is then expressed per hectare of utilized agricultural area to obtain a land rent per hectare for each region and year.

Table 2 reports the calibrated behavioral parameters: the parameters $\tilde{\alpha}_n$ for the internal nodes and the own-price elasticities. The appendix reports the full calibrated cross-price acreage-elasticity matrices for the NMNL and nested Fréchet calibrations in tables A3 and A4. For the nest "Other crops", the Fréchet-compatibility condition $\alpha_{p(n)} \leq \alpha_n$ is binding, which indicates that the calibration pushes against the lower limit on within-nest substitution at this node. The corresponding values of θ_n^{cal} range from 1.15 to 1.28. These values lie near the lower end of the range reported in the literature—2.46 in Costinot et al. (2016), 1.66 in Sotelo (2020), and 1.38 in Farrokhi and Pellegrina (2023).

The table separates the acreage response in the NMNL model, the acreage response implied by the nested Fréchet calibration, and the Fréchet yield-composition component. Because of Proposition 5, the Fréchet acreage and yield-composition elasticities sum to the corresponding NMNL acreage elasticity, which also equals the non-intensification component of the CET own-price elasticity. All Fréchet acreage elasticities exceed one, whereas only two of the estimated elasticities do so, which confirms that the Fréchet calibration is far from the estimated acreage responses.

Some of the implied Fréchet acreage elasticities are large, exceeding 3 for durum wheat, maize and sugar beet, and 10 for potatoes. From equation (26), these values are explained by the combination of low acreage shares and low land cost shares. The Fréchet acreage elasticities would then be even larger if one were to adopt the larger shape parameters estimated in the new quantitative trade model literature. The yield-composition elasticities are also large. Given that yield elasticities reported in the literature are typically between 0 and 0.25, these composition effects imply strongly negative total yield elasticities in the Fréchet model. The limited comparable evidence supports a negative composition mechanism but not

Table 2: Calibrated behavioral parameters and elasticities.

Internal node	$\tilde{\alpha}^{\text{cal}}$	Commodity	Own-price elasticities		
			NMNL	Fréchet	
			acreage	acreage	yield composition
Field crops	0.154	Barley	0.37	1.81	−1.43
Cereals	0.266	Common wheat	0.27	1.43	−1.16
Other cereals	0.273	Durum wheat	0.73	3.42	−2.68
Other crops	0.154	Maize	0.66	3.14	−2.48
Root crops	0.216	Other cereals	0.33	1.54	−1.21
Oilseeds and protein crops	0.275	Other oilseeds	0.46	2.15	−1.69
		Potatoes	1.67	10.09	−8.43
		Protein crops	0.23	1.11	−0.88
		Rapeseed	0.42	2.49	−2.06
		Sugar beet	0.48	3.24	−2.76
		Sunflower	0.44	2.18	−1.74

effects approaching these magnitudes.

4.2 Results

To illustrate behavior under each model, we simulate the effects of a 25% price increase for a single crop. We focus on three crops—common wheat, rapeseed, and potatoes—chosen to represent low, medium, and high acreage elasticities in the Fréchet model. Table 3 compares the nested Fréchet and NMNL responses in yields, acreage, and production. By Proposition 4, the nested CET and nested Fréchet calibrations generate identical production changes for any counterfactual change in prices or land productivity; for this reason, nested CET is omitted from the table.[22]

Although the nested Fréchet and nested logit are calibrated to match the same local output elasticities, the nested Fréchet embeds an endogenous selection effect: expanding crops move onto less suitable land, while contracting crops retain their best land. This yield-composition mechanism dampens output changes away from the benchmark, so nonmarginal production responses tend to be smaller in absolute value than in the nested logit, where output tracks acreage more directly.

The divergence between the nested logit and Fréchet responses increases from wheat to rapeseed and then to potatoes because the Fréchet calibration implies an increasingly strong negative yield-composition effect for these crops. Away from the benchmark, this selection effect dampens the translation of acreage gains into output gains. The divergence is modest for wheat, larger for rapeseed, and largest for potatoes, for which the matched local elasticity is obtained as the difference between a large acreage response and a nearly offsetting negative composition response. The simulated yield changes show this selection mechanism directly, with large yield declines for the crops whose prices increase. A 19% decline in common wheat yield following a 25% price increase is already much larger than the modest composition effects found in our estimates and the limited comparable evidence; the 66% decline for potatoes illustrates how quickly the Fréchet mechanism can generate implausible responses away from the benchmark. The

[22] Because the models are calibrated under the assumptions of Proposition 5, we have $s_k = \bar{s}_k$ which from Proposition 1 implies minimal acreage balance violation for the CET. In consequence, we do not discuss this result here.

Table 3: Simulation results under selected 25% crop-price increases.

	Nested Fréchet			NMNL		
Commodity	Yield (%)	Acreage (pp)	Production (%)	Yield (%)	Acreage (pp)	Production (%)
Common wheat price increase						
Barley	22.72	−3.95	−6.04	0	−1.15	−6.83
Common wheat	−18.53	12.64	5.35	0.44	2.92	7.24
Durum wheat	22.72	−0.45	−6.04	0	−0.13	−6.83
Maize	22.72	−2.07	−6.04	0	−0.60	−6.83
Other cereals	22.72	−0.14	−6.04	0	−0.04	−6.83
Other oilseeds	22.72	−0.12	−3.10	0	−0.02	−3.45
Potatoes	22.72	−0.66	−3.10	0	−0.11	−3.45
Protein crops	22.72	−0.57	−3.10	0	−0.09	−3.45
Rapeseed	22.72	−2.44	−3.10	0	−0.40	−3.45
Sugar beet	22.72	−1.48	−3.10	0	−0.24	−3.45
Sunflower	22.72	−0.77	−3.10	0	−0.13	−3.45
Rapeseed price increase						
Barley	7.10	−1.28	−1.05	0	−0.18	−1.10
Common wheat	7.10	−3.28	−1.05	0	−0.47	−1.10
Durum wheat	7.10	−0.14	−1.05	0	−0.02	−1.10
Maize	7.10	−0.67	−1.05	0	−0.10	−1.10
Other cereals	7.10	−0.05	−1.05	0	−0.01	−1.10
Other oilseeds	7.10	−0.06	−4.81	0	−0.03	−5.54
Potatoes	7.10	−0.24	−1.05	0	−0.03	−1.10
Protein crops	7.10	−0.30	−4.81	0	−0.15	−5.54
Rapeseed	−32.17	6.97	8.49	0.40	1.27	11.41
Sugar beet	7.10	−0.54	−1.05	0	−0.08	−1.10
Sunflower	7.10	−0.41	−4.81	0	−0.20	−5.54
Potatoes price increase						
Barley	7.70	−1.38	−1.13	0	−0.22	−1.28
Common wheat	7.70	−3.54	−1.13	0	−0.55	−1.28
Durum wheat	7.70	−0.16	−1.13	0	−0.02	−1.28
Maize	7.70	−0.73	−1.13	0	−0.11	−1.28
Other cereals	7.70	−0.05	−1.13	0	−0.01	−1.28
Other oilseeds	7.70	−0.04	−1.13	0	−0.01	−1.28
Potatoes	−66.06	8.16	22.70	0.07	1.57	50.45
Protein crops	7.70	−0.22	−1.13	0	−0.03	−1.28
Rapeseed	7.70	−0.95	−1.13	0	−0.15	−1.28
Sugar beet	7.70	−0.79	−4.43	0	−0.42	−5.96
Sunflower	7.70	−0.30	−1.13	0	−0.05	−1.28

Note: Nested CET is omitted, because it leads to the same production changes as nested Fréchet.

counterpart of this yield collapse is a large acreage expansion: the potato acreage share rises by about 8 percentage points, from 3% in 2021 to roughly 11% after the shock. By comparison, potato acreage shares in field crops range only from 2.1 to 3.1% in our 2016–21 sample, so the 1.57-percentage-point increase delivered by the NMNL model appears substantially more credible.

5 Conclusion

This paper has shown that several popular acreage-choice models, developed across distinct literatures, can be traced back to common theoretical roots. In doing so, it helps reconnect a literature fragmented among CGE modeling, new quantitative trade models, positive mathematical programming (PMP), and econometrics—fields in which neighboring approaches have often been developed in parallel despite sharing the same object of study and, in some cases, very similar structural restrictions.

A first implication is that the CET approach, prevalent in the CGE literature, should be used with caution whenever the object of interest is physical acreage. Because the CET allocates efficient land rather than hectares, it cannot in general track physical acreage consistently once relative land rents change. This limitation matters precisely in the applications where acreage changes are central, such as indirect land-use change, biodiversity, and climate-policy analysis. For questions focused mainly on value shares or effective-land responses, the CET remains a parsimonious device; for questions centered on hectares, its interpretation becomes much more problematic.

A second implication is that the CET and Fréchet approaches are much closer than is usually recognized. When calibrated on the same benchmark shares and elasticities, they generate identical counterfactual changes in production, with the Fréchet specification making explicit the acreage and yield changes that the CET leaves implicit.

The Fréchet approach, prevalent in the new quantitative trade model literature, prevents full specialization through a mechanism in which yields decline with crop specialization. Although this mechanism is initially intuitive, the analytical framework implies strong negative own-price yield-composition elasticities and correspondingly large own-price acreage elasticities. Negative composition effects have empirical counterparts, but neither our estimates nor the limited comparable evidence supports effects approaching the magnitudes imposed by the calibrated Fréchet model. The simulations confirm that these mechanisms can quickly generate implausible nonmarginal responses, combining large acreage reallocations with severe yield declines. Applications that hinge on the joint behavior of acreages and yields, rather than on aggregate output responses alone, should therefore treat the quantitative implications of the Fréchet-distributed yield assumption with caution.

These concerns extend more broadly to any approach built on the same idea that yields fall mechanically with specialization, including some PMP and CRETH specifications. More generally, one of the lessons of the paper is that matching local output elasticities is not sufficient to validate an acreage-choice model: different mechanisms can reproduce the same benchmark supply response while implying sharply different movements in hectares, yields, and land rents once the model is used for counterfactual analysis.

We have devoted a substantial share of the exposition to the multinomial logit approach because it has received little attention in applications, despite offering a natural bridge between equilibrium models, PMP, and econometrics. In its entropy-regularized form, it provides a transparent deterministic representation of diversification under convex management costs; in its stochastic interpretation, it reconnects equilibrium modeling to the discrete-choice tradition. The farm-level estimates further show that a nested multinomial logit model can be estimated on farm-level data and then carried into equilibrium calibration. Using French farm-accounting panel data, we obtain acreage elasticities in line with the literature and use them to calibrate the three competing frameworks on a comparable basis.

We have also clarified the link between PMP and the methods more commonly used in equilibrium modeling. The CET and Fréchet specifications can be seen as special cases of broader PMP-style representations, subject to the usual trade-off between parsimony and flexibility, while the multinomial logit belongs to the same class of regularized optimization problems as the standard quadratic PMP.

Finally, we have shown that relying on functional-form or distributional assumptions to represent the mechanism by which yields decrease with specialization may lead to implausible acreage and yield elasticities. One way to preserve this mechanism while avoiding the drawbacks identified here is to rely on spatial simulation units, such as land-class or pixel-based modeling, so that land heterogeneity is grounded in observables rather than simply assumed.

