Journal of Agricultural and Resource Economics 50(3):487–507 ISSN: 1068-5502 (Print); 2327-8285 (Online)

doi: 10.22004/ag.econ.356157

Seeding Rate Responses to Markets, Resources, and Technologies

Yuyuan Che, David A. Hennessy, and Hongli Feng

Corn and soybean seeding rates in the United States have diverged. We develop a theoretical model of seeding rate choices considering a resource budget trade-off between seeds and resources per seed. Using extensive farm-level data, we find soybean rates are more own-price elastic than corn. Specifically, a 1% increase in the seed-to-crop price ratio reduces average seeding rates by less than 0.3% for corn and by about 2.0% for soybean. More land-embodied inputs increase both rates, while more seed-embodied inputs increase corn rates but decrease soybean rates. The difference in price elasticities due to plant architecture has implications for both economic surplus division from innovations and ecological policy outcomes.

Key words: crop yield per plant, genetic technology, land-embodied technical change, plant architecture, seed price elasticity, seed-embodied technical change

Introduction

Seeds are an essential input in crop production and generally constitute a significant portion of total production expenses for farmers. Specifically, soybean seed costs about \$50 per acre, while corn seed costs about \$100 per acre, accounting for over 20% of production costs for each crop in the US Midwest (Plastina, 2023). Seed markets are oligopolies (Ciliberto, Moschini, and Perry, 2019), where supplier market power is further strengthened through possession of germplasm foundation lines and patents on seed traits. The specialized breeding and seed production processes involved in hybrid varieties often result in relatively higher seed costs. Further, genetically modified seeds may carry additional expenses (Hyde et al., 2003). Seeds endowed with technology traits sell at large premiums, suggesting that growers will seek to carefully evaluate seed variety alternatives as well as economize on seeding rates while still availing themselves of the embedded technology (Larson, Roberts, and Gwathmey, 2007).

The selection of seeding rates gives rise to considerable environmental concerns due to the widespread use of chemical coatings on seeds. Neonicotinoids are widely used insecticides applied to the surface of seeds, being applied on more than 90% of corn acres (Perry and Moschini, 2020) and more than 50% of soybean acres in the United States (Hurley and Mitchell, 2017). Although neonicotinoids can reduce crop loss risks, residues persist in soil and water, where they

Yuyuan Che (corresponding author, yuyuan.che@ttu.edu) is an assistant professor in the Department of Agricultural and Applied Economics at Texas Tech University. David A. Hennessy is a professor of economics and Cargill professor of agricultural economic systems and Hongli Feng is an assistant professor in the Department of Economics and Center for Agricultural & Rural Development (CARD) at Iowa State University.
Support for this work was provided by the Agriculture and Food Research Initiative Foundational Program Grant No. 2018-6800828356 (overseen by the National Institute of Food and Agriculture, USDA), and also by the Elton R. Smith Foundation at Michigan State University. We thank Laura Lindsey, Alex Lindsey, Maninder Singh, and group participants for their collaboration during focus group meetings in Ohio and Michigan. We are also grateful for comments made by Scott M. Swinton, Jeffrey M. Wooldridge, Jinhua Zhao, and seminar participants at the 2021 Agricultural and Applied Economics Association (AAEA) Annual Meetings.

Review coordinated by Liang Lu.

pose a threat to many nontarget plants. These chemicals can also have adverse effects on the abundance of birds (Eng, Stutchbury, and Morrissey, 2019; Li, Miao, and Khanna, 2020), butterflies (Gilburn et al., 2015; Forister et al., 2016; Van Deynze et al., 2024), bees (Rundlöf et al., 2015), and general pollinator insect species (Wei, Khachatryan, and Rihn, 2020). Due to these negative environmental consequences, neonicotinoids have been banned in some regions around the world. Some US states are considering proposals to ban their use (Nargi, 2022); as of late 2024, the US Environmental Protection Agency is reviewing their registration status (US Environmental Protection Agency, 2024). Despite a rapidly growing literature on the environmental risks associated with neonicotinoid applications, little is known about the seeding rate choices that affect the amount of these chemicals entering the environment.

Corn and soybean are major crops in the United States and so their seeding rate choices have implications for ecosystems. Average corn and soybean seeding rates have moved in opposite directions. This observation is particularly interesting as the two crops have experienced similar market, technological, and environmental shocks (Fernandez-Cornejo, 2004; Fernandez-Cornejo and Just, 2007; Torshizi and Clapp, 2021). The incongruity in corn and soybean seeding rate trends provides an ideal setting for investigating how different resources influence and offset one another in determining seeding rate choices. Insights on such trade-offs are critical for choosing policy instruments to channel seeding rates toward more socially desirable levels. For example, the same tax rate will lead to different seeding rate adjustments for corn and soybean.

The main general objective of this article is to examine how farmers' seeding rate choices for corn and soybean respond to market, resource, and technology factors. To better understand farmers' decisions, we develop a conceptual model of seeding rate choices by incorporating a resource budget trade-off between seeds and land-embodied resources allocated to each seed. To empirically test our model, we draw on a large, unique field-level dataset of more than 600,000 US seeding rate choices. The data span about 20 years for both corn and soybean and contain information on the specific hybrid planted, seed price, and farmer-chosen seeding rate. To facilitate analysis, we classify seeding rate determining factors into land-embodied (e.g., soil quality) and seed-embodied (e.g., genetics) factors and collect information on these two types of factors. The empirical analysis yields two primary findings. First, the soybean seeding rate choice is more own-price elastic than that of corn. Second, higher levels of land-embodied inputs increase both corn and soybean seeding rates, while higher levels of seed-embodied inputs increase corn seeding rates but decrease soybean seeding rates.

Due to the importance of seeding rate choices, an agronomic literature investigating the relationship between crop yield and seeding rates has emerged for corn (Assefa et al., 2016, 2018; Lindsey, Thomison, and Nafziger, 2018; Schwalbert et al., 2018; Fromme, Spivey, and Grichar, 2019; Mylonas et al., 2020) and soybean (Cox and Cherney, 2011; Thompson et al., 2015; Ferreira et al., 2016; Corassa et al., 2018; Schmitz and Kandel, 2021; Zhao et al., 2024). Much of the existing literature shows that corn and soybean optimal seeding rates should be determined by interaction effects between genotype, environment, and management (Assefa et al., 2016; Corassa et al., 2018; Schmitz and Kandel, 2021). Although seed industry structure has been examined (e.g., Ciliberto, Moschini, and Perry, 2019), few studies have investigated farmers' seeding rate choices from an economic perspective. One study by Perry, Hennessy, and Moschini (2022) examines how farmers' learning affects their seeding rate choices. They provide evidence that farmers' initial priors exhibit a bias favoring the seeding rates chosen for previously cultivated varieties. However, a notable research gap remains: Prior studies have not explicitly addressed optimal seeding rate decisions or the factors (e.g., prices, land quality, weather conditions, genetically engineered traits) that influence these choices.

Our article contributes to the literature in the following ways: First, from a conceptual perspective we contribute to the literature on seeding rate choices in response to market, resource, and technology factors by considering the role of plant architecture. To our knowledge, no existing work has systematically examined farmers' seeding rate choices both in theory and empirics. This

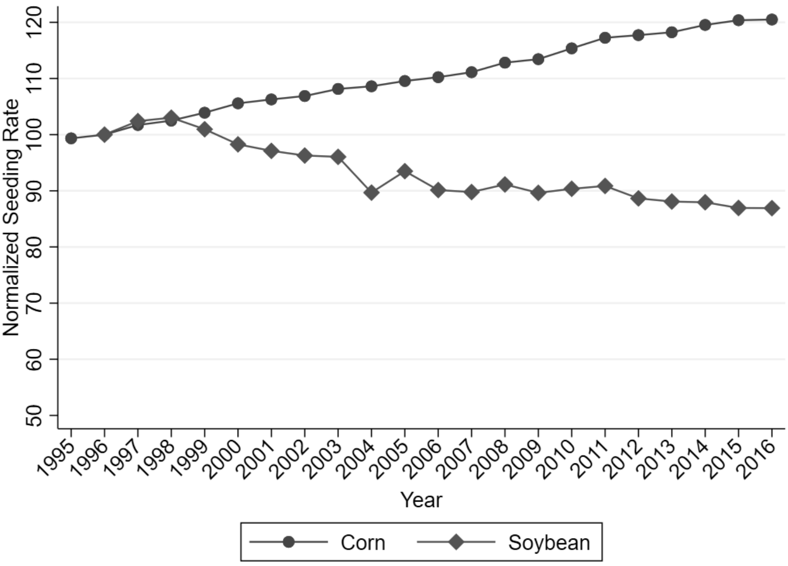


Figure 1. Normalized Seeding Rates for Corn (1995–2016) and Soybean (1996–2016) in the United States

Notes: In the TraitTrak dataset, prior to 2010, soybean units are reported in units of 50-lb bags, while all soybean units are converted to units of 140,000-seed bags since 2010. We convert soybean planting rates prior to 2010 by assuming 2,800 seeds/lb to render uniform the measurement scale over 1996–2016. In the figure, the seeding rates are normalized to the year 1996 as 100. The 100 index value represents 26,467 seeds per acre for corn and 181,252 seeds per acre for soybean, respectively.
Source: Kynetec data.

gap in scrutiny is perhaps due to the lack of detailed farm-level data and to heretofore limited awareness of the significant environmental impacts arising from seeding decisions. Most previous work that has addressed seeding rate choices has typically done so for one kind of crop and from a purely agronomic viewpoint. We are the first to develop a conceptual model of seeding rate choices in which we distinguish between the roles of two important factor attributes: seed-embodied factors and land-embodied factors.

Second, we empirically investigate the own-price elasticities of seeds across different crops, pointing to the role of plant architecture in their determination. Specifically, our analysis adds to work by Ciliberto, Moschini, and Perry (2019), who estimate a larger absolute value of seed own-price elasticity for aggregate corn seed products than for soybean and find that the seed industry extracts more surplus from corn products than from soybean products. However, they do not provide explanations for this difference in elasticities; our analysis suggests that plant architecture is one reason. In addition, our study quantifies how targeted tax or price policies on seeds and crops will mitigate neonicotinoid-related ecological impacts. For example, a 10% soybean (corn) seed tax or a 10% decrease in soybean (corn) price contributes to about a 3.6% (0.6%) increase in the ambient bird population and a 4.3% (0.6%) increase in the ambient butterfly population. Thus, our study provides a new perspective on mitigating environmental concerns through seeding rate adjustments.

The third main contribution is our use of a large field-level market dataset that allows us to quantitatively analyze farmers' seeding rate choices over a wider geographical scope and over more than 2 decades. Most agronomic studies only focus on seeding rate issues and are typically conducted only for particular field locations over a few years. Moreover, we contribute to the literature by being the first to merge publicly available market, resource, and technology data with farm-level market seed data to analyze how seeding rates respond to different factors over time.

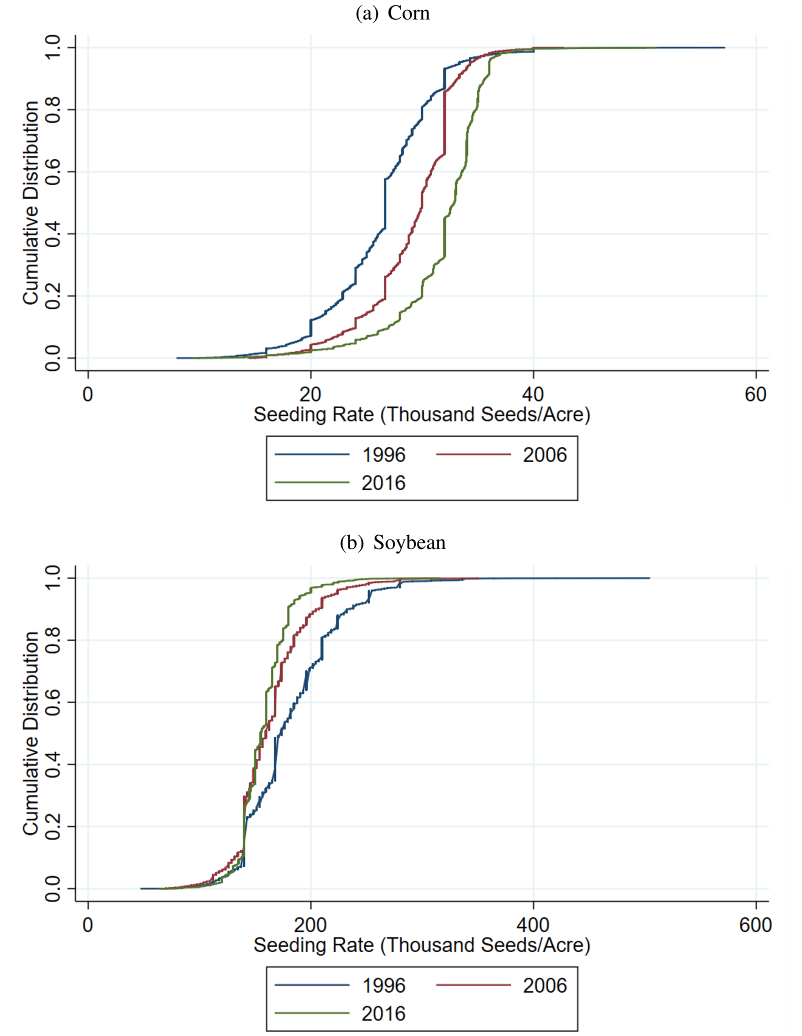


Figure 2. Cumulative Distribution for Corn and Soybean Seeding Rates in Representative Years

Scientific Facts About Seeding Rates and Plant Architecture

Corn and soybean seeding rates in the United States show different patterns in both temporal and spatial dimensions. Corn seeding rates have increased by about 1% per year, while soybean seeding rates have declined by about 0.7% per year in recent decades (see Figure 1). Figure 2 illustrates that these trends are also reflected in the cumulative distribution function (CDF) for seeding rates in some representative years.[1] The CDF lines for corn seeding rates shifted rightward from 1996 to 2016, while those for soybean seeding rates shifted leftward. This temporal pattern at the national level is also reflected at the state level.[2] In addition to temporal differences, seeding rates differ geographically because higher latitude locations need short-season varieties, more arid locations need drought-tolerant varieties, and varieties perform differently on different soils. Corn and soybean seeding rates are known to vary considerably, even in a locality. Figure 3 provides the seeding rates

[1] Detailed information about cumulative distribution functions of seeding rates can be found in the online supplement (see www.jareonline.org).

[2] Figure S7 in the online supplement reports seeding rate time trendlines in selected states.

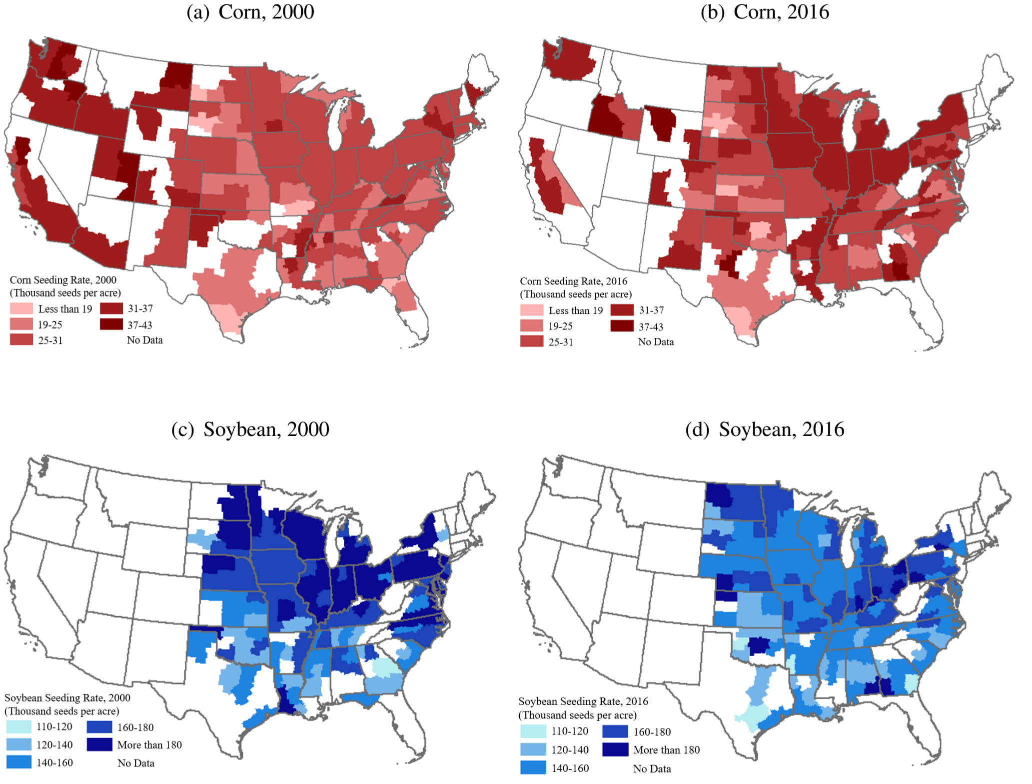


Figure 3. Seeding Rates (thousand seeds/acre) for Corn and Soybean by Crop Reporting District (CRD), 2000 and 2016
Source: Kynetec data.

distribution by crop reporting district (CRD) in 2000 and 2016 for both corn and soybean;[3] corn seeding rates in most districts were higher in 2016 when compared with 2000. In a given year, corn seeding choices varied spatially, generally being highest in the Corn Belt and Great Lakes Region. By contrast, soybean seeding rates were lower in 2016 compared with 2000 in most districts and were greater in the eastern Corn Belt and northern Great Plains than in the western Corn Belt.

The seeding rate input is a distinctive choice. While more seed on unlimited land resources, as with other inputs, should increase yield output, the seeding rate choice is special in that an increase in the rate rations fixed land and associated resources over more plants. Exogenous shocks have different effects on this trade-off depending on whether these shocks primarily affect plant profitability or resources available per acre. From the perspective of plant architecture, corn varieties have been bred to grow straight and tall rather than branch sideways (Tokatlidis, 2013); while soybeans are short and readily branch laterally. In comparison with corn, the bushy soybean plant is better positioned to expand or contract when seeking to optimally gather sunlight and soil nutrients.

Seeding rate choices have played a critical role in improving productivity, with their effects on crop yield varying among crops with different plant architectures. For corn, yield per plant is relatively insensitive to seeding rate (i.e., area available per plant) since corn has a rigid plant architecture. Corn per plant yield potential has not changed (Gonzalez et al., 2018) or has increased somewhat (Assefa et al., 2018), while improved performance of corn hybrids in high plant density conditions has been the primary driver of increased yield per acre (Gonzalez et al., 2018; Fromme, Spivey, and Grichar, 2019). Therefore, increased seeding rates have provided a large proportion of yield gain due to modern hybrids (Tollenaar and Lee, 2002; Tokatlidis and Koutroubas, 2004;

[3] CRDs are USDA-designated groupings of counties that have similar geography, climate, and cropping practices.

Duvick, 2005; Assefa et al., 2016, 2018; Gonzalez et al., 2018; Fromme, Spivey, and Grichar, 2019). In contrast, soybean yield per plant is responsive to seeding rate (i.e., area available per plant). Soybean seeding rates are lower in higher yield environments (Carciochi et al., 2019), as a decrease in seeding rates produces greater yield from individual plants (Epler and Staggenborg, 2008; Cox, Cherney, and Shields, 2010; Luca and Hungría, 2014).

The difference in plant architecture between corn and soybean is demonstrated by examining crop per plant yield responses to area per plant with seed trial data and fixed effect models.[4] We find that soybean yield per plant is more elastic than that for corn with regard to the change in area per plant. Compared with corn, the soybean plant can more readily use the resources made available due to additional area by expanding leaf area, branches, pods, and seeds per plant (i.e., when at a lower seeding rate) (Egli, 1988; Lee, Egli, and TeKrony, 2008; Cox, Cherney, and Shields, 2010). We also test the hypothesis that per plant yield responses to area availability are equal between corn and soybean; the null hypothesis is rejected at the 5% significance level.

Additionally, genetically engineered (GE) crop varieties are one of the key factors that affect seeding rate choices. GE varieties, first introduced commercially in 1996, exploit recombinant DNA tools (Moschini, 2008). These tools are used to insert one or more foreign genes into the plant's genome to express desirable traits. Two sets of attributes, herbicide tolerance in both corn and soybean and insect resistance in corn only, have become the prevalent traits in commercial GE crop offerings (Brester et al., 2019). Herbicide tolerant crops mostly embed the glyphosate tolerant (GT) trait, while insect resistant crops embed one or more genes from the bacterium *Bacillus thuringiensis* (Bt), which produce proteins that are toxic to certain insects. GE crops were originally offered as single trait varieties, but by 2010 seed "stacked" with multiple GE traits had come to dominate the US seed market.[5] We examine the different effects of GE traits on corn and soybean seeding rates in a later section.

Conceptual Model

We model profit-maximizing crop production, and our calculations are for one land unit, which we refer to as an acre. Let $s \in [0,\infty)$ represent seeding rate (i.e., seeds per acre). We consider two technology or resource related inputs: land-embodied endowments, τ, per acre divided across s seeds per acre, and seed-embodied endowments, θ, per seed. Examples of τ include better quality land and a new drainage technology, which improve resources per unit land area and not per seed. Examples of θ include seed coating or innovations in genetics, which improve resources per seed and not per unit land. In our conceptual model, we assume that land-embodied and seed-embodied endowments are exogenous.

Yield per seed is given generically as bounded function $y(s,\tau,\theta)$ with $\lim_{s\to 0} y(s,\tau,\theta) < \infty$, which is decreasing in s but increasing in both τ and θ. The rationales for these monotonicity properties are that with more seeds per acre then the available area and associated resources available to the plant will decrease for each plant while, given seeds per acre, endowment inputs will increase yield per seed.[6] This yield function is assumed to be twice continuously differentiable where function derivatives are represented by appropriately subscripted variables. The function is also assumed to satisfy the boundedness constraint $\lim_{s\to\infty} y(s,\tau,\theta)s \to K$ with $K > 0$ for any τ and θ. For the sake of simplicity, germination rate is assumed to be 100%. Yield per acre is, therefore, seeding rate times yield per seed, $Y(s,\tau,\theta) = y(s,\tau,\theta)s$, so that the boundedness constraint merely requires a finite limit on yield per acre as seeding rate increases to infinity.

---

[4] Detailed information about trial data on crop yield, seed treatment, and seeding rate from seed trial reports or extension reports by land grant universities as well as estimation models and results are presented in the online supplement.

[5] Figure S8 in the online supplement presents diffusion patterns for GE varieties over 1996–2016.

[6] At a later juncture, we will impose the resource budget constraint by setting $y(s,\tau,\theta) \equiv F(\tau/s,\theta)$, but for now we consider only the generic specification.

Price Effects

Given price per seed w and output price p, profit per plant is $py(s,\tau,\theta) - w$ and profit per acre (PPA) is

(1) $$\pi(s,\tau,\theta) = py(s,\tau,\theta)s - ws,$$

with first-order optimality condition

(2) $$\frac{d\pi(s,\tau,\theta)}{ds} = py(s,\tau,\theta) - w + py_s(s,\tau,\theta)s = 0,$$

and solution s^*. The second derivative of the PPA function is

(3) $$\frac{d\pi^2(s,\tau,\theta)}{ds^2} = 2py_s(s,\tau,\theta) + py_{ss}(s,\tau,\theta)s.$$

If we assume that $2y_s(s,\tau,\theta) + sy_{ss}(s,\tau,\theta) < 0$ for any s, τ, and θ, then the PPA function is locally concave in seeding rate at any maximum point. Consequently, there can be only one interior solution s^* to equation (2), and it must maximize profit. However, profit need not be globally concave on $s \geq 0$.

Returning to first-order condition (2), we represent the equation as

(4) $$y(s,\tau,\theta)\,|_{s=s^*}\left[1 + \frac{y_s(s,\tau,\theta)|_{s=s^*}\,s^*}{y(s,\tau,\theta)|_{s=s^*}}\right] = y(s^*,\tau,\theta)\left[1 + \frac{d\ln\left[\,y(s,\tau,\theta)|_{s=s^*}\right]}{d\ln(s)}\right] = \frac{w}{p},$$

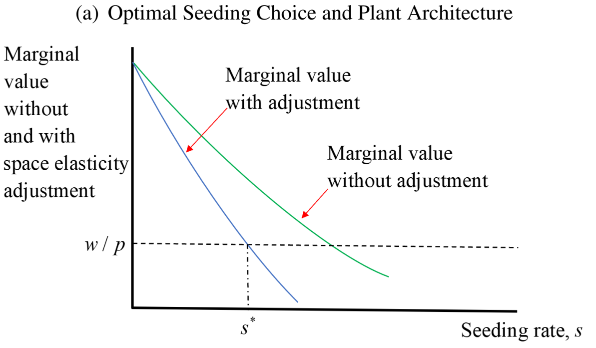
where $d\ln\left[\,y(s,\tau,\theta)|_{s=s^*}\right]/d\ln(s) < 0$ as resources per plant decline. Alternatively, as area per plant scales with s^{-1} or $a \sim s^{-1}$,

(5) $$y(s^*,\tau,\theta)\left[1 - \frac{d\ln\left[\,y(s,\tau,\theta)|_{s=s^*}\right]}{d\ln(a)}\right] = \frac{w}{p}.$$

Were yield per plant invariant to area per plant, then we would have $y(s^*,\tau,\theta) = w/p$. However, just as price per unit declines with an increase in quantity chosen in the monopoly problem, we have seeding rate set at a quantity such that $y(s^*,\tau,\theta) = w/p$ whenever yield per plant is insensitive to area available. We take $B(s,\tau,\theta) = d\ln[y(s,\tau,\theta)]/d\ln(a) \in [0,1]$ to be a measure of "plant elasticity" and $R(s,\tau,\theta) = 1 - B(s,\tau,\theta) \in [0,1]$ to be a measure of "plant rigidity."[7] Actual yield is adjusted through plant elasticity when yield per plant is responsive to area per plant. If $B(s,\tau,\theta)$ is close to 1, so that little yield is lost per acre by scaling back on seeds, then seed use will differ greatly from that, defined by $y(s,\tau,\theta)|_{s=s^*} = w/p$. Figure 4a provides a characterization.