Appendix

A Proofs

Proof of Proposition 1. From the definition of L and using equation (5), we have

$$L = \sum_{k \in \mathcal{K}} b_k \left(\frac{R}{R_k}\right)^{\eta} \bar{L}, \tag{A1}$$

$$\frac{L}{\bar{L}} = R^{\eta} \sum_{k \in \mathcal{K}} b_k \left(R_k\right)^{-\eta}. \tag{A2}$$

Taking logarithms and totally differentiating both sides of equation (A2) gives

$$\mathrm{d}\ln\frac{L}{\bar{L}} = \eta\,\mathrm{d}\ln R + \mathrm{d}\ln\left(\sum_{k \in \mathcal{K}} b_k \left(R_k\right)^{-\eta}\right), \tag{A3}$$

with

$$\mathrm{d}\ln R = \sum_{k \in \mathcal{K}} \bar{s}_k\,\mathrm{d}\ln R_k, \tag{A4}$$

and

$$\mathrm{d}\left(\sum_{k \in \mathcal{K}} b_k \left(R_k\right)^{-\eta}\right) = -\eta \sum_{k \in \mathcal{K}} b_k \left(R_k\right)^{-\eta}\,\mathrm{d}\ln R_k, \tag{A5}$$

$$\mathrm{d}\ln\left(\sum_{k \in \mathcal{K}} b_k \left(R_k\right)^{-\eta}\right) = -\eta\frac{\sum_{k \in \mathcal{K}} b_k \left(R_k\right)^{-\eta}\,\mathrm{d}\ln R_k}{\sum_{l \in \mathcal{K}} b_l \left(R_l\right)^{-\eta}}, \tag{A6}$$

$$= -\eta\frac{\sum_{k \in \mathcal{K}} b_k \left(R_k/R\right)^{-\eta}\,\mathrm{d}\ln R_k}{\sum_{l \in \mathcal{K}} b_l \left(R_l/R\right)^{-\eta}}. \tag{A7}$$

At the calibration benchmark, $b_k = \bar{s}_k \left(R/R_k\right)^{1-\eta}$, so we have

$$\mathrm{d}\ln\left(\sum_{k\in\mathcal{K}} b_k \left(R_k\right)^{-\eta}\right) = -\eta \frac{\sum_{k\in\mathcal{K}} \bar{s}_k \left(R/R_k\right) \mathrm{d}\ln R_k}{\sum_{l\in\mathcal{K}} \bar{s}_l \left(R/R_l\right)}. \tag{A8}$$

This can be further simplified by noting that if the baseline is consistent with the balance of area then from equation (9) the denominator is equal to 1 and

$$\mathrm{d}\ln\left(\sum_{k\in\mathcal{K}} b_k \left(R_k\right)^{-\eta}\right) = -\eta \sum_{k\in\mathcal{K}} \bar{s}_k \left(R/R_k\right) \mathrm{d}\ln R_k, \tag{A9}$$

$$= -\eta \sum_{k\in\mathcal{K}} s_k \,\mathrm{d}\ln R_k. \tag{A10}$$

Finally, combining equations (A3), (A4) and (A10), we obtain equation (11). □

Proof of Proposition 2. The proof proceeds in two steps. First, we show that for benchmark shares $\bar{s}_k$ and parameters satisfying $\theta = 1 - \eta$, the counterfactual predictions of the two approaches are the same for production and different for land demand. Second, we show that they can indeed be calibrated on the same parameters.

From equations (7) and (21), simple algebra leads to the same expression for changes in the shares:

$$\hat{\bar{s}}_k = \frac{\hat{R}_k^{\theta}}{\sum_{l\in\mathcal{K}} \bar{s}_l \hat{R}_l^{\theta}}. \tag{A11}$$

Similarly, equations (12) and (25) yield the following relative changes in production:

$$\hat{Y}_k = \hat{a}_k^L \left\{\left[1 - \vartheta_k^X \left(\frac{\hat{P}_X}{\hat{P}_k}\right)^{1-\sigma_k}\right] / \left(1 - \vartheta_k^X\right)\right\}^{\sigma_k/(1-\sigma_k)} \hat{\bar{s}}_k^{(\theta-1)/\theta}. \tag{A12}$$

In both models, the land rents R_k have the same definition and can be recovered from the following equation, expressed in relative deviations

$$\hat{P}_k = \left[\left(1 - \vartheta_k^X\right)^{\sigma_k} \left(\vartheta_k^L \hat{R}_k / \hat{a}_k^L + \vartheta_k^M \hat{P}_M\right)^{1-\sigma_k} + \vartheta_k^X \left(\hat{P}_X\right)^{1-\sigma_k}\right]^{1/(1-\sigma_k)}. \tag{A13}$$

Thus, counterfactual changes in production are the same.

Counterfactual changes in land demand are given by $\hat{L}_k = \hat{s}_k = \hat{\bar{s}}_k$ in the Fréchet model and by $\hat{L}_k = \hat{\bar{s}}_k^{\eta/(\eta-1)}$ in the CET model (from equation (5)).

From equations (A11) and (A12), the only information about the baseline situation required to obtain counterfactual results is the set of land-rent shares $\bar{s}_k$ and cost shares ϑ_k^x. It is possible to calibrate the Fréchet model either on the land-rent shares $\bar{s}_k = \dot{R}_k L_k/(RL)$ or on the acreage shares $s_k = L_k/L$, because the two variables are equal in the model due to $\dot{R}_k = R$. With the CET model, the share of a crop in total land revenues is defined by $\bar{s}_k = R_k L_k/(R\bar{L})$, but it corresponds to the same concept as in the Fréchet approach. Thus, the Fréchet and the CET models can be calibrated on the same initial situation. □

Proof of Proposition 3. Under the common per-hectare land cost, the CET/Fréchet non-intensification elasticity becomes

$$-\eta\frac{1-\bar{s}_k}{\vartheta_k^L} = -\eta(1-s_k)\frac{P_k y_k}{R},$$

where we used $s_k = \bar{s}_k$, which always holds in Fréchet and holds in CET under the land cost assumption. For the Fréchet model, the same expression is obtained from $(\theta-1)(1-s_k)/\vartheta_k^L$ when $\theta - 1 = -\eta$. The multinomial logit acreage elasticity is $\alpha P_k y_k(1-s_k)/P_M$. These expressions are identical for all k when $\alpha = -\eta P_M/R$. Since all three models use the same CES yield technology, the intensification elasticity is $\sigma_k\vartheta_k^X/(1-\vartheta_k^X)$ in each model. □

B Properties of the Fréchet distribution

This appendix presents the properties of Fréchet-distributed random variables that are used in the paper (see Mattsson et al., 2014, for proofs, extensions, and links with other extreme-value distributions).

B.1 Basic Fréchet properties

We denote by $Z \sim \text{Fréchet}(\theta, \nu)$ a random variable following a Fréchet distribution with shape parameter $\theta > 0$ and scale parameter $\nu > 0$. Its cumulative distribution function is

$$\Pr(Z \le z) = \exp\left[-(z/\nu)^{-\theta}\right] \quad \forall z \in \mathbb{R}_{>0}. \tag{A14}$$

If $\theta > 1$, then Z has a finite mean given by

$$\mathrm{E}(Z) = \nu\Gamma(1 - 1/\theta), \tag{A15}$$

where $\Gamma(z) = \int_0^\infty t^{z-1}\,\mathrm{e}^{-t}\,\mathrm{d}t$, $\forall z \in \mathbb{R}_{>0}$, is the gamma function.

If $Z \sim \text{Fréchet}(\theta, \nu)$ and $t > 0$, then $Y = tZ \sim \text{Fréchet}(\theta, t\nu)$.

Let Z_k, $k \in \mathcal{K}$, be independent Fréchet random variables with common shape parameter $\theta > 0$ and scale parameters $\nu_k > 0$. Then the probability that Z_k attains the maximum among $\{Z_l\}_{l\in\mathcal{K}}$ is

$$\Pr\left(k \in \arg\max_{l\in\mathcal{K}} Z_l\right) = \frac{\nu_k^\theta}{\sum_{l\in\mathcal{K}}\nu_l^\theta}. \tag{A16}$$

Let $\dot{Z}_k = Z_k | k \in \arg\max_{l\in\mathcal{K}} Z_l$ denote the conditional random variable equal to Z_k if Z_k is the maximum. $\dot{Z}_k \sim \text{Fréchet}(\theta, \nu)$, where $\nu = \left(\sum_{l\in\mathcal{K}}\nu_l^\theta\right)^{1/\theta}$. So, all the conditional random variables $\dot{Z}_k$ follow the same distribution and have the same expected value if $\theta > 1$:

$$\mathrm{E}(\dot{Z}_k) = \mathrm{E}\left(Z_k | k \in \arg\max_{l\in\mathcal{K}} Z_l\right) = \nu\Gamma(1 - 1/\theta). \tag{A17}$$

B.2 Nested Fréchet properties

Here, we present the properties of a multivariate distribution with dependence within nests as used in section 4. The trade literature considers a simpler, one-nest version; see Eaton and Kortum (2002, n. 14) and Ramondo and Rodríguez-Clare (2013). Lind and Ramondo (2023) presents a general version.

To keep notation consistent with the recursive structure used in section 3, let node 1 denote the root of the nesting tree, $\mathcal{N}$ the set of non-root nodes, $\mathcal{K} \subset \mathcal{N}$ the set of crops, and $\mathcal{I} \equiv \{1\} \cup (\mathcal{N} \setminus \mathcal{K})$ the set of internal nodes. We begin with the two-level case in which the children of the root, denoted $n \in C(1)$, are non-overlapping nests and the children of each such node are crops $k \in C(n)$. The random vector $(Z_k)_{k \in \mathcal{K}}$ then has the following joint cumulative distribution function:

$$F(z) = \exp\left\{ - \sum_{n \in C(1)} \left[\sum_{k \in C(n)} \left(\frac{z_k}{\nu_k} \right)^{-\theta/(1-\rho_n)} \right]^{1-\rho_n} \right\} \quad \forall z \in \mathbb{R}^{|K|}_{>0}, \tag{A18}$$

with parameters $\theta > 0$, $\nu_k > 0$, and $0 \leq \rho_n < 1$ for every $n \in C(1)$.

Note that

$$\lim_{z_l \to \infty, l \neq k} F(z) = \exp\left[- (z_k/\nu_k)^{-\theta} \right], \tag{A19}$$

so the marginal distributions are Fréchet, and if $\theta > 1$, $\mathrm{E}(Z_k) = \nu_k \Gamma(1 - 1/\theta)$.