One interpretation of equation (5) is that there are two ways in which seeding rate changes the marginal value of seed. One is to change production per plant, through $y(s,\tau,\theta)$, and the other is to affect responsiveness to the area resource. A parameterization will illustrate. Notice that were $y(s,\tau,\theta) = s^{\varepsilon(\tau,\theta)}$ with $\varepsilon(\tau,\theta) \in (-1,0)$, then $B(s,\tau,\theta) = -\varepsilon(\tau,\theta)$ and $R(s,\tau,\theta) = 1 + \varepsilon(\tau,\theta)$, where each is independent of seeding rate for this technology. Therefore we can write $R(s,\tau,\theta) \equiv \hat{R}(\tau,\theta) = 1 + \varepsilon(\tau,\theta)$ for this technology. When $\varepsilon(\tau,\theta) \approx -1$, then yield per plant is more space elastic but $Y(s,\tau,\theta) = y(s,\tau,\theta)s$ is space inelastic. When $\varepsilon(\tau,\theta) \approx 0$, then yield per plant is insensitive to seeding rate and area available (i.e., the plant is rigid so that responsiveness to the area resource is constant, up to some external effect θ that might include genetics) and only the effect of seeding rate on production per plant matters.

[7] Our empirical analysis uses seed trial data to estimate plant elasticity for both corn and soybean. Our results reveal that plant elasticity is greater for soybean than for corn (i.e., soybean yield per plant is more responsive to available area per plant compared to corn).



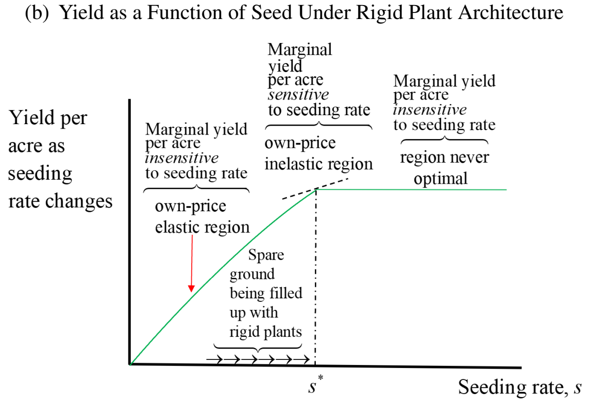


Figure 4. Seeding Rate and Plant Architecture

Notes: In Figure 4a, were yield per plant invariant to area per plant, then we would have $y(s^*, \tau, \theta) = w/p$ (green line). The yield is adjusted through plant elasticity when yield per plant is responsive to area per plant (blue line). Figure 4b depicts responsiveness at the extreme when plant elasticity ≈ 0 or $\varepsilon(\tau, \theta) \approx 0$. We see this picture as representing the corn plant in which yield per acre is very elastic with respect to seeding rate when spare ground is available but inelastic when this ground has been filled. Thus, when the input to output price ratio w/p is sufficiently low, then the absolute value of own-price elasticity of demand for seed is very low.

For this technology,

$$y(s,\tau,\theta)|_{s=s^*}\left[1+\frac{y_s(s,\tau,\theta)|_{s=s^*}\,s^*}{y(s,\tau,\theta)|_{s=s^*}}\right] = (s^*)^{\varepsilon(\tau,\theta)}\,[1+\varepsilon(\tau,\theta)] = \frac{w}{p}, \tag{6}$$

and we have optimal seeding rate as

$$s^* = \left(\frac{w}{p[1+\varepsilon(\tau,\theta)]}\right)^{1/\varepsilon(\tau,\theta)} = \left(\frac{w}{p\hat{R}(\tau,\theta)}\right)^{1/\varepsilon(\tau,\theta)}, \tag{7}$$

where we may think of $p\hat{R}(\tau,\theta)$ as the effective price ratio as adjusted for plant architecture. Notice that plant rigidity separates the price ratio from the effective price ratio where the effective ratio is larger. When the plant becomes less rigid, or more elastic with respect to space, then the effective price ratio faced increases.

Figure 4b depicts responsiveness at the extreme when $\varepsilon(\tau,\theta) \approx 0$. We see this picture as representing the corn plant (Tian et al., 2011; Andorf et al., 2019) in which yield per acre is very elastic with respect to seeding rate when spare ground is available but inelastic when this ground has been filled. Thus, when the input to output price ratio w/p is sufficiently low, then the absolute value of own-price elasticity of demand for seed is very low. Given that soybean yield per plant is more responsive to available area per plant compared to corn, we have our first hypothesis:

HYPOTHESIS 1. *The soybean seed own-price demand is more elastic than corn.*

This perspective supports the idea that the corn seed market is vulnerable to high mark-ups. The comparative infertility of seed from highly productive hybrids curtails the option of saving seed from past harvests; in addition, farmers cannot respond at the intensive margin to higher prices by spreading seed over larger areas.

External Shocks

We turn next to understanding the effects of an external shock, be it a new technology shock or a change in natural resources available. Given the resource budget constraint, yield per seed is $y(s,\tau,\theta) = F(\tau/s,\theta)$. The function is assumed to be increasing in both arguments. We denote $F_1(\cdot) = dF(\cdot)/d(\tau/s) > 0$ and $F_2(\cdot) = dF(\cdot)/d\theta > 0$, while the function as a whole is assumed to be twice continuously differentiable and concave. PPA is $\pi(s,\tau,\theta) = pF(\tau/s,\theta) - ws$ with optimality condition

(8) $$F\left(\frac{\tau}{s},\theta\right)\bigg|_{s=s^*} - \frac{\tau}{s^*}F_1\left(\frac{\tau}{s},\theta\right)\bigg|_{s=s^*} = \frac{w}{p},$$

and cross derivatives

(9a) $$\frac{d^2\pi(\cdot)}{dsd\tau} = -\frac{\tau}{(s^*)^2}F_{1,1}\left(\frac{\tau}{s},\theta\right)\bigg|_{s=s^*} > 0;$$

(9b) $$\begin{aligned}\frac{d^2\pi(\cdot)}{dsd\theta} &= F_2\left(\frac{\tau}{s},\theta\right)\bigg|_{s=s^*} - \frac{\tau}{s^*}F_{1,2}\left(\frac{\tau}{s},\theta\right)\bigg|_{s=s^*} \\ &= F_2(\cdot)\left[1 - \frac{\tau}{s^*}\frac{F_{1,2}(\cdot)}{F_2(\cdot)}\bigg|_{s=s^*}\right] \overset{\text{sign}}{=} 1 - \frac{d\ln\left[F_2(\cdot)|_{s=s^*}\right]}{d\ln(\tau/s)}.\end{aligned}$$

Derivative (9a) asserts that an increase in per acre resources complements seed use, so optimal seed use should increase with an increase in the land-embodied endowments regardless of plant architecture, $ds^*/d\tau > 0$. For example, seeding rates for both corn and soybean are expected to increase on higher-quality land, with improved soil moisture, and greater nutrient availability, such as under conventional tillage compared to no-till. The additional resources provided by increased land-embodied endowments can be better used by applying more seeds per acre.

Derivative (9b) cannot be so readily signed where many possibilities can be envisioned. One possibility is that resources provided to each plant substitute for resources provided to each acre. If that were so, then optimal seed use should increase with an increase in endowment provided per plant, $ds^*/d\theta > 0$. This is because an increase in endowments per plant will then decrease the marginal value of endowments per acre where value can be restored by reducing resources per plant (i.e., increasing the seeding rate). More generally, if the marginal value of resources per plant is inelastic with respect to resources per acre, then an increase in resources per plant will increase the seeding rate. This scenario is more typical for crops like corn, where yield per plant is inelastic with regard to the area per plant. Conversely, if the marginal value of resources per plant is elastic with respect to resources per acre, as is often the case with soybean, then an increase in resources per plant will result in a lower seeding rate.

An example of resource substitution can occur when the per plant resource is the genetic trait for glyphosate tolerance, and the per acre endowment is the glyphosate herbicide used for weed control. For the rigid corn plant, the GT trait gives farmers confidence that higher seeding rates will be beneficial, as effective weed management ensures each plant can access sufficient resources. This resource substitution allows farmers to optimize land use by increasing seeding rates. A similar example is Bt corn, where the per plant resource is the genetic modification that enables the plant to produce Bt toxins, providing protection against pests like the European corn borer, while the per acre endowment is reduced pest pressure. The Bt trait gives farmers confidence that higher seeding rates will be advantageous, as reduced pest damage allows each plant to thrive with less competition for resources. Conversely, an example of resource complementarity can occur when the GT trait enables effective weed control through the application of glyphosate, freeing up resources like nutrients, sunlight, and soil moisture that would have been consumed by weeds. With reduced weed competition, soybean plants can use these resources more effectively, leading to improved growth and yield with the existing seeding rate. In this case, the improved resource availability diminishes the need for higher seeding rates to compete for these resources, as weed competition is minimized.

Considering the plant architecture characteristics of corn and soybean and the above examples, we have our second hypothesis:

HYPOTHESIS 2A. *The optimal seeding rate will increase with an increase in per acre endowments (i.e., land-embodied inputs) for both corn and soybean.*

HYPOTHESIS 2B. *Optimal seeding rate for soybean is more likely than that for corn to decrease in response to an increase in resources per plant (i.e., seed-embodied inputs).*

Both Hypothesis 1 and Hypothesis 2 provide avenues for empirical scrutiny, and it is to testing these hypotheses that we now turn.

Data Description

We combine data from several sources to construct our field–year panel dataset, covering information about seeding rates, locations, prices, soil conditions, agricultural practices, and genetic technologies.

Market Data

The main econometric analysis that we perform relies on the TraitTrak dataset, which contains a large sample of field-level data for land sown to corn and soybean. The TraitTrak dataset is assembled by Kynetec USA, Inc., a market research company whose business is to collect data from annual surveys from randomly sampled farmers in the United States. The sampled farmers are chosen to be representative at the CRD level. Data collected are reviewed and verified by specially trained analysts to ensure accuracy, high completion levels, internal consistency, and compatibility with external information sources. The unit of observation is land tract level so that each surveyed farmer may report multiple corn and soybean plantings in a given year. Each surveyed farmer was asked to specify their seeding rate, seed trait, seed cost, and genetic technology choices during the previous growing season. Farmers have a large set of seed varieties to choose from. For example, the 20 most commonly planted varieties only account for about 6% and 7% of corn and soybean varieties, respectively.[8]

The original dataset reports 442,803 field-level corn seed observations over 1995–2016 and 213,062 soybean seed observations over 1996–2016 across 235 CRDs in 31 states, where each observation is a unique combination of the year, farmer, and seed variety. We also include a tillage variable (specifically, the share in all reported fields at the CRD level of fields that apply conventional tillage) in some specifications. The tillage data are obtained from AgroTrak, another Kynetec dataset. Each plot is identified as using one of three alternatives: "conventional tillage," "conservation tillage," or "no-till."[9]

[8] Table S4 in the online supplement provides summary statistics for the 20 most commonly planted varieties of corn (1995–2016) and soybean (1996–2016).

[9] Table S5 in the online supplement provides details on data screening.

At the time when farmers make seeding rate choice decisions, post-harvest-time market crop prices are not yet realized, so each crop's futures prices are used to represent farmers' expected postharvest prices (Gardner, 1976). To be specific, monthly average preplanting settlement price in February of each year's December futures contract for corn (Chicago Board of Trade, CBOT) and November contract for soybean (CBOT) are applied to represent locked-in harvest prices.