The probability that Z_k is the maximum is given by

$$\Pr\left(k \in \arg\max_{l \in \mathcal{K}} Z_l \right) = \Pr\left(\arg\max_{l \in \mathcal{K}} Z_l \subset C(n) \right) \Pr\left(k \in \arg\max_{l \in C(n)} Z_l \right), \tag{A20}$$

for $k \in C(n)$, where

$$\Pr\left(\arg\max_{l \in \mathcal{K}} Z_l \subset C(n) \right) = \frac{\left(\sum_{l \in C(n)} \nu_l^{\theta/(1-\rho_n)} \right)^{1-\rho_n}}{\sum_{m \in C(1)} \left(\sum_{l \in C(m)} \nu_l^{\theta/(1-\rho_m)} \right)^{1-\rho_m}}, \tag{A21}$$

and

$$\Pr\left(k \in \arg\max_{l \in C(n)} Z_l \right) = \frac{\nu_k^{\theta/(1-\rho_n)}}{\sum_{l \in C(n)} \nu_l^{\theta/(1-\rho_n)}}. \tag{A22}$$

As in the independent case, all the conditional random variables $\dot{Z}_k$ follow the same distribution, Fréchet (θ, ν), where

$$\nu = \left[\sum_{n \in C(1)} \left(\sum_{k \in C(n)} \nu_k^{\theta/(1-\rho_n)} \right)^{1-\rho_n} \right]^{1/\theta}. \tag{A23}$$

B.3 Application to the acreage model

To connect these results to the notation used in section 2.2 and section 4, let R_k denote the unconditional land rent of crop k, as in equation (19). In the nested Fréchet specification, the parcel-level random land rents are generated by a nested Fréchet vector whose crop-specific scale parameters are proportional to these unconditional land rents. Since a common proportionality factor cancels out of all share equations, we can write the recursive objects directly in terms of land rents. The previous two-level representation then extends directly to a general tree. For every $n \in \mathcal{I}$, let $\rho_n \in [0, 1)$ denote its dependence parameter, with the convention $\rho_1 = 0$ at the root, and define the within-nest shape parameter $\theta_n \equiv \theta/(1 - \rho_n)$, so that $\theta_1 = \theta$. For the nested Fréchet to define a valid distribution—equivalently, for the implied acreage shares to be consistent with random rent maximization—the correlation parameters cannot be chosen freely across levels: each ρ_n must weakly increase as one moves down the tree, so that $\rho_{p(n)} \leq \rho_n$ for every $n \in \mathcal{N} \setminus \mathcal{K}$, or equivalently $\theta_{p(n)} \leq \theta_n$. This is the Daly–Zachary–McFadden condition for nested logit models (Daly and Zachary, 1978; McFadden, 1978), transposed to the nested Fréchet through the isomorphism between the two specifications. Intuitively, alternatives sharing a deeper nest are closer substitutes, and their parcel-level rents are therefore more correlated than across the broader groupings above them.[23]

Define the composite land-rent index

$$R_n = \left(\sum_{c \in C(n)} R_c^{\theta_n} \right)^{1/\theta_n} \qquad \forall n \in \mathcal{I}, \tag{A24}$$

where R_k is the primitive unconditional land rent for crop $k \in \mathcal{K}$ and $R_1 = R$. The corresponding conditional acreage shares are

$$s_{c|n} \equiv \frac{s_c}{s_n} = \frac{R_c^{\theta_n}}{\sum_{u \in C(n)} R_u^{\theta_n}} = \left(\frac{R_c}{R_n} \right)^{\theta_n} \qquad \forall n \in \mathcal{I},\ \forall c \in C(n), \tag{A25}$$

with $s_1 = 1$. The acreage share of a crop is therefore the product of the conditional shares along its path in the tree.

From the above, we can derive recursive formulas for acreage elasticities. A total differentiation of the composite land-rent indices gives

$$\mathrm{d} \ln R_n = \sum_{c \in C(n)} \frac{s_c}{s_n} \mathrm{d} \ln R_c \qquad \forall n \in \mathcal{I}, \tag{A26}$$

while the conditional share equation implies

$$\mathrm{d} \ln s_c = \mathrm{d} \ln s_n + \theta_n \left(\mathrm{d} \ln R_c - \mathrm{d} \ln R_n \right) \qquad \forall n \in \mathcal{I},\ \forall c \in C(n). \tag{A27}$$

Let $\chi_{n,l}^F \equiv \partial \ln R_n / \partial \ln R_l$ denote the transmission of a change in crop-l unconditional land rent to node

[23] When $\theta_n > 1$ at every internal node, the recursive rent indices (A24) and conditional shares (A25) also characterize the rent-maximizing land allocation for a technology in which per-hectare yields decline with conditional acreage shares at every level of the tree. This deterministic reading generalizes to the tree the decreasing-yield interpretation of the one-level Fréchet model (Mérel et al., 2011) discussed in section 2.2; it does not require the cross-level ordering $\theta_{p(n)} \leq \theta_n$, which is needed only for the parcel-level random-rent microfoundation.

n, and $\mathcal{E}^F_{n,l} \equiv \partial \ln s_n / \partial \ln R_l$ the associated acreage elasticity. For crops, we have $\chi^F_{l,l} = 1$ and $\chi^F_{k,l} = 0$ for $k \neq l$. The two previous equations imply the bottom-up recursion

$$\chi^F_{n,l} = \sum_{c \in C(n)} \frac{s_c}{s_n} \chi^F_{c,l} \qquad \forall n \in \mathcal{I}, \tag{A28}$$

and, starting from $\mathcal{E}^F_{1,l} = 0$ at the root, the top-down recursion

$$\mathcal{E}^F_{c,l} = \mathcal{E}^F_{n,l} + \theta_n \left(\chi^F_{c,l} - \chi^F_{n,l} \right) \qquad \forall n \in \mathcal{I},\ \forall c \in C(n). \tag{A29}$$

Consider a crop k, and write its path from the root as pairs $(n, c) \in \text{path}(1 \to k)$. In the common modeling framework used in the paper, with one land-intensification input, the output of crop k can be written as

$$Y_k = L a^L_k s_k^{(\theta-1)/\theta} \prod_{(n,c) \in \text{path}(1 \to k),\, n \neq 1} \left(s_{c|n} \right)^{\rho_n/\theta} \left[1 - \left(\frac{P_X/P_k}{a^X_k} \right)^{1-\sigma_k} \right]^{\sigma_k/(1-\sigma_k)}, \tag{A30}$$

which reduces to equation (25) when there is only the root nest above crop k. This expression is obtained by combining the acreage share of crop k, s_k, with the expected productivity conditional on crop k being selected. As in the one-level case, the expected conditional productivity is proportional to the ratio of the common conditional land rent to the crop-specific unconditional land rent, R/R_k. Hence

$$Y_k = L s_k a^L_k \frac{R}{R_k} \left[1 - \left(\frac{P_X/P_k}{a^X_k} \right)^{1-\sigma_k} \right]^{\sigma_k/(1-\sigma_k)}. \tag{A31}$$

Using the recursive share equation,

$$s_{c|n} = \left(\frac{R_c}{R_n} \right)^{\theta_n}, \tag{A32}$$

we obtain

$$\frac{R_c}{R_n} = s_{c|n}^{1/\theta_n}. \tag{A33}$$

Along the path from the root to crop k, this implies

$$\frac{R_k}{R} = \prod_{(n,c) \in \text{path}(1 \to k)} s_{c|n}^{1/\theta_n} = s_k^{1/\theta} \prod_{(n,c) \in \text{path}(1 \to k),\, n \neq 1} s_{c|n}^{-\rho_n/\theta}, \tag{A34}$$

because $s_k = \prod_{(n,c) \in \text{path}(1 \to k)} s_{c|n}$ and $\rho_1 = 0$. Taking the inverse and substituting into the previous equation gives the output formula above. The term in conditional shares therefore captures the additional selection effect created by dependence within nests.

From equation (A31), the elasticity of the output of crop k with respect to the price of crop l is

$$\frac{\partial \ln Y_k}{\partial \ln P_l} = \underbrace{\frac{\mathcal{E}^F_{k,l}}{\vartheta^L_l}}_{\text{Acreage}} + \underbrace{\left(\underbrace{-\frac{\mathbf{1}\{k=l\} - s_l}{\vartheta^L_l}}_{\text{Composition}} + \underbrace{\mathbf{1}\{k=l\}\sigma_k \frac{\vartheta^X_k}{1-\vartheta^X_k}}_{\text{Intensification}} \right)}_{\text{Yield}}, \tag{A35}$$

where $\mathbf{1}\{k=l\}$ denotes the indicator function, equal to 1 if $k=l$ and 0 otherwise, and ϑ^L_l is the land share in the unit cost of crop l. In the one-level case, this expression collapses to equation (26) in the paper.

C Nested CET acreage allocation

This appendix defines the nested CET acreage system used in section 4. The notation follows the nested multinomial logit and nested Fréchet: node 1 is the root of the tree, $\mathcal{N}$ is the set of non-root nodes, $\mathcal{K} \subset \mathcal{N}$ is the set of crops, $\mathcal{I} \equiv \{1\} \cup (\mathcal{N} \setminus \mathcal{K})$ is the set of internal nodes, $C(n)$ is the set of children of node n, and $p(n)$ is the parent of non-root node n. For each node n, let $\bar{L}_n$ denote the efficient-land aggregate allocated to that node, with $\bar{L}_1 = \bar{L}$. For every $n \in \mathcal{I}$, the aggregate is a CET function of its children:

$$\bar{L}_n = \left(\sum_{c \in C(n)} b_{c|n}^{1/\eta_n} \bar{L}_c^{(\eta_n - 1)/\eta_n} \right)^{\eta_n/(\eta_n - 1)}, \tag{A36}$$

where $b_{c|n} > 0$ are calibration shifters and $\eta_n < 0$ is the transformation elasticity at node n. The farmer chooses the allocation of efficient land to maximize total land returns subject to the recursive constraints (A36). Let R_c denote the rent associated with child c, where R_k is the crop-specific land rent for a crop k. The dual composite rent at internal node n is

$$R_n = \left(\sum_{c \in C(n)} b_{c|n} R_c^{1-\eta_n} \right)^{1/(1-\eta_n)}. \tag{A37}$$

The corresponding conditional efficient-land allocation and conditional land-rent share are

$$\bar{L}_c = b_{c|n} \left(\frac{R_n}{R_c} \right)^{\eta_n} \bar{L}_n \qquad \forall n \in \mathcal{I},\ \forall c \in C(n), \tag{A38}$$

$$\bar{s}_{c|n} \equiv \frac{R_c \bar{L}_c}{R_n \bar{L}_n} = b_{c|n} \left(\frac{R_c}{R_n} \right)^{1-\eta_n} \qquad \forall n \in \mathcal{I},\ \forall c \in C(n). \tag{A39}$$

The unconditional land-rent share of a crop is the product of the conditional shares along its path in the tree. These are value shares, as in the one-level CET model, and need not coincide with physical acreage shares.

A total differentiation of the composite rent index gives

$$\mathrm{d}\ln R_n = \sum_{c\in C(n)} \frac{\bar{s}_c}{\bar{s}_n}\,\mathrm{d}\ln R_c \qquad \forall n \in \mathcal{I}, \tag{A40}$$

while the conditional share equation implies

$$\mathrm{d}\ln \bar{s}_{c|n} = (1-\eta_n)\left(\mathrm{d}\ln R_c - \mathrm{d}\ln R_n\right) \qquad \forall n \in \mathcal{I},\ \forall c \in C(n). \tag{A41}$$

Let $\chi^C_{n,l} \equiv \partial \ln R_n / \partial \ln R_l$ denote the transmission of a change in land rent for crop l to node n, and let $\mathcal{E}^C_{n,l} \equiv \partial \ln \bar{s}_n / \partial \ln R_l$ denote the associated elasticity of the land-rent share of node n. For crops, $\chi^C_{l,l} = 1$ and $\chi^C_{k,l} = 0$ for $k \neq l$. Equation (A40) gives the bottom-up recursion

$$\chi^C_{n,l} = \sum_{c\in C(n)} \frac{\bar{s}_c}{\bar{s}_n}\chi^C_{c,l} \qquad \forall n \in \mathcal{I}. \tag{A42}$$

Starting from $\mathcal{E}^C_{1,l} = 0$ at the root, equation (A41) gives the top-down recursion

$$\mathcal{E}^C_{c,l} = \mathcal{E}^C_{n,l} + (1-\eta_n)\left(\chi^C_{c,l} - \chi^C_{n,l}\right) \qquad \forall n \in \mathcal{I},\ \forall c \in C(n). \tag{A43}$$

The efficient-land demand of crop k can be written as a product of conditional allocations along its path. Combining (A38) and (A39),

$$\bar{L}_k = \bar{L} \prod_{(n,c)\in \mathrm{path}(1\to k)} b_{c|n}^{1/(1-\eta_n)}\,\bar{s}_{c|n}^{\eta_n/(\eta_n-1)}. \tag{A44}$$

Using the same within-crop CES block as in the main text, output is therefore

$$Y_k = a^L_k \bar{L}\left[1-\left(\frac{P_X/P_k}{a^X_k}\right)^{1-\sigma_k}\right]^{\sigma_k/(1-\sigma_k)} \prod_{(n,c)\in \mathrm{path}(1\to k)} b_{c|n}^{1/(1-\eta_n)}\,\bar{s}_{c|n}^{\eta_n/(\eta_n-1)}. \tag{A45}$$

This expression reduces to equation (12) when the tree contains only the root nest above the crops.