Location, Soil and Weather Data

Seeding rates differ geographically due to climate-related effects. Including latitude and longitude coordinates can account for these effects so that they are less likely to confound with interactions of primary interest. Spatial coordinates are obtained from the 2016 Census US Gazetteer files for counties.[10] Land capability classification (*LCC*) data are from National Resource Inventory files. We use *LCC* to denote the fraction of land in a county that is best for crop production, namely land capability categories I or II among the eight categories available, where only categories I through IV are suitable for cropping. The Palmer's Z (*PZ*) index measures soil moisture availability for crop growth (Heim, 2002) by accounting for evapotranspiration, soil water storage capacity, and precipitation (Karl, 1986). National Oceanic and Atmospheric Administration (NOAA) files provide monthly *PZ* values for climate divisions in the conterminous United States.[11] We calculate the area intersection between climate divisions and each county and then calculate area-weighted *PZ* values for each county. Since *PZ* values have been normalized to 0 on average in that location (Xu et al., 2013), we transform *PZ* values to capture moisture stress from dryness ($PZ \leq 0$, *DRY*) and wetness ($PZ \geq 0$, *WET*). Our wetness and dryness calculations are applied to March *PZ* values, when farmers begin to make seeding rate decisions.

Agricultural Practice Data

Advances in crop management techniques such as increased irrigation area are critical factors for both seeding rate choices and yield outcomes. Conditional on location, available irrigation is correlated with water supply for crop growth (Brown, 1986; Assefa et al., 2016). We calculate the ratio of irrigated harvested acres to total harvested acres, denoted by *IR* for irrigation ratio. County-level irrigated harvested acres and total harvested acres are obtained from the USDA National Agricultural Statistics Service (NASS). Agronomic optimal seeding rates vary with planting dates, where delayed planting motivates an increase in optimal seeding rates for certain varieties (Van Roekel and Coulter, 2011; Lindsey and Thomison, 2016). We obtain the median planting date (*MPD*) from NASS. We detrend *MPD* and include the deviation of detrended *MPD* from its mean value across the study period as an explanatory variable (*PD*).[12]

The definitions of variables used in the market estimation are presented in Table 1, in which we also classify the variables into the following groups: seeding rate choices, prices, land-embodied inputs, seed-embodied inputs, and other controls. Table 2 reports descriptive statistics for the corresponding variables for corn and soybean.

---

[10] Latitude and longitude information are available at https://www.census.gov/geographies/reference-files/time-series/geo/gazetteer-files.2016.html.

[11] Detailed data are available at https://www1.ncdc.noaa.gov/pub/data/cirs/climdiv/, last accessed on December 2, 2024.

[12] Details on median planting dates are included in the online supplement.

Table 1. Variable Definitions

Variable	Description	Data Source
Seeding choices		
s	Seeding rate (thousand seeds per acre)	TraitTrak
Prices		
PR	The ratio of seed costs over crop futures prices	TraitTrak, Quandl
Land-embodied inputs		
LCC	The fraction of land in a county that is in land capability categories I or II	NRI
WET	The maximum among 0 and the Palmer's Z in March	NOAA
DRY	Negative value of the minimum among 0 and the Palmer's Z in March	NOAA
TI	Share of farms using conventional tillage, by CRD	AgroTrak
Seed-embodied inputs		
GT	An indicator function for corn and soybean seeds where *GT* = 1 whenever seed trait is glyphosate tolerant, and 0 otherwise	TraitTrak
BT	An indicator function for corn seed where *BT* = 1 whenever seed trait is either rootworm resistant or cornborer resistant or both, and 0 otherwise	TraitTrak
Controls		
IR	The ratio of irrigated harvested acres to total harvested acres by CRD	NASS
PD	The deviation of detrended median planting date (MPD) from the mean value of MPD during all the study years	NASS
t	Time trend variable centered at the year 2007	
LAT	The latitude of a county's internal point, with value increasing as one moves northward	Gazetteer files
LON	Absolute value of longitude of a county's internal point, with value increasing as one moves westward	Gazetteer files

Notes: Internal point here refers to the geographic center within each county and is represented by a set of geographic coordinates (latitude and longitude).

Empirical Methods

We now explore how crop seeding rate choices respond to price changes as well as land-embodied and seed-embodied factors. The main estimation equation is

$$\begin{aligned}(10)\qquad s^l_{i,t} = \beta_0 + \beta_1 PR^l_{i,t} + \beta_2 LE^l_{i,t} + \beta_3 SE^l_{i,t} + \beta_4 AG^l_{i,t} + \beta_5 t + \beta_6 LOC_{i,t} + \beta_7 t * LOC_{i,t} \\ + \delta^l_f + h^l_v + \varepsilon^l_{i,t},\end{aligned}$$

where each field is denoted as i, each farmer (who may manage one or multiple fields) is denoted as f, seed variety is denoted as v, and the time indicator is denoted as t. The dependent variable is $s^l_{i,t}$, the seeding rate (thousand seeds per acre) for field i and crop l at time t. The main independent variables of interest are grouped into several vectors. Price incentives are represented by *PR*, the ratio of seed purchase costs to harvest-time crop contract futures prices quoted at planting time. The set of land-embodied factors, *LE*, is *LCC*, *WET*, *DRY*, and *TI* (the share of farms with conventional tillage in the total number of farms at CRD). The set of seed-embodied factors, *SE*, is given as genetic technologies *GT* and *Bt* for corn but only *GT* for soybean. The set of agricultural practices or inputs as control variables, *AG*, contains *IR* and *PD*. *LOC* is the set of location variables, comprised of latitude (*LAT*) and longitude (*LON*).

The remaining terms are farmer fixed effects denoted by δ^l_f, variety fixed effects denoted by h^l_v, and the error term denoted by $\varepsilon^l_{i,t}$. The presence of farmer fixed effects is intended to control for unobserved factors, idiosyncratic to a farmer, to account for any omitted variables such as education, age, and other personal characteristics that are correlated with seeding rate choices. The presence of

Table 2. Variable Descriptive Statistics

Category	Variable	*N*	Mean	Std. Dev.	Min.	Max.
Corn						
Seeding choices	*s*	360,999	29.870	4.376	8.000	53.333
Prices	*PR*	360,999	42.066	14.740	0.000	114.490
Land-embodied inputs	*LCC*	360,595	0.495	0.228	0.000	0.935
	WET	360,999	0.535	0.993	0.000	9.240
	DRY	360,999	0.864	0.974	0.000	5.890
	TI	360,529	0.406	0.187	0.000	1.000
Seed-embodied inputs	*GT*	360,999	0.557	0.497	0	1
	BT	360,999	0.559	0.497	0	1
Controls	*IR*	360,215	0.126	0.213	0.000	1.000
	PD	345,968	0.026	0.067	−0.099	0.152
	t	360,999	0.640	5.409	−9	9
	LAT	360,999	41.431	2.677	26.083	48.831
	LON	360,999	91.431	6.189	68.722	123.988
Soybean						
Seeding choices	*s*	173,056	167.521	33.370	14.000	490.000
Prices	*PR*	173,056	3.984	1.293	−0.938	9.566
Land-embodied inputs	*LCC*	173,001	0.504	0.221	0.000	0.935
	WET	173,056	0.535	1.050	0.000	9.240
	DRY	173,056	0.886	0.968	0.000	5.290
	TI	172,829	0.360	0.178	0.000	1.000
Seed-embodied inputs	*GT*	173,056	0.802	0.399	0	1
Controls	*IR*	172,871	0.073	0.147	0.000	0.795
	PD	167,113	0.001	0.004	−0.007	0.008
	t	173,056	0.122	5.621	−9	9
	LAT	173,056	40.880	3.207	28.288	48.828
	LON	173,056	90.909	5.298	73.656	106.352

Notes: Refer to Table 1 for a detailed description of the variables.

variety fixed effects controls for the impact of excluded factors that could affect seeding rate choices but may reasonably be presumed to be constant for a given variety.[13]

Results and Discussions

Price Effects on Seeding Rate Choices

Table 3 reports equation (10) market estimation results for four specifications, each differing by crop and the type of fixed effects included. For each crop, we choose the estimation with variety fixed effects as our reference model, since the fixed effects estimator is based on within-variety variation. Price ratio (i.e., seed costs over crop future prices) is found to be statistically significant,

[13] Potential endogeneity issues may arise from time-varying unobservables that influence both seeding rate decisions and agricultural practices (e.g., tillage, variety selection, planting dates, and irrigation). While fixed effects account for time-invariant factors, they may not fully capture these dynamic influences. To address this concern, we conduct additional regressions that exclude potentially endogenous variables related to these agricultural practices. The results, presented in Table S6 of the online supplement, are consistent with our primary findings.

Table 3. Regression Results with Fixed Effects for Corn and Soybean

	Corn		Soybean	
	s (thousand seeds per acre)			
Variable	**1**	**2**	**3**	**4**
Price				
PR	−0.00121***	−0.00203***	−1.153***	−0.825***
	(0.000382)	(0.000460)	(0.0590)	(0.0711)
Land-embodied inputs				
LCC	1.716***	1.444***	−1.648	0.237
	(0.216)	(0.224)	(3.536)	(3.761)
WET	−0.0137**	−0.0117**	−0.527***	−0.476***
	(0.00535)	(0.00569)	(0.0721)	(0.0781)
DRY	0.0334***	0.0219***	−0.150*	−0.189**
	(0.00537)	(0.00580)	(0.0770)	(0.0832)
TI	0.566***	0.525***	6.461***	3.289***
	(0.0545)	(0.0579)	(0.806)	(0.865)
Seed-embodied inputs				
GT	0.213***	0.311	−3.694***	−5.122***
	(0.0146)	(0.293)	(0.189)	(1.432)
BT	0.158***	0.329		
	(0.0101)	(0.218)		
Controls				
IR	0.199	−0.127	4.022	3.845
	(0.211)	(0.230)	(3.846)	(4.297)
PD	2.910	−9.023	−693.9	3,062
	(8.240)	(8.400)	(3,539)	(3,842)
t	0.596***	0.416***	−6.249**	−9.525***
	(0.106)	(0.110)	(2.557)	(2.803)
LAT	0.0592*	0.107***	1.060*	0.635
	(0.0328)	(0.0342)	(0.549)	(0.595)
LON	−0.108***	−0.124***	−1.618***	−1.113***
	(0.0153)	(0.0166)	(0.288)	(0.311)
*t*LAT*	0.00436***	0.0139***	−0.129***	−0.0930***
	(0.000542)	(0.000724)	(0.00711)	(0.0110)
*t*LON*	−0.00630***	−0.00729***	0.119***	0.109***
	(0.000256)	(0.000292)	(0.00401)	(0.00474)
Farmer fixed effects	yes	yes	yes	yes
Variety fixed effects	no	yes	no	yes
Constant	35.89***	35.67***	278.3***	247.3***
	(1.575)	(1.704)	(30.60)	(33.60)
No. of obs.	342,807	333,250	163,462	157,375
R^2	0.775	0.796	0.636	0.678

Notes: Standard errors in parentheses. Single, double, and triple asterisks (*, **, ***) indicate [statistical] significance at the 10%, 5%, and 1% level. Refer to Table 1 for a detailed description of the variables.
Source: Kynetec data.

Table 4. Seed Own-Price Elasticities

	Corn		Soybean		H_0: Elasticity for Corn = Elasticity for Soybean	
Year	**Elasticity**	**Std. Err.**	**Elasticity**	**Std. Err.**	***t*-Statistic**	***p*-Value**
1998	−0.216	0.049	−1.066	0.092	8.166	0.000
1999	−0.242	0.055	−1.543	0.133	9.036	0.000
2000	−0.250	0.057	−1.880	0.162	9.489	0.000
2001	−0.270	0.061	−2.093	0.180	9.564	0.000
2002	−0.266	0.060	−1.855	0.160	9.296	0.000
2003	−0.240	0.055	−1.763	0.152	9.429	0.000
2004	−0.297	0.067	−2.314	0.200	9.583	0.000
2005	−0.292	0.066	−2.230	0.192	9.527	0.000
2006	−0.198	0.045	−1.730	0.149	9.837	0.000
2007	−0.194	0.044	−1.140	0.149	6.085	0.000
2008	−0.320	0.073	−2.265	0.195	9.340	0.000
2009	−0.342	0.078	−2.309	0.199	9.207	0.000
2010	−0.228	0.052	−1.585	0.137	9.288	0.000
2011	−0.265	0.060	−1.904	0.164	9.377	0.000
2012	−0.286	0.065	−1.996	0.172	9.298	0.000
2013	−0.362	0.082	−2.341	0.202	9.085	0.000
2014	−0.397	0.090	−2.825	0.244	9.354	0.000
2015	−0.419	0.095	−3.053	0.263	9.411	0.000
2016	−0.216	0.049	−1.066	0.092	8.166	0.000
1998–2016	−0.285	0.065	−1.962	0.169	9.257	0.000

Notes: We test the hypothesis that price elasticities for corn are equal to those for soybean using Welch's *t*-test. We reject the null hypothesis at the 1% significance level.

with an expected negative coefficient value for both corn and soybean. Table 4 presents the own-price elasticities of seed demand at the average seeding rates. From 1998 to 2016, a 1% increase in seed price or 1% decrease in corn (soybean) price would reduce the corn (soybean) seeding rate by less than 0.3% (about 2.0%) of the average seeding rate. Thus, on average, the seeding rate for soybean would decrease by 1.7 percentage points more than that for corn in response to a 1% increase in seed price or 1% decrease in crop price. We also test the hypothesis that price elasticities for corn are equal to those for soybean using Welch's *t*-test (Welch, 1947). We reject the null hypothesis at the 1% significance level. These estimates support Hypothesis 1 in our conceptual model, namely that the demand for soybean seed is more own-price elastic than that for corn.