From (A45), the non-intensification component of the output response is

$$\begin{aligned}
\mathrm{d}\ln Y_k\big|^C_{\text{non-int.}} &= \sum_{(n,c)\in \mathrm{path}(1\to k)} \frac{\eta_n}{\eta_n - 1}\,\mathrm{d}\ln \bar{s}_{c|n} \\
&= \sum_{(n,c)\in \mathrm{path}(1\to k)} \frac{\eta_n}{\eta_n - 1}\left(\mathrm{d}\ln \bar{s}_c - \mathrm{d}\ln \bar{s}_n\right) \\
&= \sum_{(n,c)\in \mathrm{path}(1\to k)} (-\eta_n)\left(\mathrm{d}\ln R_c - \mathrm{d}\ln R_n\right).
\end{aligned} \tag{A46}$$

Since each crop rent depends only on its own output price, holding P_X and P_M fixed gives $\partial \ln R_m / \partial \ln P_l =$

$\mathbf{1}\{m = l\}/\vartheta_l^L$. Hence the nested CET supply elasticity can be written as

$$\begin{aligned}
\frac{\partial \ln Y_k}{\partial \ln P_l} &= \underbrace{\frac{1}{\vartheta_l^L} \sum_{(n,c)\in \text{path}(1\to k)} \frac{\eta_n}{\eta_n - 1} \left(\mathcal{E}_{c,l}^C - \mathcal{E}_{n,l}^C\right)}_{\text{Acreage and yield composition}} + \underbrace{\mathbf{1}\{k = l\}\sigma_k \frac{\vartheta_k^X}{1 - \vartheta_k^X}}_{\text{Intensification}}, \\
&= \frac{1}{\vartheta_l^L} \sum_{(n,c)\in \text{path}(1\to k)} (-\eta_n) \left(\chi_{c,l}^C - \chi_{n,l}^C\right) + \mathbf{1}\{k = l\}\sigma_k \frac{\vartheta_k^X}{1 - \vartheta_k^X}. \qquad \text{(A47)}
\end{aligned}$$

D Elasticities of the nested multinomial logit model

This appendix defines the cross-price elasticities of the nested multinomial logit model developed in section 3, using the internal-node set $\mathcal{I}$ defined in section 3.1. From the definition of the composite real profits (48), a total differentiation gives

$$\mathrm{d}\varpi_n = \sum_{c\in C(n)} \frac{s_c}{s_n} \mathrm{d}\varpi_c \qquad \forall n \in \mathcal{I}, \tag{A48}$$

while the conditional share equation (49) implies

$$\mathrm{d} \ln s_c = \mathrm{d} \ln s_n + \alpha_n \left(\mathrm{d}\varpi_c - \mathrm{d}\varpi_n\right) \qquad \forall n \in \mathcal{I},\ \forall c \in C(n). \tag{A49}$$

These two equations provide a convenient recursive way to calculate all acreage elasticities in the tree.

Let $\chi_{n,l}^L \equiv \partial\varpi_n/\partial\varpi_l$ denote the transmission of a change in crop-l real profit to node n, and $\mathcal{E}_{n,l}^L \equiv \partial \ln s_n/\partial\varpi_l$ the associated semi-elasticity of the acreage share of node n. For crops, we have $\chi_{l,l}^L = 1$ and $\chi_{k,l}^L = 0$ for $k \neq l$. For internal nodes, the previous equation gives the bottom-up recursion

$$\chi_{n,l}^L = \sum_{c\in C(n)} \frac{s_c}{s_n} \chi_{c,l}^L. \tag{A50}$$

Starting from $\mathcal{E}_{1,l}^L = 0$ at the root, the acreage-share semi-elasticities are then obtained by top-down recursion:

$$\mathcal{E}_{c,l}^L = \mathcal{E}_{n,l}^L + \alpha_n \left(\chi_{c,l}^L - \chi_{n,l}^L\right) \qquad \forall n \in \mathcal{I},\ \forall c \in C(n). \tag{A51}$$

For a crop k, the acreage semi-elasticity with respect to the real profit of crop l is therefore $\mathcal{E}_{k,l}^L$.

To convert these semi-elasticities into price elasticities, we use the envelope theorem. Since the real profit of crop l is $\varpi_l = (P_l y_l - P_X x_l - P_M c_l)/P_M$, its derivative with respect to the crop price is

$$\frac{\partial \varpi_l}{\partial \ln P_l} = \frac{P_l y_l}{P_M}. \tag{A52}$$

Hence the acreage elasticity of crop k with respect to the price of crop l is

$$\frac{\partial \ln s_k}{\partial \ln P_l} = \frac{P_l y_l}{P_M} \mathcal{E}_{k,l}^L. \tag{A53}$$

These are the acreage elasticities used in the calibration moments collected in $\boldsymbol{\varphi}$. In the one-level case, they reduce to the acreage component of equation (42), since $\mathcal{E}^{L}_{k,k} = \alpha(1 - s_k)$.

E Nested equivalence results

This appendix establishes the two nested equivalence results used in section 4. The first extends the exact CET–Fréchet counterfactual equivalence of Proposition 2; the second extends the local three-model equivalence of Proposition 3 used to calibrate the nested CET and nested Fréchet models from the calibrated nested multinomial logit parameters. Throughout, $\mathcal{I}$ denotes the set of internal nodes, including the root, defined in section 3.1.

Proposition 4. *Assume that the nested CET and nested Fréchet models use the same nesting tree and within-crop substitution elasticities and are calibrated on the same benchmark cost shares and conditional land-rent shares $\bar{s}_{c|n}$ at every arc (n, c). For nested Fréchet parameters satisfying $\theta_n > 1$ at every internal node and $\theta_{p(n)} \leq \theta_n$ at every nonroot internal node, suppose that the CET and Fréchet parameters are mapped according to*

$$\theta_n = 1 - \eta_n \qquad \forall n \in \mathcal{I}, \tag{A54}$$

the two models deliver identical counterfactual changes in composite land rents, conditional shares, and crop production for any changes in prices and land productivity. They generally deliver different counterfactual changes in land demand: the nested Fréchet model allocates physical hectares, whereas the nested CET model allocates efficient land.

Proof. Expressed in hat algebra, the composite-rent recursions at an internal node n are

$$\hat{R}^{C}_{n} = \left[\sum_{c \in C(n)} \bar{s}_{c|n} \left(\hat{R}^{C}_{c} \right)^{1-\eta_n} \right]^{1/(1-\eta_n)} \quad \text{and} \quad \hat{R}^{F}_{n} = \left[\sum_{c \in C(n)} \bar{s}_{c|n} \left(\hat{R}^{F}_{c} \right)^{\theta_n} \right]^{1/\theta_n}. \tag{A55}$$

where superscripts C and F denote the nested CET and nested Fréchet models. Their conditional-share changes are, respectively,

$$\hat{\bar{s}}^{C}_{c|n} = \left(\frac{\hat{R}^{C}_{c}}{\hat{R}^{C}_{n}} \right)^{1-\eta_n} \quad \text{and} \quad \hat{s}^{F}_{c|n} = \hat{\bar{s}}^{F}_{c|n} = \left(\frac{\hat{R}^{F}_{c}}{\hat{R}^{F}_{n}} \right)^{\theta_n}. \tag{A56}$$

Because the two models have the same within-crop substitution elasticities and benchmark cost shares and face the same price and productivity changes, their leaf rents satisfy the same unit-cost equations in relative changes, so $\hat{R}^{C}_{k} = \hat{R}^{F}_{k}$ for every crop k. Under (A54), the two recursions in (A55) are identical. Working from the leaves to the root therefore gives $\hat{R}^{C}_{n} = \hat{R}^{F}_{n}$ at every node. Equation (A56) then gives $\hat{\bar{s}}^{C}_{c|n} = \hat{s}^{F}_{c|n}$ at every arc.

Let $\hat{I}_k$ denote the common change in the crop-specific land-productivity and intensification terms. From (A45), nested CET production satisfies

$$\hat{Y}^{C}_{k} = \hat{I}_k \prod_{(n,c) \in \text{path}(1 \to k)} \left(\hat{\bar{s}}^{C}_{c|n} \right)^{\eta_n/(\eta_n - 1)}. \tag{A57}$$

In the nested Fréchet model, equation (A31) and the conditional-share equations imply

$$\hat{Y}_k^F = \hat{I}_k \hat{s}_k^F \frac{\hat{R}_1^F}{\hat{R}_k^F} \tag{A58}$$

$$= \hat{I}_k \prod_{(n,c)\in \text{path}(1\to k)} \left(\hat{s}_{c|n}^F\right)^{(\theta_n - 1)/\theta_n}. \tag{A59}$$

The parameter mapping gives

$$\frac{\theta_n - 1}{\theta_n} = \frac{\eta_n}{\eta_n - 1}. \tag{A60}$$

Since the conditional-share changes are identical, equations (A57) and (A59) establish $\hat{Y}_k^C = \hat{Y}_k^F$ for every crop.

The land-demand changes do not share these exponents. With fixed aggregate land, nested Fréchet acreage and nested CET efficient-land demand satisfy

$$\hat{L}_k^F = \prod_{(n,c)\in \text{path}(1\to k)} \hat{s}_{c|n}^F, \qquad \hat{\tilde{L}}_k^C = \prod_{(n,c)\in \text{path}(1\to k)} \left(\hat{\tilde{s}}_{c|n}^C\right)^{\eta_n/(\eta_n - 1)}, \tag{A61}$$

which generally differ when relative rents change. □

Proposition 5. *Assume that the nested CET, nested Fréchet, and nested multinomial logit models use the same CES yield technology, share the same nesting tree, and are evaluated at a common benchmark with acreage shares s_k, yields y_k, and land cost shares ϑ_k^L. Suppose that the observed land cost per hectare is common across crops, so that there exists a scalar R satisfying $\vartheta_k^L = R/(P_k y_k)$ for all crops k. For nested Fréchet parameters satisfying $\theta_n > 1$ at every internal node and $\theta_{p(n)} \le \theta_n$ at every nonroot internal node, the three models have identical local supply-elasticity matrices $\partial \ln Y_k / \partial \ln P_l$, for all crops k, l, if, at every $n \in \mathcal{I}$,*

$$\theta_n - 1 = -\eta_n = \frac{\alpha_n R}{P_M}. \tag{A62}$$

Proof. The three models use the same within-crop CES yield technology, so the intensification component of the supply elasticity is the same in all cases:

$$\mathbf{1}\{k = l\} \sigma_k \frac{\vartheta_k^X}{1 - \vartheta_k^X}. \tag{A63}$$

It is therefore sufficient to compare the non-intensification components.