Effects of Land-Embodied and Seed-Embodied Inputs on Seeding Rate Choices

In addition to price effects, seeding rate choices are affected by a complex combination of land-embodied inputs, seed-embodied inputs, and other control variables. As is shown in Table 3, for land-embodied inputs we find that corn seeding rates are higher on better quality land (i.e., LCC higher). The effects of land quality on soybean seeding rate choices are not as clear. March severe wetness leads to seeding rate decline for both crops, since excess moisture or flooding can restrict the plant's ability to access valuable plant-available nutrients. Although dryness is estimated to increase corn seeding rates, it has negative impacts on soybean seeding rates.

Conventional tillage usually incorporates most crop residue into soil, and so more nutrients per acre are released into soil relative to conservation tillage or no-till. The practice can also kill resource-consuming weeds, remove soil pans that block root access to deeply placed soil resources and help to warm springtime soils, among other effects on increasing land resources available to the crop. Consistent with Hypothesis 2A, estimation results show that a larger proportion of conventional tillage will increase seeding rates for both corn and soybean. For other agricultural practices such as irrigation and planting date, we do not know their exact roles in seeding rate choices and include them as control variables.

Turning to seed-embodied inputs, farmers choose lower soybean seeding rates with GT treatment. For corn, we observe that farmers increase seeding rates with GT or *Bt* treatment when only farmer fixed effects are included. This increasing effect disappears after including variety fixed effects since variety fixed effects capture the GT and *Bt* impacts. Thus, these findings are consistent with Hypothesis 2B in the conceptual model (i.e., that the more space elastic plant can adapt to additional resources per plant in ways other than increasing seeding rates). To be specific, GT corn increases resources per plant by better controlling resource-consuming weeds and so will provide confidence to farmers that sharing resources over more seed will be beneficial. As corn is relatively rigid, the best way to use these resources is to increase the seeding rate. The soybean plant, however, can expand to consume these resources.

Distinctive Seed Price Elasticities: Policy Implications

The difference in seed price elasticities across crops is important for various reasons. First, the difference determines a company's capacity to extract surplus through pricing power. Both corn seed and soybean seed industries are oligopolistic, where the same firms are active in both markets (Ciliberto, Moschini, and Perry, 2019). Corn seed firms have competed intensively on product quality since the advent of commercialized hybrids in the 1920s. The seed has had in-built intellectual property protection because saved seed from hybrid variety crop is not very productive. Soybean seed savings undermined innovation until technological developments over the past 30 years made seed saving unprofitable for farmers (Mascarenhas and Busch, 2006).

Farmers might still diminish oligopolistic pricing power through spreading seed more sparingly were price to increase. As our analysis shows, this can be done with less loss in revenue for soybean than for corn. Ciliberto, Moschini, and Perry (2019) apply discrete choice market demand analysis to show that corn seed demand is comparatively less elastic than is soybean seed but do not discuss why this is so. A consequence of this elasticity difference is that the division of surplus from GE varieties has favored the seed industry over farmers for corn but farmers over the seed industry for soybean. How the partitioning of surplus affects the rate of innovation is an issue that has not received attention. Our claim here is that the difference across crops in the elasticity of crop yield to space available (or seeding rate) is of great consequence for the division of economic surplus and also for the magnitude of that surplus.

Second, seed price elasticity values have implications for managing neonicotinoid-related ecological impacts. Given that the majority of corn and soybean seeds are coated with neonicotinoids (Hurley and Mitchell, 2017), higher seeding rates will impose a larger chemical load on the environment. With our own-price elasticity estimates of seed demand and drawing upon values from the literature on neonicotinoids and biodiversity, we next develop rough conservative estimates of ecological effects resulting from farmers' seeding rate responses to price changes. An increase in a seed tax or lower commodity price would also reduce acres allocated to that crop and so lower seed demand that way. To simplify the calculation, we do not account for any extensive margin response (i.e., crop acre changes due to a tax on seeds). In addition, as we do not have the information to do otherwise, we assume that the potential tax does not differentiate among different types of seeds and is applied on all seeds rather than just chemical-coated seeds. Thus, farmers' choices will not change concerning seed without chemical coats.

We first draw on the semi-elasticities of bird population with respect to neonicotinoid use as reported by Li, Miao, and Khanna (2020). They report the percentage impact of a 100 kg increase (which represents a 12% increase on average) in neonicotinoid use on U.S. bird populations, measured by the number of birds observed. Then we draw on generalized linear model (negative binomial) regression estimates regarding how changes in neonicotinoid area treatments affect

Table 5. Price Effects on Biodiversity Through Neonicotinoid Use and Seeding Rate Choice

Due to 10% Tax on Seed or 10% Decrease in Crop Price	Corn	Soybean
Percentage change in bird population		
Grassland bird	0.6%	3.9%
Nongrassland bird	0.5%	3.3%
Insectivorous bird	0.6%	3.7%
Noninsectivorous bird	0.5%	3.3%
Percentage change in butterfly population		
Monarch	0.6%	4.3%

Notes: Detailed calculations can be found in Table S7 of the online supplement.

butterfly populations (measured by hourly counts by county–year from June through August) in the US Midwest as reported by Van Deynze et al. (2024).[14]

We find that a tax on seed or a decrease in crop price would increase the population of both birds and butterflies (Table 5). For the bird populations, a 10% soybean seed tax or 10% decrease in soybean price contributes to a 3.9% increase in the grassland bird population and a 3.3% increase in the nongrassland bird population. This tax or price change also increases the insectivorous bird population by 3.7% and the noninsectivorous bird population by 3.3%. In addition, the tax or price change also leads to an increase in the population of butterflies; a 10% tax on soybean seed or 10% decrease in soybean price causes about 4.3% increase in monarch. A 10% tax on corn seed or 10% decrease in corn price can also improve bird and butterfly populations, but the magnitudes of effects are smaller than those for soybean.

Conclusions

Seeding rate choices are critical for determining both farm enterprise profitability and environmental outcomes. Despite their significance, these choices have received slight attention in comparison to other input choices such as pesticides and fertilizers. This article seeks to better understand how farmers' seeding rate choices for two major crops respond to market, resource, and technology factors. We develop a theoretical model to understand the trade-off between within-plot extensive margin (more plants) and intensive margin (more resources to a given plant), in which we account for how elastic yield per plant is to area availability where corn and soybean are very different in that regard. With a large sample of field-level market data, we examine how farmers' seeding rate choices respond to different stimuli.

We find that, first, soybean seeding rate choice is more price elastic than is the case for corn. Second, better soil quality increases corn seeding rates while more conventional tillage increases corn and soybean seeding rates. Third, for seed endowments, GT and *Bt* traits increase corn seeding rates, while the GT trait decreases soybean seeding rates. These findings suggest that seeding rate decisions can be specific for different farm management and soil conditions. When considering taxes, subsidies or other policies intended to influence farmers' seeding rate choices, it is important to keep these factors in mind.

Our findings also have implications for managing economic surplus and mitigating environmental risks. First, elasticity magnitude determines a company's capacity to extract surplus through pricing power. Seed companies likely have less power in the soybean seed market. Second, a tax on seed or a decrease in crop prices has a positive effect on bird and butterfly biodiversity through reducing seeding rates and mitigating neonicotinoids' adverse impacts, and this effect is larger for soybean than for corn. Neonicotinoids also likely affect other wildlife, including honey

[14] Table S7 in the online supplement outlines the parameters sourced from previous literature as well as a step-by-step explanation of how these parameters and our own-price elasticities were used to estimate the percentage changes in bird and butterfly populations resulting from a 10% tax on seeds or a 10% decrease in crop prices.

bees, wild bees, and mammals, but more data are needed to quantify how policies will affect these creatures.

While our study represents a substantial step forward in understanding seeding rate choices, several matters merit further attention. One is that our analysis has not sought to quantify how seeding rate changes would affect social welfare, especially the social welfare effects of a tax or subsidy on seed use. Another is whether seeding rate choices are affected by behavioral factors, since many researchers think that soybean seeding rates chosen by farmers are excessive for profit maximization (Brhel et al., 2019), especially in high-productivity environments (Gaspar et al., 2020). Farmers and consultants from focus group meetings reveal some distinct perspectives, where farmers rely most heavily on their own experience when making seeding rate choices.[15] Discrepancies between market estimations and surveyed farmers' responses suggest that farmers may not be fully rational, or at least do not comply with standard models of rational economic behavior. Some economic inquiries have found evidence that farmers misjudge their choices in many contexts including crop insurance (Du, Feng, and Hennessy, 2017) and pesticides (Perry, Hennessy, and Moschini, 2019). These misjudgments may lead to inefficiency, and so a deeper understanding of these behavioral factors could help improve policy design and enhance efficiency.

[First submitted February 2024; accepted for publication March 2025.]

References

Andorf, C., W. D. Beavis, M. Hufford, S. Smith, W. P. Suza, K. Wang, M. Woodhouse, J. Yu, and T. Lübberstedt. 2019. "Technological Advances in Maize Breeding: Past, Present and Future." *Theoretical and Applied Genetics* 132(3):817–849. doi: 10.1007/s00122-019-03306-3.

Assefa, Y., P. Carter, M. Hinds, G. Bhalla, R. Schon, M. Jeschke, S. Paszkiewicz, S. Smith, and I. A. Ciampitti. 2018. "Analysis of Long Term Study Indicates Both Agronomic Optimal Plant Density and Increase Maize Yield per Plant Contributed to Yield Gain." *Scientific Reports* 8(1): 4937. doi: 10.1038/s41598-018-23362-x.

Assefa, Y., P. V. Vara Prasad, P. Carter, M. Hinds, G. Bhalla, R. Schon, M. Jeschke, S. Paszkiewicz, and I. A. Ciampitti. 2016. "Yield Responses to Planting Density for US Modern Corn Hybrids: A Synthesis-Analysis." *Crop Science* 56(5):2802–2817. doi: 10.2135/cropsci2016.04.0215.

Brester, G. W., J. Atwood, M. J. Watts, and A. Kawalski. 2019. "The Influence of Genetic Modification Technologies on U.S. and EU Crop Yields." *Journal of Agricultural and Resource Economics* 44(01):16–31. doi: 10.22004/ag.econ.281311.

Brhel, J., L. Thompson, S. Stepanović, J. Luck, and N. Mueller. 2019. "Soybean Seeding Rates." *Nebraska Institute of Agriculture and Natural Resources Cropwatch* Available online at https://cropwatch.unl.edu/2019/soybean-seeding-rates/.

Brown, D. M. 1986. "Corn Yield Response to Irrigation, Plant Population and Nitrogen in a Cool, Humid Climate." *Canadian Journal of Plant Science* 66(3):453–464. doi: 10.4141/cjps86-063.

Carciochi, W. D., R. Schwalbert, F. H. Andrade, G. M. Corassa, P. Carter, A. P. Gaspar, J. Schmidt, and I. A. Ciampitti. 2019. "Soybean Seed Yield Response to Plant Density by Yield Environment in North America." *Agronomy Journal* 111(4):1923–1932. doi: 10.2134/agronj2018.10.0635.

Ciliberto, F., G. Moschini, and E. D. Perry. 2019. "Valuing Product Innovation: Genetically Engineered Varieties in Us Corn and Soybeans." *RAND Journal of Economics* 50(3):615–644. doi: 10.1111/1756-2171.12290.

Corassa, G. M., T. J. C. Amado, M. L. Strieder, R. Schwalbert, J. L. F. Pires, P. R. Carter, and I. A. Ciampitti. 2018. "Optimum Soybean Seeding Rates by Yield Environment in Southern Brazil." *Agronomy Journal* 110(6):2430–2438. doi: 10.2134/agronj2018.04.0239.

[15] We implemented three focus group meetings with corn and soybean growers and consultants in August 2018, during which participants were asked about factors influencing seeding rate choices. Details on focus group meetings are presented in the online supplement.

Cox, W. J., and J. H. Cherney. 2011. "Growth and Yield Responses of Soybean to Row Spacing and Seeding Rate." *Agronomy Journal* 103(1):123–128. doi: 10.2134/agronj2010.0316.