Let $\chi_{n,l}$ denote the transmission of a crop-l rent or real-profit shock to node n. In the three nested systems, this object satisfies the same bottom-up recursion when evaluated at the same benchmark shares:

$$\chi_{n,l} = \sum_{c\in C(n)} \frac{s_c}{s_n} \chi_{c,l} \qquad \forall n \in \mathcal{I}, \tag{A64}$$

with leaf conditions $\chi_{l,l} = 1$ and $\chi_{k,l} = 0$ for $k \ne l$. Hence the same $\chi_{n,l}$ can be used for the three models. For the CET, this derives from $\bar{s}_n = s_n$, which is implied by the common land costs across crops.

From equation (A47), the nested CET non-intensification elasticity is

$$\left.\frac{\partial \ln Y_k}{\partial \ln P_l}\right|_{\text{non-int.}}^{C} = \frac{1}{\vartheta_l^L} \sum_{(n,c)\in\text{path}(1\to k)} (-\eta_n) \left(\chi_{c,l} - \chi_{n,l}\right). \tag{A65}$$

For the nested Fréchet, equation (A35) gives an acreage component plus a composition component. Unfolding the top-down recursion in section B gives

$$\mathcal{E}_{k,l}^F = \sum_{(n,c)\in\text{path}(1\to k)} \theta_n \left(\chi_{c,l} - \chi_{n,l}\right). \tag{A66}$$

The composition term in equation (A35) is

$$\frac{\chi_{1,l} - \chi_{k,l}}{\vartheta_l^L} = -\frac{1}{\vartheta_l^L} \sum_{(n,c)\in\text{path}(1\to k)} \left(\chi_{c,l} - \chi_{n,l}\right), \tag{A67}$$

because the path increments telescope from the root to crop k. Thus the Fréchet non-intensification elasticity is

$$\left.\frac{\partial \ln Y_k}{\partial \ln P_l}\right|_{\text{non-int.}}^{F} = \frac{1}{\vartheta_l^L} \sum_{(n,c)\in\text{path}(1\to k)} (\theta_n - 1) \left(\chi_{c,l} - \chi_{n,l}\right). \tag{A68}$$

The composition term is what lowers each Fréchet path weight from θ_n to $\theta_n - 1$.

For the nested multinomial logit, unfolding the top-down recursion in section D gives

$$\mathcal{E}_{k,l}^L = \sum_{(n,c)\in\text{path}(1\to k)} \alpha_n \left(\chi_{c,l} - \chi_{n,l}\right), \tag{A69}$$

where $\mathcal{E}_{k,l}^L$ is the acreage semi-elasticity with respect to the real profit of crop l. By equation (A53), the corresponding price elasticity is obtained by multiplying by $P_l y_l / P_M$. The common per-hectare land-cost assumption implies $\vartheta_l^L = R/(P_l y_l)$, or $P_l y_l / P_M = (R/P_M)/\vartheta_l^L$. Therefore the nested logit non-intensification elasticity is

$$\left.\frac{\partial \ln Y_k}{\partial \ln P_l}\right|_{\text{non-int.}}^{L} = \frac{1}{\vartheta_l^L} \sum_{(n,c)\in\text{path}(1\to k)} \frac{\alpha_n R}{P_M} \left(\chi_{c,l} - \chi_{n,l}\right). \tag{A70}$$

Comparing (A65), (A68), and (A70), the three non-intensification components coincide for every pair of crops (k, l) when

$$\theta_n - 1 = -\eta_n = \frac{\alpha_n R}{P_M} \tag{A71}$$

at every internal node n. Adding back the common intensification term gives equality of the full local supply-elasticity matrices. □

F Structural farm model underlying the estimation

This appendix derives the structural farm-level model that underlies the econometric specification of section 3.3. It extends the multinomial logit framework of section 2.3 and its nested version of section 3.1 in three directions: (*i*) the single-input CES yield function is replaced by a quadratic per-hectare technology with two yield-enhancing inputs; (*ii*) the entropy-regularized management cost is nested, so that the within-farm land allocation takes a nested logit form; and (*iii*) the set of crops a farmer operates is itself chosen, which generates endogenous regime switching.

The farmer's problem is solved by backward induction: intensification is optimized first, crop by crop; the resulting per-hectare profits are then taken as given to solve the within-regime acreage allocation; and the resulting within-regime surplus is finally taken as given to solve the regime choice.

We keep the theory notation of the main text and add a farm index i and a period index t, which we suppress whenever it does not create ambiguity. The nested structure is described by the tree of figure 3, with root node 1, non-root nodes $\mathcal{N}$, crop leaves $\mathcal{K} \subset \mathcal{N}$, internal nodes $\mathcal{I} \equiv \{1\} \cup (\mathcal{N} \setminus \mathcal{K})$, parent map $p(n)$ for non-root nodes, and children sets $C(n)$. To match the econometric equations (50)–(56), we report at each stage the empirical counterpart of the structural objects.

Per-hectare technology and variable profit. The farmer now uses two yield-enhancing inputs, $j \in \mathcal{J}$, instead of the single input X of section 2. Per-hectare input use is stacked in the vector $\mathbf{x}_k = (x_{k,j})_{j \in \mathcal{J}}$, with prices $\mathbf{P}_X = (P_{X,j})_{j \in \mathcal{J}}$ generalizing the scalar input price P_X. In contrast to the CES yield function of section 2, per-hectare yield is a quadratic function of input use,

$$y_k = \bar{a}_k^y + \mathbf{b}_k^\top \mathbf{x}_k - 0.5\, \mathbf{x}_k^\top \boldsymbol{\Gamma}_k^{-1} \mathbf{x}_k, \tag{A72}$$

where $\bar{a}_k^y$ is the primitive yield-level shifter, $\mathbf{b}_k$ a vector of linear coefficients, and $\boldsymbol{\Gamma}_k$ a symmetric positive-definite matrix, so that y_k is strictly concave in $\mathbf{x}_k$. This quadratic form is the two-input counterpart of the technology used by Koutchadé et al. (2021); it delivers linear input demands and keeps the per-hectare problem tractable. The parameters $\bar{a}_k^y$, $\mathbf{b}_k$, $\boldsymbol{\Gamma}_k$, and c_k denote structural objects; the farm heterogeneity, observed shifters, and idiosyncratic shocks of the empirical model are reintroduced separately at the end of the appendix.

For a given acreage allocation, the farmer chooses inputs crop by crop to maximize the per-hectare gross margin $P_k y_k - (\mathbf{P}_X)^\top \mathbf{x}_k$. The first-order conditions $P_k(\mathbf{b}_k - \boldsymbol{\Gamma}_k^{-1}\mathbf{x}_k) = \mathbf{P}_X$ give the linear input demands

$$\mathbf{x}_k = \boldsymbol{\Gamma}_k \mathbf{b}_k - P_k^{-1} \boldsymbol{\Gamma}_k \mathbf{P}_X = \boldsymbol{\Gamma}_k \left(\mathbf{b}_k - P_k^{-1} \mathbf{P}_X\right), \tag{A73}$$

which is the structural counterpart of equation (51). We maintain throughout this derivation the interior-domain restriction $\boldsymbol{\Gamma}_k \left(\mathbf{b}_k - P_k^{-1}\mathbf{P}_X\right) \geq \mathbf{0}$, so that the unconstrained input demand is feasible. Substituting (A73) into (A72) gives a constant term $0.5\, \mathbf{b}_k^\top \boldsymbol{\Gamma}_k \mathbf{b}_k$. Defining the reduced-form yield shifter as $a_k^y \equiv \bar{a}_k^y + 0.5\, \mathbf{b}_k^\top \boldsymbol{\Gamma}_k \mathbf{b}_k$ yields

$$y_k = a_k^y - 0.5\, P_k^{-2}\, (\mathbf{P}_X)^\top \boldsymbol{\Gamma}_k \mathbf{P}_X, \tag{A74}$$

the structural counterpart of equation (50). The per-hectare variable profit, obtained by evaluating

$P_k y_k - (\mathbf{P}_X)^\top \mathbf{x}_k$ at the optimum, is

$$\pi_k = P_k a_k^y - (\mathbf{P}_X)^\top \mathbf{\Gamma}_k \mathbf{b}_k + 0.5\, P_k^{-1}\; (\mathbf{P}_X)^\top \mathbf{\Gamma}_k \mathbf{P}_X. \tag{A75}$$

Equations (A74) and (A75) are linked by Hotelling's lemma, $\partial \pi_k / \partial P_k = y_k$, a property we use below to compute elasticities. As in section 2.3, the crop-specific real profit nets out a linear management cost $P_M c_k$ and is expressed in units of the management input M,

$$\varpi_k = \left(\pi_k - P_M c_k\right)/P_M = \left(P_k y_k - (\mathbf{P}_X)^\top \mathbf{x}_k - P_M c_k\right)/P_M, \tag{A76}$$

which generalizes the single-input real profit of section 2.3 to two inputs.

The prices entering equations (A73)–(A76) are those on which farmers can condition when they make their production decisions. Input prices $\mathbf{P}_X$ are observed, since inputs are purchased within the current season. Output prices P_k are not: acreages are chosen first, input use is decided next, and the price at which output is sold is realized only after harvest. The P_k above are therefore expected prices, and we assume that no further information about them accrues between the acreage and the input decisions, so that a single expectation governs both stages. In our empirical application, we accordingly use current-year input prices and previous-year output prices as proxies.

Acreage allocation within a production regime. A production regime r defines a feasible subset of crops $\mathcal{K}^+(r)$. For any node n, let $\mathcal{C}_r(n) \subseteq \mathcal{C}(n)$ be the children active under regime r, including operated crop children and internal children with at least one operated crop descendant. Conditional on operating regime r, the farmer allocates land across the operated crops exactly as in section 3.1, by maximizing the per-hectare profit net of the nested entropy management cost $P_M f(\mathbf{s})$,

$$\max_{\mathbf{s} \in \Delta(r)} \sum_{k \in \mathcal{K}^+(r)} s_k \left(P_k y_k - (\mathbf{P}_X)^\top \mathbf{x}_k\right) - P_M f(\mathbf{s}). \tag{A77}$$

Here $\Delta(r)$ is the simplex over the operated crops. $f(\mathbf{s})$ is the nested management function of section 3.1, with management-cost shifters c_k and nest scales α_n, $n \in \mathcal{I}$. We use $0 \ln 0 = 0$ for an inactive child of an active node; since every child of a node with $s_n = 0$ also has zero share, the entire entropy contribution of such a node is defined by continuity to be zero. Hence, f restricted to $\Delta(r)$ reduces to a sum over the operated sub-tree, consistent with the reduced children sets $\mathcal{C}_r(n)$ used below. Just as in the main text, the solution is governed by the crop-specific real profits ϖ_k of (A76). Defining the composite real profits recursively over the operated sub-tree,

$$\varpi_n(r) = \alpha_n^{-1} \ln\left(\sum_{c \in \mathcal{C}_r(n)} \exp(\alpha_n \varpi_c(r)) \right) \qquad \forall n \in \mathcal{I} \text{ with } \mathcal{C}_r(n) \neq \emptyset, \tag{A78}$$

where $\varpi_k(r) = \varpi_k$ for operated crop leaves, the first-order conditions of (A77) deliver unconditional shares recursively over the operated sub-tree,

$$s_c(r) = \exp[\alpha_n\left(\varpi_c(r) - \varpi_n(r)\right)]\, s_n(r) \qquad \forall n \in \mathcal{I},\ \forall c \in \mathcal{C}_r(n), \tag{A79}$$

with the top node normalized to $s_1(r) = 1$. Equations (A78)–(A79) are the structural counterparts of the inclusive values and acreage-share equations in section 3.1, using the full three-level tree represented in figure 3; the mapping to the empirical scales and shifters is collected at the end of the appendix.