Cox, W. J., J. H. Cherney, and E. Shields. 2010. "Soybeans Compensate at Low Seeding Rates but Not at High Thinning Rates." *Agronomy Journal* 102(4):1238–1243. doi: 10.2134/agronj2010.0047.

Du, X., H. Feng, and D. A. Hennessy. 2017. "Rationality of Choices in Subsidized Crop Insurance Markets." *American Journal of Agricultural Economics* 99(3):732–756. doi: 10.1093/ajae/aaw035.

Duvick, D. N. 2005. "The Contribution of Breeding to Yield Advances in Maize (*Zea mays* L.)." In D. L. Sparks, ed., *Advances in Agronomy,* Vol. 86. Academic Press, 83–145. doi: 10.1016/S0065-2113(05)86002-X.

Egli, D. B. 1988. "Plant Density and Soybean Yield." *Crop Science* 28(6):977–981. doi: 10.2135/cropsci1988.0011183X002800060023x.

Eng, M. L., B. J. M. Stutchbury, and C. A. Morrissey. 2019. "A Neonicotinoid Insecticide Reduces Fueling and Delays Migration in Songbirds." *Science* 365(6458):1177–1180. doi: 10.1126/science.aaw9419.

Epler, M., and S. Staggenborg. 2008. "Soybean Yield and Yield Component Response to Plant Density in Narrow Row Systems." *Crop Management* 7(1):1–13. doi: 10.1094/CM-2008-0925-01-RS.

Fernandez-Cornejo, J. 2004. *The Seed Industry in U.S. Agriculture: An Exploration of Data and Information on Crop Seed Markets, Regulation, Industry Structure, and Research and Development*. Agriculture Information Bulletin AIB-786. USDA Economic Research Service.

Fernandez-Cornejo, J., and R. E. Just. 2007. "Researchability of Modern Agricultural Input Markets and Growing Concentration." *American Journal of Agricultural Economics* 89(5):1269–1275. doi: 10.1111/j.1467-8276.2007.01095.x.

Ferreira, A. S., A. A. Balbinot Jr, F. Werner, C. Zucareli, J. C. Franchini, and H. Debiasi. 2016. "Plant Density and Mineral Nitrogen Fertilization Influencing Yield, Yield Components and Concentration of Oil and Protein in Soybean Grains." *Bragantia* 75(3):362–370. doi: 10.1590/1678-4499.479.

Forister, M. L., B. Cousens, J. G. Harrison, K. Anderson, J. H. Thorne, D. Waetjen, C. C. Nice, M. De Parsia, M. L. Hladik, R. Meese, H. Van Vliet, and A. M. Shapiro. 2016. "Increasing Neonicotinoid Use and the Declining Butterfly Fauna of Lowland California." *Biology Letters* 12(8):20160475. doi: 10.1098/rsbl.2016.0475.

Fromme, D. D., T. A. Spivey, and W. J. Grichar. 2019. "Agronomic Response of Corn (*Zea mays* L.) Hybrids to Plant Populations." *International Journal of Agronomy* 2019:1–8. doi: 10.1155/2019/3589768.

Gardner, B. L. 1976. "Futures Prices in Supply Analysis." *American Journal of Agricultural Economics* 58(1):81–84. doi: 10.2307/1238581.

Gaspar, A. P., S. Mourtzinis, D. Kyle, E. Galdi, L. E. Lindsey, W. P. Hamman, E. G. Matcham, H. J. Kandel, P. Schmitz, J. D. Stanley, J. P. Schmidt, D. S. Mueller, E. D. Nafziger, J. Ross, P. R. Carter, A. J. Varenhorst, K. A. Wise, I. A. Ciampitti, W. D. Carciochi, M. I. Chilvers, B. Hauswedell, A. U. Tenuta, and S. P. Conley. 2020. "Defining Optimal Soybean Seeding Rates and Associated Risk Across North America." *Agronomy Journal* 112(3):2103–2114. doi: 10.1002/agj2.20203.

Gilburn, A. S., N. Bunnefeld, J. M. Wilson, M. S. Botham, T. M. Brereton, R. Fox, and D. Goulson. 2015. "Are Neonicotinoid Insecticides Driving Declines of Widespread Butterflies?" *PeerJ* 3:e1402. doi: 10.7717/peerj.1402.

Gonzalez, V. H., M. Tollenaar, A. Bowman, B. Good, and E. A. Lee. 2018. "Maize Yield Potential and Density Tolerance." *Crop Science* 58(2):472–485. doi: 10.2135/cropsci2016.06.0547.

Heim, R. R. 2002. "A Review of Twentieth-Century Drought Indices Used in the United States." *Bulletin of the American Meteorological Society* 83(8):1149–1166. doi: 10.1175/1520-0477-83.

Hurley, T., and P. Mitchell. 2017. “Value of Neonicotinoid Seed Treatments to Us Soybean Farmers: Value of Neonicotinoid Seed Treatments to Us Soybean Farmers.” *Pest Management Science* 73(1):102–112. doi: 10.1002/ps.4424.

Hyde, J., M. A. Martin, P. V. Preckel, L. L. Buschman, C. R. Edwards, P. E. Sloderbeck, and R. A. Higgins. 2003. “The Value of Bt Corn in Southwest Kansas: A Monte Carlo Simulation Approach.” *Journal of Agricultural and Resource Economics* 28(1):1–19. doi: 10.22004/ag.econ.30721.

Karl, T. R. 1986. “The Sensitivity of the Palmer Drought Severity Index and Palmer’s Z-Index to Their Calibration Coefficients Including Potential Evapotranspiration.” *Journal of Applied Meteorology and Climatology* 25(1):77–86. doi: 10.1175/1520-0450(1986)025<0077:TSOTPD>2.0.CO;2.

Larson, J. A., R. K. Roberts, and C. O. Gwathmey. 2007. “Herbicide-Resistant Technology Price Effects on the Plant Density Decision for Ultra-Narrow-Row Cotton.” *Journal of Agricultural and Resource Economics* 32(2):1–19. doi: 10.22004/ag.econ.8640.

Lee, C. D., D. B. Egli, and D. M. TeKrony. 2008. “Soybean Response to Plant Population at Early and Late Planting Dates in the Mid-South.” *Agronomy Journal* 100(4):971–976. doi: 10.2134/agronj2007.0210.

Li, Y., R. Miao, and M. Khanna. 2020. “Neonicotinoids and Decline in Bird Biodiversity in the United States.” *Nature Sustainability* 3(12):1027–1035. doi: 10.1038/s41893-020-0582-x.

Lindsey, A. J., and P. R. Thomison. 2016. “Drought-Tolerant Corn Hybrid and Relative Maturity Yield Response to Plant Population and Planting Date.” *Agronomy Journal* 108(1):229–242. doi: 10.2134/agronj2015.0200.

Lindsey, A. J., P. R. Thomison, and E. D. Nafziger. 2018. “Modeling the Effect of Varied and Fixed Seeding Rates at a Small-Plot Scale.” *Agronomy Journal* 110(6):2456–2461. doi: 10.2134/agronj2018.07.0426.

Luca, M. J. D., and M. Hungría. 2014. “Plant Densities and Modulation of Symbiotic Nitrogen Fixation in Soybean.” *Scientia Agricola* 71(3):181–187. doi: 10.1590/S0103-90162014000300002.

Mascarenhas, M., and L. Busch. 2006. “Seeds of Change: Intellectual Property Rights, Genetically Modified Soybeans and Seed Saving in the United States.” *Sociologia Ruralis* 46(2):122–138. doi: 10.1111/j.1467-9523.2006.00406.x.

Moschini, G. 2008. “Biotechnology and the Development of Food Markets: Retrospect and Prospects.” *European Review of Agricultural Economics* 35(3):331–355. doi: 10.1093/erae/jbn014.

Mylonas, I., E. Sinapidou, E. Remountakis, I. Sistanis, C. Pankou, E. Ninou, I. Papadopoulos, F. Papathanasiou, A. Lithourgidis, F. Gekas, C. Dordas, C. Tzantarmas, A. Kargiotidou, M. Tokamani, R. Sandaltzopoulos, and I. S. Tokatlidis. 2020. “Improved Plant Yield Efficiency Alleviates the Erratic Optimum Density in Maize.” *Agronomy Journal* 112(3):1690–1701. doi: 10.1002/agj2.20187.

Nargi, L. 2022. “Some States Are Moving to Ban Neonic Pesticides. Is This the Best Way to Support Pollinators — and Farmers?” *Ambrook Research* Available online at ambrook.com/research/legislation/states-ban-neonic-pesticides-neonicotinoids-new-york-california.

Perry, E. D., D. A. Hennessy, and G. Moschini. 2019. “Product Concentration and Usage: Behavioral Effects in the Glyphosate Market.” *Journal of Economic Behavior & Organization* 158:543–559. doi: 10.1016/j.jebo.2018.12.027.

———. 2022. “Uncertainty and Learning in a Technologically Dynamic Industry: Seed Density in U.S. Maize.” *American Journal of Agricultural Economics* 104(4):1388–1410. doi: 10.1111/ajae.12276.

Perry, E. D., and G. Moschini. 2020. “Neonicotinoids in U.S. Maize: Insecticide Substitution Effects and Environmental Risk.” *Journal of Environmental Economics and Management* 102:102320. doi: 10.1016/j.jeem.2020.102320.

Plastina, A. 2023. "Estimated Costs of Crop Production in Iowa." Available online at https://www.extension.iastate.edu/agdm/crops/pdf/a1-20-2023.pdf.

Rundlöf, M., G. K. S. Andersson, R. Bommarco, I. Fries, V. Hederström, L. Herbertsson, O. Jonsson, B. K. Klatt, T. R. Pedersen, J. Yourstone, and H. G. Smith. 2015. "Seed Coating with a Neonicotinoid Insecticide Negatively Affects Wild Bees." *Nature* 521(7550):77–80. doi: 10.1038/nature14420.

Schmitz, P. K., and H. J. Kandel. 2021. "Individual and Combined Effects of Planting Date, Seeding Rate, Relative Maturity, and Row Spacing on Soybean Yield." *Agronomy* 11(3):605. doi: 10.3390/agronomy11030605.

Schwalbert, R., T. J. Amado, T. A. N. Horbe, L. O. Stefanello, Y. Assefa, P. Prasad, C. W. Rice, and I. A. Ciampitti. 2018. "Corn Yield Response to Plant Density and Nitrogen: Spatial Models and Yield Distribution." *Agronomy Journal* 110(3):970–982. doi: 10.2134/agronj2017.07.0425.

Thompson, N. M., J. A. Larson, D. M. Lambert, R. K. Roberts, A. Mengistu, N. Bellaloui, and E. R. Walker. 2015. "Mid-South Soybean Yield and Net Return as Affected by Plant Population and Row Spacing." *Agronomy Journal* 107(3):979–989. doi: 10.2134/agronj14.0453.

Tian, F., P. J. Bradbury, P. J. Brown, H. Hung, Q. Sun, S. Flint-Garcia, T. R. Rocheford, M. D. McMullen, J. B. Holland, and E. S. Buckler. 2011. "Genome-Wide Association Study of Leaf Architecture in the Maize Nested Association Mapping Population." *Nature Genetics* 43(2): 159–162. doi: 10.1038/ng.746.

Tokatlidis, I., and S. Koutroubas. 2004. "A Review of Maize Hybrids' Dependence on High Plant Populations and Its Implications for Crop Yield Stability." *Field Crops Research* 88(2-3): 103–114. doi: 10.1016/j.fcr.2003.11.013.

Tokatlidis, I. S. 2013. "Adapting Maize Crop to Climate Change." *Agronomy for Sustainable Development* 33(1):63–79. doi: 10.1007/s13593-012-0108-7.

Tollenaar, M., and E. Lee. 2002. "Yield Potential, Yield Stability and Stress Tolerance in Maize." *Field Crops Research* 75(2-3):161–169. doi: 10.1016/S0378-4290(02)00024-2.

Torshizi, M., and J. Clapp. 2021. "Price Effects of Common Ownership in the Seed Sector." *Antitrust Bulletin* 66(1):39–67. doi: 10.1177/0003603X20985783.

US Environmental Protection Agency. 2024. "Schedule for Review of Neonicotinoid Pesticides." Available online at https://www.epa.gov/pollinator-protection/schedule-review-neonicotinoid-pesticides [Accessed December 12, 2024].

Van Deynze, B., S. M. Swinton, D. A. Hennessy, N. M. Haddad, and L. Ries. 2024. "Insecticides, More Than Herbicides, Land Use, and Climate, Are Associated with Declines in Butterfly Species Richness and Abundance in the American Midwest." *PLoS One* 19(6):e0304319. doi: 10.1371/journal.pone.0304319.

Van Roekel, R. J., and J. A. Coulter. 2011. "Agronomic Responses of Corn to Planting Date and Plant Density." *Agronomy Journal* 103(5):1414–1422. doi: 10.2134/agronj2011.0071.