Endogenous regime choice. The farmer does not operate every crop in every period. Operating regime r yields the within-regime surplus $\varpi_1(r)$ defined by the recursion (A78), but also entails crop-specific quasi-fixed costs—reflecting crop-specific capital, agronomic constraints, or setup costs—associated with the crops grown. The net regime surplus, in real terms, is $\varpi_1(r) - \sum_{k\in\mathcal{K}^+(r)} \beta_k^r + \xi(r)$, where β_k^r is the regime fixed cost of crop k expressed in units of input M and $\xi(r)$ is an idiosyncratic, regime-specific taste shock drawn independently across regimes from a type I extreme-value (Gumbel) distribution with scale $1/\varsigma$. The farmer selects the regime that maximizes this net regime surplus. Standard discrete-choice arguments then give logit regime probabilities,

$$\Pr(r) = \frac{\exp\left[\varsigma\left(\varpi_1(r) - \sum_{k\in\mathcal{K}^+(r)} \beta_k^r\right)\right]}{\sum_{r'\in\mathcal{R}} \exp\left[\varsigma\left(\varpi_1(r') - \sum_{k\in\mathcal{K}^+(r')} \beta_k^{r'}\right)\right]}. \tag{A80}$$

This is the structural counterpart of equation (54). The unconditional expected acreage share of crop k then aggregates the within-regime shares over regimes that operate it,

$$\mathrm{E}[s_k] = \sum_{r\in\mathcal{R}} \Pr(r)\, s_k(r). \tag{A81}$$

Elasticities. The separability of the technology from the allocation, already present in section 2.3, carries over here. From (A74), writing $q_k \equiv 0.5\, P_k^{-2}\, (\mathbf{P}_X)^\top\, \mathbf{\Gamma}_k \mathbf{P}_X$ for the quadratic yield loss so that $y_k = a_k^y - q_k$, the own-price yield elasticity, evaluated on the maintained domain where $y_k > 0$, is

$$\frac{\partial \ln y_k}{\partial \ln P_k} = \frac{2q_k}{y_k} > 0, \tag{A82}$$

which is governed by the curvature matrix $\mathbf{\Gamma}_k$ and replaces the CES intensification term of equation (42). For the acreage margin, the real profit (A76) and Hotelling's lemma give $\partial\varpi_l/\partial \ln P_l = P_l y_l / P_M$, so the within-regime acreage elasticities follow from the nested recursion of Appendix D applied to the regime-specific semi-elasticities $\mathcal{E}_{k,l}^L(r) \equiv \partial \ln s_k(r)/\partial\varpi_l$,

$$\frac{\partial \ln s_k(r)}{\partial \ln P_l} = \frac{P_l y_l}{P_M}\, \mathcal{E}_{k,l}^L(r). \tag{A83}$$

With more than one feasible regime, a price change also reshuffles probability mass across regimes. The nested log-sum-exp value satisfies the envelope property $\partial\varpi_1(r)/\partial\varpi_l = s_l(r)$, the same property underlying (A79). Differentiating the logit regime probabilities (A80) and combining this envelope property with Hotelling's lemma gives the regime-switching elasticity

$$\frac{\partial \ln \Pr(r)}{\partial \ln P_l} = \varsigma\, \frac{P_l y_l}{P_M}\big(s_l(r) - \mathrm{E}[s_l]\big). \tag{A84}$$

This elasticity is positive for regimes that allocate more land to crop l than the population average, and negative otherwise. It vanishes when a single regime is feasible, since then $s_l(r) = \mathrm{E}[s_l]$ trivially.

Differentiating the unconditional share (A81) and combining (A83) and (A84) gives the full acreage-margin elasticity,

$$\frac{\partial \ln \mathrm{E}[s_k]}{\partial \ln P_l} = \sum_{r\in\mathcal{R}} w_k(r) \frac{P_l y_l}{P_M} \left[\mathcal{E}^L_{k,l}(r) + \varsigma\big(s_l(r) - \mathrm{E}[s_l]\big)\right], \qquad w_k(r) \equiv \frac{\Pr(r)\, s_k(r)}{\mathrm{E}[s_k]}, \tag{A85}$$

where the weights $w_k(r)$ sum to one across regimes and reflect each regime's contribution to crop k's expected acreage, so that a regime in which k is barely grown carries little weight even if $\Pr(r)$ is large. The own-price elasticities reported in table 1 combine (A82) and (A85); Appendix G details how these formulas are integrated over the latent farm heterogeneity and aggregated to the national level.

Stochastic specification and empirical counterparts. The derivation above is deterministic, conditional on the farmer's structural parameters. The econometric model of section 3.3 converts it into a likelihood in two steps. First, each structural parameter is allowed to vary across farms and is written as a farm-specific random coefficient plus an index of observed covariates: the yield shifter a^y_k becomes $\beta^y_{k,i} + (\delta^y_{k,0})^\top \mathbf{z}_{k,it}$ in (50); the input-demand intercept $\boldsymbol{\Gamma}_k \mathbf{b}_k$ becomes $\boldsymbol{\beta}^x_{k,i} + (\boldsymbol{\Delta}^x_{k,0})^\top \mathbf{z}_{k,it}$ in (51); the price-response parameters $\boldsymbol{\Gamma}_k$ become $\boldsymbol{\Gamma}_{k,i}$ in (50) and (51); the nesting parameters α_n become $\alpha_{n,i}$ in (52); and the real management cost c_k becomes $\beta^s_{k,i} + (\delta^s_{k,0})^\top \mathbf{z}_{k,it}$ in (55).

Second, additive idiosyncratic shocks are appended to the behavioral equations: $\varepsilon^y_{k,it}$ and $\boldsymbol{\varepsilon}^x_{k,it}$ are added to the yield and input equations, and $\varepsilon^s_{k,it}$ is added to the management shifter, generating the stochastic component of the acreage equation.

Given the timing of farmers' production decisions—that is, the fact that acreage choices are made before yield and input decisions—we assume $\boldsymbol{\varepsilon}^{xy} \equiv (\varepsilon^y, \boldsymbol{\varepsilon}^x)$ and ε^s to be independent. We do, however, allow ε^y and $\boldsymbol{\varepsilon}^x$ to be correlated, because idiosyncratic shocks, especially climatic shocks, can simultaneously affect yields and input use. Finally, all of these idiosyncratic shocks are assumed to be independent of the random parameters that characterize farm-specific behavior.

G From farm-level to national elasticities

This appendix details how the farm-level elasticity formulas of Appendix F are evaluated and aggregated into the national elasticities reported in tables 1 and A2. Two issues must be addressed. First, the formulas depend on farm-specific parameters and shocks that are not observed, so the farm-level elasticities are defined as expectations over these latent objects. Second, the object of interest is the price response of aggregate French acreage and production, which dictates how farm-level responses are weighted.

National aggregates. All elasticities are evaluated at the 2021 environment: 2021 covariates and input prices, and expected output prices proxied by previous-year prices, as in section 3.3; the period index t refers to 2021 throughout this appendix. Let ℓ_i denote the field-crop area that farm i represents in the population, that is, its own area multiplied by its FADN extrapolation weight, and let E_i denote the expectation over the production regimes, as in equation (A81), and over the posterior distribution of the farm's latent objects defined below. The national acreage and production of crop k implied by the model are

$$L_k = \sum_i \ell_i \, \mathrm{E}_i \left[s_{k,it} \right] \quad \text{and} \quad Y_k = \sum_i \ell_i \, \mathrm{E}_i \left[s_{k,it} \, y_{k,it} \right], \tag{A86}$$

where the acreage shares are given by equations (A79)–(A81) and $y_{k,it}$ is the expected yield of equation (A74) on which the farmer's decisions are based: the additive shocks $\varepsilon^y_{k,it}$ and $\boldsymbol{\varepsilon}^x_{k,it}$ have zero mean, so they drop out of expected yields, input demands, and profits, and play a role only in the inference on the latent objects. The national elasticities are defined as the price responses of these aggregates, $\partial \ln L_k / \partial \ln P_l$ and $\partial \ln Y_k / \partial \ln P_l$.

Integration over latent farm heterogeneity. For given values of the random parameters $\boldsymbol{\zeta}_i$ and acreage shocks $\boldsymbol{\varepsilon}^s_{it}$, every object entering the elasticity formulas is available in closed form: yields and input demands from equations (A73) and (A74), real profits from equation (55), within-regime shares and inclusive values from the recursion (A78)–(A79), regime probabilities from equation (A80), and the within-regime semi-elasticities $\mathcal{E}^L_{k,l}(r)$ from the recursions of Appendix D applied to the operated sub-tree. The pair $(\boldsymbol{\zeta}_i, \boldsymbol{\varepsilon}^s_{it})$ is not observed. We integrate it out under its posterior distribution given the farm's observed choices over its sample years, in the spirit of the "statistical calibration" procedure of Koutchadé et al. (2018), with one difference: because the elasticities are nonlinear functions of the latent objects, we do not plug in their posterior means but average the formulas over draws from the posterior distribution.

Conditioning on the farm's observed choices anchors the computation to the data: at the posterior draws, the predicted regime probabilities and acreage shares closely track the farm's observed 2021 allocation, so the elasticities are evaluated at an approximation of the observed benchmark. A model-based evaluation is in any case unavoidable, because equation (A85) involves the regime probabilities and within-regime shares of all feasible regimes, including regimes the farm does not operate in 2021, which have no observed counterpart.

Aggregation. The elasticities are nonlinear in the latent objects and heterogeneous across farms, so expectations and aggregation are applied to levels and to their price derivatives, and ratios are formed last. For each posterior draw, the price derivative of the expected acreage share follows from multiplying equation (A85) by $\mathrm{E}[s_k]$,

$$\frac{\partial \, \mathrm{E}[s_k]}{\partial \ln P_l} = \frac{P_l y_l}{P_M} \sum_{r \in \mathcal{R}} \Pr(r) \, s_k(r) \left[\mathcal{E}^L_{k,l}(r) + \varsigma \left(s_l(r) - \mathrm{E}[s_l] \right) \right], \tag{A87}$$

and the price derivative of the expected yield follows from equation (A82), $\partial y_k / \partial \ln P_k = 2 q_k$, with q_k the quadratic yield loss defined in Appendix F. These derivatives are averaged over the posterior draws within each farm, jointly with the corresponding levels so as to preserve the dependence between shares and yields induced by the farm-specific parameters, and then summed across farms. The price response of national acreage is

$$\frac{\partial \ln L_k}{\partial \ln P_l} = \frac{\sum_i \ell_i \, \mathrm{E}_i \left[\partial s_{k,it} / \partial \ln P_l \right]}{\sum_i \ell_i \, \mathrm{E}_i \left[s_{k,it} \right]}. \tag{A88}$$

This is the acreage-weighted acreage elasticity of table 1. The price response of national production decomposes as

$$\frac{\partial \ln Y_k}{\partial \ln P_l} = \frac{\sum_i \ell_i \, \mathrm{E}_i \left[y_{k,it} \, \partial s_{k,it} / \partial \ln P_l \right]}{\sum_i \ell_i \, \mathrm{E}_i \left[s_{k,it} \, y_{k,it} \right]} + \mathbf{1}\{l = k\} \frac{\sum_i \ell_i \, \mathrm{E}_i \left[s_{k,it} \, \partial y_{k,it} / \partial \ln P_k \right]}{\sum_i \ell_i \, \mathrm{E}_i \left[s_{k,it} \, y_{k,it} \right]}, \tag{A89}$$

where the indicator reflects that expected yields respond to the crop's own expected price but not to the prices of other crops. The first term is the output-weighted acreage elasticity—the average of farm-level acreage elasticities weighted by each farm's share of national crop-k production—and the second term is the output-weighted yield elasticity; both are reported in table 1, and the cross-price matrix of table A2 corresponds to the first term. The difference between the output-weighted and acreage-weighted acreage elasticities is the between-farm composition effect discussed in section 3.4; it is nonzero insofar as farms' acreage responses covary with their yield levels.

H Supplementary figures

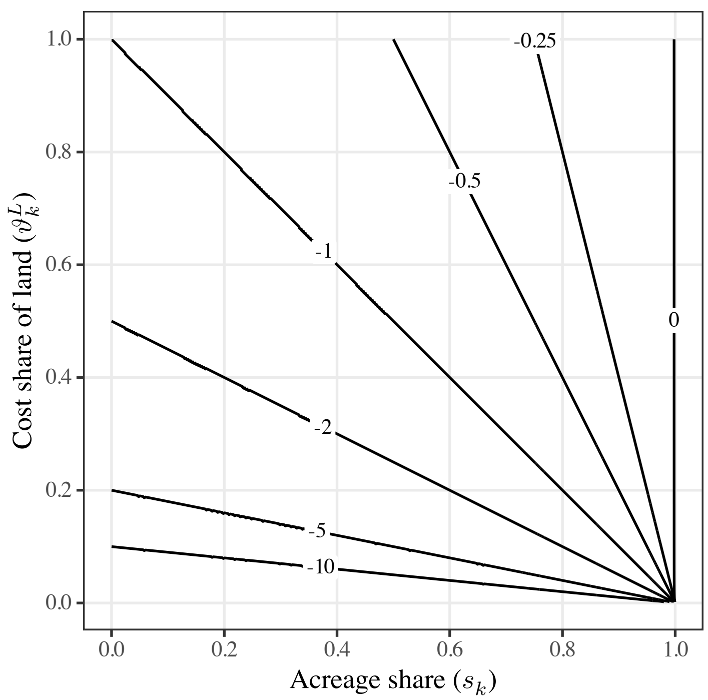

Figure A1: Yield-composition elasticity ($-(1 - s_k)/\vartheta_k^L$) with Fréchet-distributed yields.

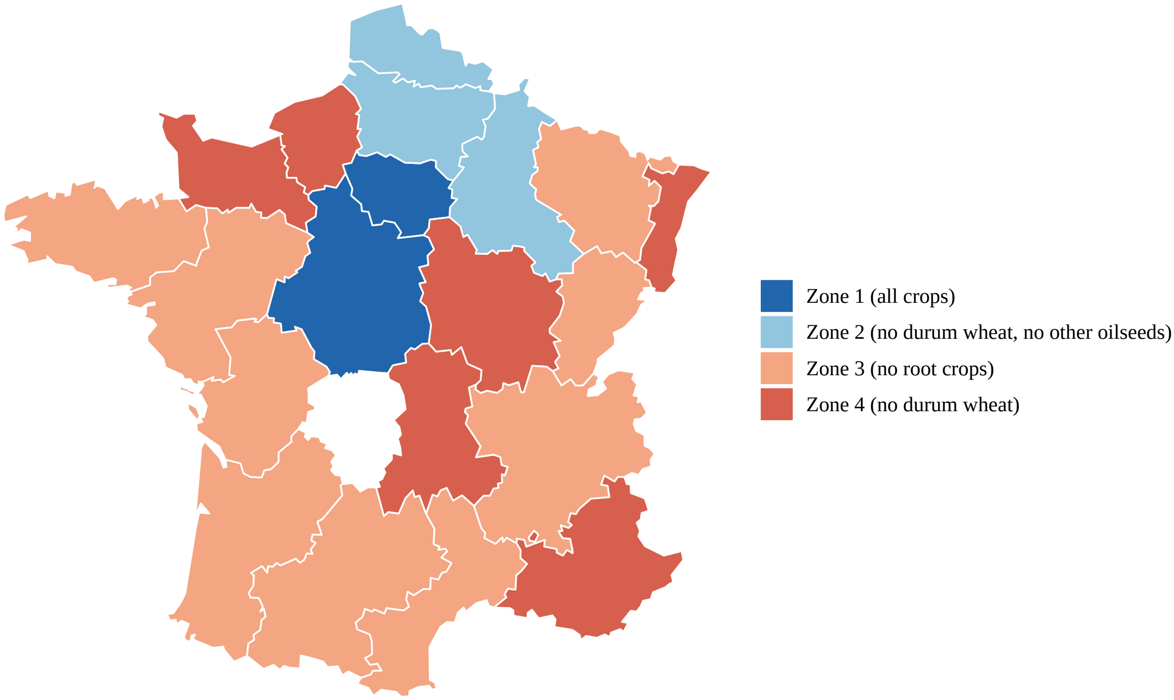

Figure A2: French regions by crop-choice set. The blank area corresponds to the *Limousin* region, which contains an insufficient number of specialized field-crop farms to be included in the estimation sample.

I Supplementary tables

Table A1: Summary statistics of the farm sample.

	Common wheat	Barley	Durum wheat	Maize	Other cereals	Protein crops	Rapeseed	Sunflower	Other oilseeds	Potatoes	Sugar beet
Production frequency and crop shares											
Prod. freq. (%)	100.0	78.4	7.2	40.7	8.7	25.1	69.3	16.6	5.5	13.9	45.1
Mean acreage share (unconditional)	0.42	0.17	0.02	0.10	0.01	0.02	0.13	0.03	0.01	0.03	0.07
Std. dev. share	0.14	0.14	0.07	0.19	0.03	0.05	0.11	0.09	0.04	0.09	0.10
Mean acreage share (conditional)	0.42	0.22	0.21	0.25	0.08	0.09	0.19	0.19	0.13	0.19	0.16
Std. dev. (cond.)	0.14	0.12	0.13	0.23	0.08	0.05	0.08	0.12	0.09	0.16	0.07
Yield (t/ha)[a]											
Mean	7.39	6.59	5.71	8.60	4.53	3.25	3.34	2.43	2.57	3.83	82.40
Std. dev.	1.80	1.62	1.79	3.09	1.95	1.34	0.87	0.77	1.05	1.33	19.70
Output price (€/t)[a]											
Mean	164.71	151.17	211.72	159.81	186.36	259.10	386.09	385.18	410.77	263.25	25.29
Std. dev.	44.95	25.80	45.87	105.41	66.21	103.68	65.42	178.74	101.13	195.60	3.99
Fertilizers price index (2020 = 1)[a,b]											
Mean	2.02	1.96	2.13	2.19	0.76	0.41	2.35	0.72	1.42	3.52	3.56
Std. dev.	0.59	0.31	0.20	0.33	0.06	0.01	0.32	0.12	0.08	0.79	0.91
Pesticides price index (2020 = 1)[a,b]											
Mean	1.95	1.49	2.65	1.00	0.75	1.73	2.33	0.25	1.06	5.27	2.59
Std. dev.	0.70	0.30	0.92	0.24	0.29	0.27	0.63	0.08	0.44	2.83	0.94

Notes: Prod. freq. = share of farms producing the crop (%); unconditional share = average over all farms; conditional share = average over producing farms only; [a] statistics computed over farms that produce the crop; [b] allocated to crops using `winputall` package (Koutchadé et al., 2024).
Source: FADN data, panel of French specialized field-crop farms.

Table A2: Estimated output-weighted cross-price acreage elasticities for France in 2021.

Response crop	Price driver										
	Barley	Common wheat	Durum wheat	Maize	Other cereals	Other oilseeds	Potatoes	Protein crops	Rapeseed	Sugar beet	Sunflower
Barley	0.46	−0.32	−0.06	−0.12	−0.02	−0.01	−0.04	−0.01	−0.05	−0.04	−0.01
Common wheat	−0.10	0.33	−0.03	−0.08	−0.01	−0.01	−0.08	−0.01	−0.05	−0.04	−0.02
Durum wheat	−0.11	−0.20	0.73	−0.24	−0.01	−0.00	−0.14	−0.01	−0.04	−0.05	−0.04
Maize	−0.11	−0.26	−0.07	0.74	−0.01	−0.01	−0.07	−0.00	−0.04	−0.03	−0.03
Other cereals	−0.16	−0.41	−0.13	−0.39	1.09	−0.02	−0.01	−0.02	−0.03	−0.01	−0.05
Other oilseeds	−0.03	−0.12	−0.01	−0.18	−0.00	0.63	−0.01	−0.01	−0.25	−0.01	−0.12
Potatoes	−0.02	−0.13	−0.08	−0.03	−0.00	−0.00	1.52	−0.01	−0.03	−0.17	−0.00
Protein crops	−0.05	−0.14	−0.05	−0.04	−0.01	−0.04	−0.04	0.40	−0.27	−0.10	−0.09
Rapeseed	−0.05	−0.20	−0.02	−0.04	−0.01	−0.03	−0.08	−0.06	0.53	−0.10	−0.07
Sugar beet	−0.04	−0.15	−0.05	−0.02	−0.00	−0.00	−0.27	−0.01	−0.09	0.57	−0.01
Sunflower	−0.03	−0.16	−0.04	−0.06	−0.01	−0.02	−0.01	−0.05	−0.18	−0.02	0.50

Table A3: Calibrated nested multinomial logit cross-price acreage elasticities for France.

Response crop	Price driver										
	Barley	Common wheat	Durum wheat	Maize	Other cereals	Other oilseeds	Potatoes	Protein crops	Rapeseed	Sugar beet	Sunflower
Barley	0.37	−0.27	−0.02	−0.08	−0.00	−0.00	−0.04	−0.00	−0.04	−0.03	−0.01
Common wheat	−0.09	0.27	−0.02	−0.07	−0.00	−0.00	−0.04	−0.00	−0.04	−0.03	−0.01
Durum wheat	−0.10	−0.27	0.73	−0.08	−0.00	−0.00	−0.04	−0.00	−0.04	−0.03	−0.01
Maize	−0.10	−0.27	−0.02	0.66	−0.00	−0.00	−0.04	−0.00	−0.04	−0.03	−0.01
Other cereals	−0.10	−0.27	−0.02	−0.08	0.33	−0.00	−0.04	−0.00	−0.04	−0.03	−0.01
Other oilseeds	−0.04	−0.14	−0.01	−0.04	−0.00	0.46	−0.04	−0.02	−0.22	−0.03	−0.05
Potatoes	−0.04	−0.14	−0.01	−0.04	−0.00	−0.00	1.67	−0.00	−0.04	−0.16	−0.01
Protein crops	−0.04	−0.14	−0.01	−0.04	−0.00	−0.01	−0.04	0.23	−0.22	−0.03	−0.05
Rapeseed	−0.04	−0.14	−0.01	−0.04	−0.00	−0.01	−0.04	−0.02	0.42	−0.03	−0.05
Sugar beet	−0.04	−0.14	−0.01	−0.04	−0.00	−0.00	−0.21	−0.00	−0.04	0.48	−0.01
Sunflower	−0.04	−0.14	−0.01	−0.04	−0.00	−0.01	−0.04	−0.02	−0.22	−0.03	0.44

Table A4: Calibrated nested Fréchet cross-price acreage elasticities for France.