Wei, X., H. Khachatryan, and A. Rihn. 2020. "Consumer Preferences for Labels Disclosing the Use of Neonicotinoid Pesticides: Evidence from Experimental Auctions." *Journal of Agricultural and Resource Economics* 45(3):496–517. doi: 10.22004/ag.econ.302462.

Welch, B. L. 1947. "The Generalization of 'Student's' Problem When Several Different Population Varlances Are Involved." *Biometrika* 34(1-2):28–35. doi: 10.1093/biomet/34.1-2.28.

Xu, Z., D. A. Hennessy, K. Sardana, and G. Moschini. 2013. "The Realized Yield Effect of Genetically Engineered Crops: U.S. Maize and Soybean." *Crop Science* 53(3):735–745. doi: 10.2135/cropsci2012.06.0399.

Zhao, Y., D. A. Hennessy, L. E. Lindsey, M. P. Singh, and A. J. Lindsey. 2024. "Information Conveyed by Management Zones and Optimal Soybean Seeding Rate." *Agronomy Journal* 116(1):289–301. doi: 10.1002/agj2.21509.

Journal of Agricultural and Resource Economics 50(3):S1–S15 ISSN: 1068-5502 (Print); 2327-8285 (Online)

doi: 10.22004/ag.econ.356157

Online Supplement:* Seeding Rate Responses to Markets, Resources, and Technologies

Yuyuan Che, David A. Hennessy, and Hongli Feng

Density Estimates and Cumulative Distribution for Seeding Rates

We use kernel density estimators to approximate the density function from observations on seeding rates. The Epanechnikov kernel is applied to determine the weights as this kernel is the most efficient in minimizing the mean integrated squared error (Salgado-Ugarte et al., 1994). We also graph the empirical cumulative distribution of seeding rates. More kernel density estimates and cumulative distributions of seeding rates in different categories are presented below.

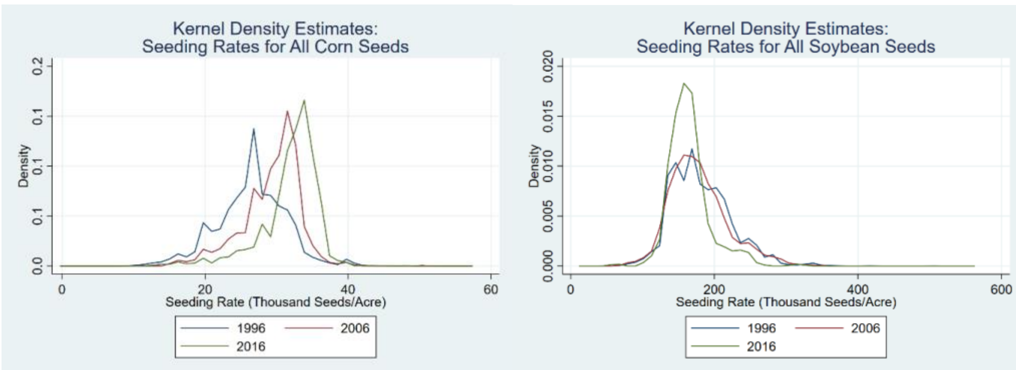


Figure S1. Kernel Density Estimates for Corn and Soybean Seeding Rates

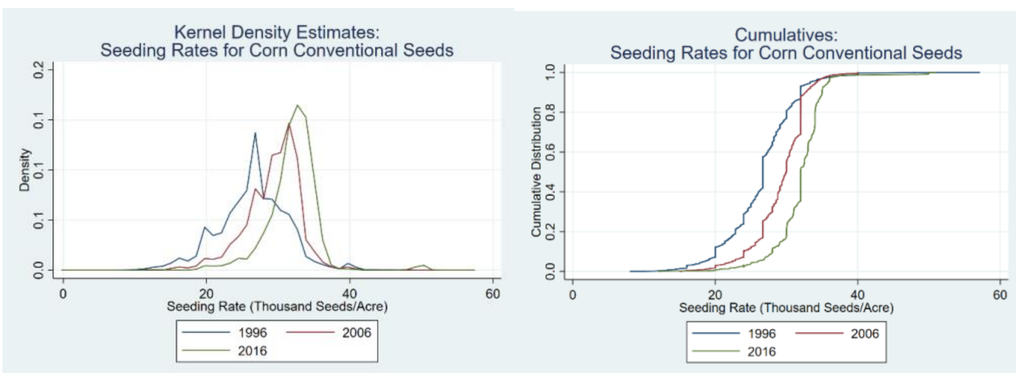


Figure S2. Kernel Density Estimates and Cumulative Distributions for the Seeding Rates of Corn Conventional Seeds

---

The material contained herein is supplementary to the article named in the title and published in the *Journal of Agricultural and Resource Economics* (*JARE*).

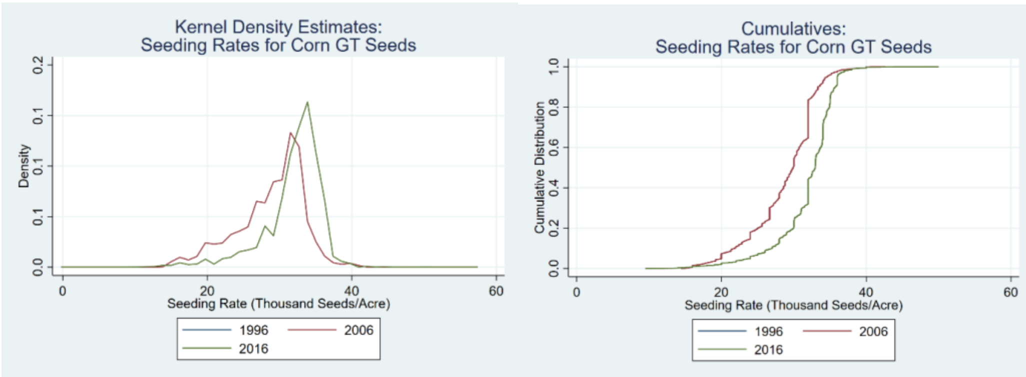


Figure S3. Kernel Density Estimates and Cumulative Distributions for the Seeding Rates of Corn Seeds with the Glyphosate Tolerant (GT) Trait

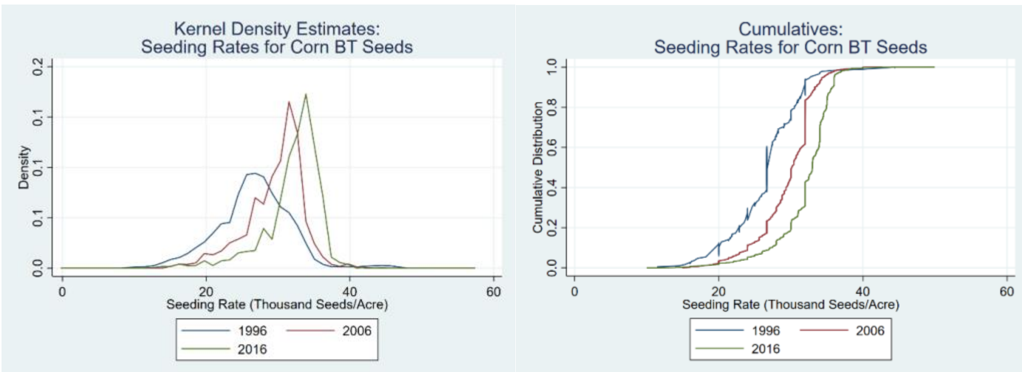


Figure S4. Kernel Density Estimates and Cumulative Distributions for the Seeding Rates of Corn Seeds with the *Bacillus thuringiensis* (*Bt*) Trait

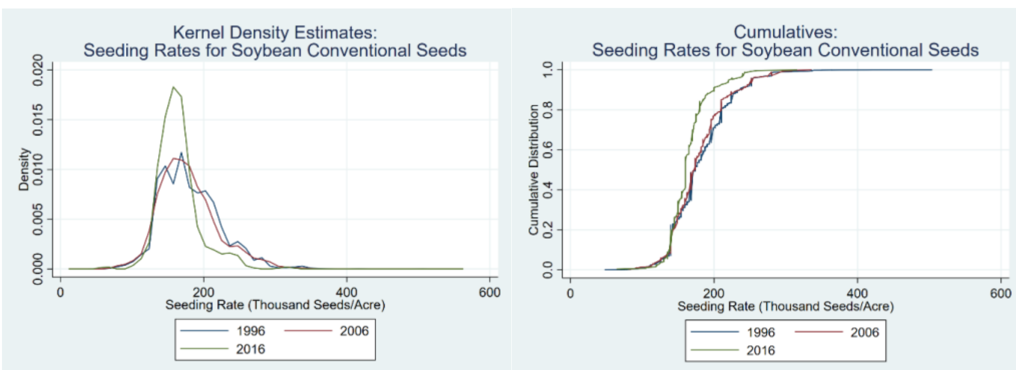


Figure S5. Kernel Density Estimates and Cumulative Distributions for the Seeding Rates of Soybean Conventional Seeds

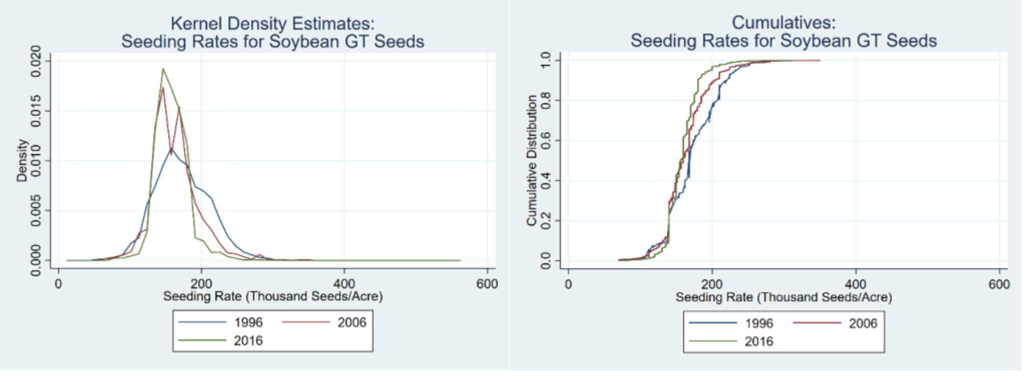


Figure S6. Kernel Density Estimates and Cumulative Distributions for the Seeding Rates of Soybean GT Seeds

Seeding Rate Time Trendlines in Selected States

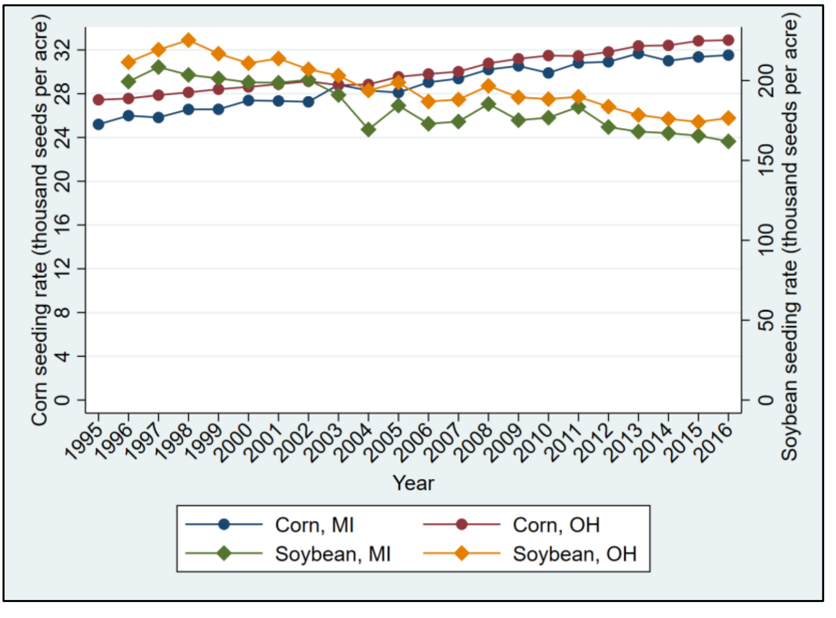


Figure S7. Average Seeding Rates for Corn (1995–2016) and Soybean (1996–2016) in Michigan and Ohio (Kynetec data)

Plant Architecture Analysis

We collect trial data on crop yield, seed treatment, and seeding rate from seed trial reports or extension reports by land grant universities.[1] Table S1 reports the mean values of yield and area per plant by crop and region in the trial datasets. We examine whether corn and soybean present different plant architectures as measured by estimating plant elasticity (i.e., crop per plant yield responses to area per plant). Letting y denote yield per plant and a denote area per plant, we apply a log-log ordinary least squares (OLS) regression model with year-fixed, county-fixed, and variety-fixed effects. The estimation equation is

$$\text{(S1)} \qquad \ln\left(y_{c,t}^{l}\right) = \alpha_0 + \alpha_1 \ln\left(a_{c,t}^{l}\right) + \psi_t + b_c + d_v + \xi_{c,t} \, ,$$

where c denotes county, t denotes year, l denotes crop (i.e., corn or soybean) and ψ_t denotes year fixed effects, which capture aggregate time trends and also annual weather effects; b_c represents county-fixed effects, included to capture some unobserved factors, idiosyncratic to each county; d_v represents variety-fixed effects, intended to capture the fact that modern varieties are associated with higher per-plant yield potential. Having introduced variety fixed effects, the estimated yield response can be interpreted as pertaining to a fixed technology. Also, seed treatments are explicitly randomized in the field experimental design, further reducing potential endogeneity in the models. The term $\xi_{c,t}$ is the error.