Response crop	Price driver										
	Barley	Common wheat	Durum wheat	Maize	Other cereals	Other oilseeds	Potatoes	Protein crops	Rapeseed	Sugar beet	Sunflower
Barley	1.81	−1.16	−0.07	−0.32	−0.01	−0.01	−0.31	−0.03	−0.31	−0.24	−0.08
Common wheat	−0.38	1.43	−0.07	−0.32	−0.01	−0.01	−0.31	−0.03	−0.31	−0.24	−0.08
Durum wheat	−0.39	−1.16	3.42	−0.32	−0.01	−0.01	−0.31	−0.03	−0.31	−0.24	−0.08
Maize	−0.39	−1.16	−0.07	3.14	−0.01	−0.01	−0.31	−0.03	−0.31	−0.24	−0.08
Other cereals	−0.39	−1.16	−0.07	−0.32	1.54	−0.01	−0.31	−0.03	−0.31	−0.24	−0.08
Other oilseeds	−0.34	−1.02	−0.06	−0.28	−0.01	2.15	−0.31	−0.04	−0.49	−0.24	−0.12
Potatoes	−0.34	−1.02	−0.06	−0.28	−0.01	−0.01	10.09	−0.03	−0.31	−0.37	−0.08
Protein crops	−0.34	−1.02	−0.06	−0.28	−0.01	−0.02	−0.31	1.11	−0.49	−0.24	−0.12
Rapeseed	−0.34	−1.02	−0.06	−0.28	−0.01	−0.02	−0.31	−0.04	2.49	−0.24	−0.12
Sugar beet	−0.34	−1.02	−0.06	−0.28	−0.01	−0.01	−0.48	−0.03	−0.31	3.24	−0.08
Sunflower	−0.34	−1.02	−0.06	−0.28	−0.01	−0.02	−0.31	−0.04	−0.49	−0.24	2.18

References

Arkolakis, C., Costinot, A. and Rodríguez-Clare, A. (2012). New trade models, same old gains? *The American Economic Review*, 102(1), 94–130.

Bareille, F. and Largier, B. (forthcoming). A meta-analysis on the productive value of crop biodiversity. *American Journal of Agricultural Economics*.

Carpentier, A., Gohin, A., Sckokai, P. and Thomas, A. (2015). Economic modelling of agricultural production: past advances and new challenges. *Revue d'Études en Agriculture et Environnement*, 96(1), 131–165.

Carpentier, A. and Letort, E. (2012). Accounting for heterogeneity in multicrop micro-econometric models: Implications for variable input demand modeling. *American Journal of Agricultural Economics*, 94(1), 209–224.

Carpentier, A. and Letort, E. (2014). Multicrop production models with multinomial logit acreage shares. *Environmental and Resource Economics*, 59(4), 537–559.

Chambers, R. G. and Just, R. E. (1989). Estimating multioutput technologies. *American Journal of Agricultural Economics*, 71(4), 980–995.

Chavas, J. and Holt, M. (1990). Acreage decisions under risk: The case of corn and soybeans. *American Journal of Agricultural Economics*, 72(3), 529–538.

Chomitz, K. M. and Gray, D. A. (1996). Roads, land use, and deforestation: A spatial model applied to Belize. *The World Bank Economic Review*, 10(3), 487–512.

Costinot, A., Donaldson, D. and Smith, C. B. (2016). Evolving comparative advantage and the impact of climate change in agricultural markets: Evidence from 1.7 million fields around the world. *Journal of Political Economy*, 124(1), 205–248.

Daly, A. and Zachary, S. (1978). Improved multiple choice models. In D. A. Hensher and M. Q. Dalvi (eds.) *Identifying and Measuring the Determinants of Mode Choice*, (pp. 335–357). London: Teakfield.

Delyon, B., Lavielle, M. and Moulines, E. (1999). Convergence of a stochastic approximation version of the EM algorithm. *The Annals of Statistics*, 27(1).

Eaton, J. and Kortum, S. (2002). Technology, geography, and trade. *Econometrica*, 70(5), 1741–1779.

Farrokhi, F. and Pellegrina, H. S. (2023). Trade, technology, and agricultural productivity. *Journal of Political Economy*, 131(9), 2509–2555.

Fuglie, K. O., Morgan, S. and Jelliffe, J. (2024). *World agricultural production, resource use, and productivity, 1961–2020*. Economic Information Bulletin 268, USDA, Economic Research Service.

Fujimori, S., Hasegawa, T., Masui, T. and Takahashi, K. (2014). Land use representation in a global CGE model for long-term simulation: CET vs. logit functions. *Food Security*, 6(5), 685–699.

Galichon, A. (2026). *Discrete Choice Models: Mathematical Methods, Econometrics, and Data Science*. Princeton University Press.

Gohin, A. (2020). The land use impacts of the EU biodiesel policy: Assessing the direct, indirect and induced effects. *Journal of Agricultural Economics*, 71(2), 305–329.

Gohin, A. and Matthews, A. (2024). Adding mirror clauses within the European Green Deal: Hype or hope? *Applied Economic Perspectives and Policy*, 46(3), 1103–1126.

Gouel, C. and Laborde, D. (2021). The crucial role of domestic and international market-mediated adaptation to climate change. *Journal of Environmental Economics and Management*, 106, 102408.

Hendricks, N. P., Smith, A. and Sumner, D. A. (2014). Crop supply dynamics and the illusion of partial adjustment. *American Journal of Agricultural Economics*, 96(5), 1469–1491.

Hennessy, D. A. (2006). On monoculture and the structure of crop rotations. *American Journal of Agricultural Economics*, 88(4), 900–914.

Hertel, T. W., Lee, H.-L., Rose, S. and Sohngen, B. (2009). Modeling land-use related greenhouse gas sources and sinks and their mitigation potential. In T. W. Hertel, S. K. Rose and R. S. Tol (eds.) *Economic Analysis of Land Use in Global Climate Change Policy*, chapter 6, (pp. 123–153). Routledge.

Hertel, T. W. and Tsigas, M. E. (1988). Tax policy and U.S. agriculture: A general equilibrium analysis. *American Journal of Agricultural Economics*, 70(2), 289–302.

Horridge, M. (2021). *Using CRETH to make quantities add up without efficiency bias*. CoPS Working Paper G-325, Victoria University, Centre of Policy Studies/IMPACT Centre.

Howitt, R. E. (1995). Positive mathematical programming. *American Journal of Agricultural Economics*, 77(2), 329–342.

Kim, H. and Moschini, G. (2018). The dynamics of supply: U.S. corn and soybeans in the biofuel era. *Land Economics*, 94(4), 593–613.

Koutchadé, O. P., Carpentier, A. and Féménia, F. (2018). Modeling heterogeneous farm responses to European Union biofuel support with a random parameter multicrop model. *American Journal of Agricultural Economics*, 100(2), 434–455.

Koutchadé, O. P., Carpentier, A. and Féménia, F. (2021). Modeling corners, kinks, and jumps in crop acreage choices: Impacts of the EU support to protein crops. *American Journal of Agricultural Economics*, 103(4), 1502–1524.

Koutchadé, O. P., Carpentier, A. and Féménia, F. (2024). *Variable Inputs Allocation among Crops: A Time-Varying Random Parameters Approach*. Working Paper 24-07, UMR SMART, INRAE, L'Institut Agro Rennes-Angers.

Li, Y., Miao, R. and Khanna, M. (2019). Effects of ethanol plant proximity and crop prices on land-use change in the United States. *American Journal of Agricultural Economics*, 101(2), 467–491.

Lichtenberg, E. (1989). Land quality, irrigation development, and cropping patterns in the northern High Plains. *American Journal of Agricultural Economics*, 71(1), 187–194.

Lind, N. and Ramondo, N. (2023). Trade with correlation. *The American Economic Review*, 113(2), 317–353.

Lubowski, R. N., Plantinga, A. J. and Stavins, R. N. (2006). Land-use change and carbon sinks: Econometric estimation of the carbon sequestration supply function. *Journal of Environmental Economics and Management*, 51(2), 135–152.

Martinet, V. (2013). Effect of soil heterogeneity on the welfare economics of biofuel policies. *Land Use Policy*, 32, 218–229.

Mattsson, L.-G., Weibull, J. W. and Lindberg, P. O. (2014). Extreme values, invariance and choice probabilities. *Transportation Research Part B: Methodological*, 59, 81–95.

McFadden, D. (1978). Modeling the choice of residential location. In A. Karlqvist, L. Lundqvist, F. Snickars and J. W. Weibull (eds.) *Spatial Interaction Theory and Planning Models*, (pp. 75–96). Amsterdam: North-Holland.

Mérel, P. and Howitt, R. E. (2014). Theory and application of positive mathematical programming in agriculture and the environment. *Annual Review of Resource Economics*, 6(1), 451–470.

Mérel, P., Simon, L. K. and Yi, F. (2011). A fully calibrated generalized constant-elasticity-of-substitution programming model of agricultural supply. *American Journal of Agricultural Economics*, 93(4), 936–948.

Miao, R., Khanna, M. and Huang, H. (2016). Responsiveness of crop yield and acreage to prices and climate. *American Journal of Agricultural Economics*, 98(1), 191–211.

Pates, N. J. and Hendricks, N. P. (2021). Fields from afar: Evidence of heterogeneity in United States corn rotational response from remote sensing data. *American Journal of Agricultural Economics*, 103(5), 1759–1782.

Ramondo, N. and Rodríguez-Clare, A. (2013). Trade, multinational production, and the gains from openness. *Journal of Political Economy*, 121(2), 273–322.

Sands, R. D. and Leimbach, M. (2003). Modeling agriculture and land use in an integrated assessment framework. *Climatic Change*, 56(1–2), 185–210.

Searchinger, T., Heimlich, R., Houghton, R. A., Dong, F., Elobeid, A., Fabiosa, J., Tokgoz, S., Hayes, D. and Yu, T.-H. (2008). Use of U.S. croplands for biofuels increases greenhouse gases through emissions from land-use change. *Science*, 319(5867), 1238–1240.

Shoven, J. B. and Whalley, J. (1984). Applied general-equilibrium models of taxation and international trade: An introduction and survey. *Journal of Economic Literature*, 22(3), 1007–1051.

Sogalla, R., Wanner, J. and Watabe, Y. (2024). *New Trade Models, Same Old Emissions?* Working paper 11596, CESifo.

Sotelo, S. (2020). Domestic trade frictions and agriculture. *Journal of Political Economy*, 128(7), 2690–2738.

Souza-Rodrigues, E. (2018). Deforestation in the Amazon: A unified framework for estimation and policy analysis. *The Review of Economic Studies*, 86(6), 2713–2744.

Stigler, M. (2020). Supply response at the field-level: disentangling area and yield effects. Working Paper.

Taheripour, F., Zhao, X., Horridge, M., Farrokhi, F. and Tyner, W. (2020). Land use in computable general equilibrium models. *Journal of Global Economic Analysis*, 5(2), 63–109.