Table S2 shows equation (S1) regression estimates for per plant yield responses to area per plant. Comparing the coefficients on area per plant in log form, we find that soybean yield per plant is more elastic than corn with regard to the change in area per plant, i.e., the soybean plant's yield is more responsive to area available than is corn. Compared with corn, the soybean plant can more readily use the resources made available due to additional area by expanding leaf area, branches, pods, and seeds per plant (Egli, 1988; Lee et al., 2008; Cox et al., 2010), i.e., at a lower seeding rate.

In addition, we combine the field trial data from different states for corn and soybean and run the regressions by including state-fixed effects. Standard errors are clustered by year. The results are presented in Table S3. We have also conducted a Welch's t-test for the null hypothesis that "corn space elasticity equals soybean space elasticity." The null hypothesis is rejected at the 5% significance level.

Table S1. The Mean of Yield and Area per Plant by Crop and Region (seed trials data)

Variable	**Corn, Ohio**	**Corn, Colorado**	**Soybean, Ohio**	**Soybean, Michigan**
Yield per Plant (in 0.001 bushel)	6.510	6.435	0.455	0.551
Area per Plant (in 0.001 acre)	0.033	0.041	0.008	0.009
Seeding rate range (in 1,000 seeds/acre)	[22, 47]	[8, 37]	[50, 300]	[80, 160]
Observations	113	193	191	516

[1] Detailed information about seed trial reports and extension reports can be found at https://agcrops.osu.edu/on-farm-research and https://webdoc.agsci.colostate.edu/csucrops/reports/corn/cornreport_2018.pdf, accessed December 18, 2024.

Table S2. Regression of Yield per Plant on Area per Plant with Fixed Effects by Crop and Region

Variable	Corn, Ohio	Corn, Colorado	Soybean, Ohio	Soybean, Michigan
	Log (Yield per Plant)			
Log (Area per Plant)	0.896***	0.335**	0.970***	0.943***
	(0.0380)	(0.131)	(0.0177)	(0.0103)
Year FE	yes	no	yes	yes
County FE	yes	yes	yes	yes
Variety FE	yes	yes	yes	yes
Constant	3.814***	-2.126*	3.471***	3.286***
	(0.403)	(1.203)	(0.213)	(0.119)
Observations	113	193	191	513
R-squared	0.981	0.921	0.985	0.964

Notes: (i) Standard errors clustered by year in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$. (ii) We only have one year's data for Colorado, so year fixed effects are not included in the second column.

Table S3. Regression of Yield per Plant on Area per Plant with Fixed Effects by Crop

Variable	Corn	Soybean
	Log (Yield per Plant)	
Log (Area per Plant)	0.814***	0.952***
	(0.071)	(0.010)
Constant	1.861**	3.178***
	(0.649)	(0.120)
State FE	yes	yes
Year FE	yes	yes
County FE	yes	yes
Variety FE	yes	yes
Observations	306	704
R-squared	0.923	0.974

Notes: (i) Standard errors clustered by year in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$. (ii) We test the hypothesis that plant elasticity for corn is equal to that for soybean using Welch's t-test. The resulting t-statistic is -1.914, with a p-value of 0.028. Therefore, we reject the null hypothesis at the 5% significance level.

Supplemental Information for Seeding Rate Data

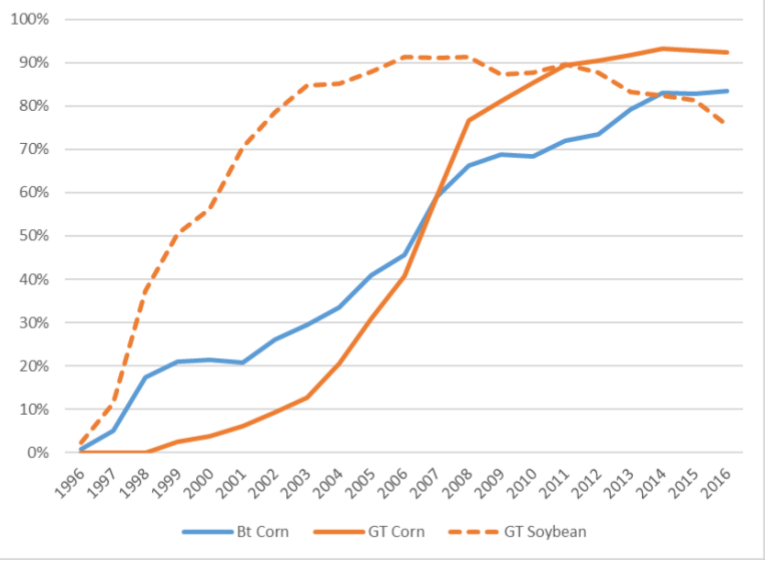


Figure S8. Area Percentages of Genetically Engineered Corn and Soybean in the United States, 1996–2016

Notes: Acre percentages are calculated based on Kynetec data. "*Bt* Corn" refers to corn varieties with the *Bacillus thuringiensis* (*Bt*) trait alone or in combination with other traits, "GT Corn" refers to corn varieties with the glyphosate tolerant (GT) trait alone or in combination with other traits, and "GT Soybean" refers to soybean varieties with the GT trait.

Table S4. Summary Statistics for the 20 Most Commonly Planted Varieties of Corn (1995–2016) and Soybeans (1996–2016)

Corn				Soybean			
Variety	**Obs**	**Percent**	**Cumulative**	**Variety**	**Obs**	**Percent**	**Cumulative**
3394	2,537	0.63%	0.63%	93M11	1,941	1.03%	1.03%
DKC52-59	1,684	0.42%	1.05%	AG3701	1,094	0.58%	1.62%
DKC61-69	1,594	0.40%	1.44%	AG3302	769	0.41%	2.03%
3489	1,477	0.37%	1.81%	93M42	752	0.40%	2.43%
3751	1,402	0.35%	2.16%	92Y51	743	0.40%	2.82%
3730	1,319	0.33%	2.48%	93B01	738	0.39%	3.22%
DKC63-42	1,294	0.32%	2.80%	93B82	715	0.38%	3.60%
DKC52-62	1,275	0.32%	3.12%	AG3803	715	0.38%	3.98%
33G26	1,263	0.31%	3.43%	HUTCHESON	688	0.37%	4.34%
34B23	1,221	0.30%	3.74%	AG2703	628	0.33%	4.68%
33P67	1,206	0.30%	4.04%	AG3832	579	0.31%	4.99%
33A14	1,205	0.30%	4.33%	92Y80	578	0.31%	5.29%
36B08	1,150	0.29%	4.62%	92M91	559	0.30%	5.59%
33B51	1,026	0.25%	4.87%	94Y01	547	0.29%	5.88%
DKC48-12 RIB	1,021	0.25%	5.13%	AG4403	513	0.27%	6.16%
3315	972	0.24%	5.37%	94Y70	508	0.27%	6.43%
3563	952	0.24%	5.60%	92Y30	505	0.27%	6.70%
34H31	890	0.22%	5.82%	94B01	486	0.26%	6.95%
35F44	883	0.22%	6.04%	AG2031	485	0.26%	7.21%
34G81	856	0.21%	6.26%	93Y70	477	0.25%	7.47%
Other	378,035	93.74%	100.00%	Other	173,756	92.53%	100.00%
Total	403,262	100.00%		Total	187,776	100.00%	

Table S5. Data Screening Procedures and Outcomes

Summary	Data Screening Details
Original observations	The original dataset reports 442,803 corn seed observations over 1995-2016 and 213,062 soybean seed observations over 1996-2016 across 235 CRDs in 31 states.
Remove observations reporting zero seeding rate	For corn we remove 66 observations reporting zero seeding rate. No soybean observations report zero seeding rate.
Remove observations reporting no seed variety identity	Some surveyed farmers did not report the identity of seed variety. We drop these observations because we cannot include variety fixed effects for them. Thus we obtain a reduced sample of 403,262 and 187,776 observations for corn and soybean, respectively.
Limited availability of tillage variable	The AgroTrak® data including tillage information has limited availability over the period 1998-2016, so combining seed and tillage data results in a further reduced sample size to 360,999 for corn and 173,056 for soybean.

Detrending Median Planting Date

Let $d_{c,t}$ be median planting date in state c and year t. A linear trend equation will be estimated as adjusted in Deng et al. (2007):

(S2) $$d_{c,t} = \lambda_0 + \lambda_1(2017 - t) + \phi_{ct},$$

where $t \in [1995, 2016]$ for corn, $t \in [1996, 2016]$ for soybean, and $\phi_{c,t}$ is the error term. The parameters λ_0 and λ_1 are to be estimated. The detrended median planting date is calculated as:

(S3) $$d_{c,t}^D = \frac{d_{c,t}}{\hat{d}_{c,t}} \times \hat{d}_{c,2017},$$

where $\hat{d}_{c,t}$ is the predicted median planting date. Thus the dates are adjusted to the year 2017 technological level. We then calculate the deviation between detrended median planting date $d_{c,t}^D$ and its mean value (i.e., detrended less mean value) across the study period to use as an explanatory variable in our seeding rate estimation.

Additional Regression Results with Kynetec Data

Table S6. Additional Regression Results with Fixed Effects for Corn and Soybean (Kynetec data)

		Corn			Soybean		
		(1)	(2)	(3)	(4)	(5)	(6)
Category	Variable	*s* (thousand seeds per acre)					
Price	*PR*	-0.00191***	-0.00190***	-0.00190***	-0.814***	-0.815***	-0.810***
		(0.000460)	(0.000460)	(0.000460)	(0.0711)	(0.0711)	(0.0709)
Land-embodied inputs	*LCC*	1.513***	1.513***	1.514***	0.547	0.558	0.520
		(0.224)	(0.224)	(0.223)	(3.760)	(3.761)	(3.743)
	WET	-0.0119**	-0.0119**	-0.0118**	-0.475***	-0.477***	-0.472***
		(0.00569)	(0.00569)	(0.00569)	(0.0781)	(0.0781)	(0.0779)
	DRY	0.0244***	0.0244***	0.0244***	-0.178**	-0.180**	-0.176**
		(0.00579)	(0.00579)	(0.00579)	(0.0832)	(0.0832)	(0.0831)
Seed-embodied inputs	*GT*	0.299			-5.179***		
		(0.293)			(1.432)		
	BT	0.335					
		(0.218)					
Controls	*IR*	0.0160	0.0170		4.064	4.149	
		(0.230)	(0.230)		(4.297)	(4.297)	
	PD	-10.01	-10.01		2,977	2,916	
		(8.400)	(8.400)		(3,842)	(3,843)	
	t	0.409***	0.410***	0.286***	-9.478***	-9.395***	-7.233***
		(0.110)	(0.110)	(0.0336)	(2.803)	(2.803)	(0.513)
	LAT	0.119***	0.119***	0.114***	0.375	0.367	0.375
		(0.0342)	(0.0342)	(0.0333)	(0.599)	(0.599)	(0.550)
	LON	-0.133***	-0.133***	-0.131***	-0.789**	-0.792**	-1.032***
		(0.0166)	(0.0166)	(0.0157)	(0.312)	(0.312)	(0.293)
	*t*LAT*	0.0144***	0.0144***	0.0144***	-0.0902***	-0.0912***	-0.0948***
		(0.000722)	(0.000722)	(0.000702)	(0.0110)	(0.0110)	(0.0103)
	*t*LON*	-0.00730***	-0.00730***	-0.00731***	0.108***	0.108***	0.109***
		(0.000292)	(0.000292)	(0.000267)	(0.00473)	(0.00473)	(0.00465)
	Farmer FE	yes	yes	yes	yes	yes	yes
	Variety FE	yes	yes	yes	yes	yes	yes
	Constant	36.17***	36.53***	36.37***	248.0***	244.3***	249.6***
		(1.703)	(1.691)	(1.682)	(33.60)	(33.59)	(31.78)
	No. of obs	333,250	333,250	333,250	157,375	157,375	157,375
	R-squared	0.796	0.796	0.796	0.678	0.678	0.678

Notes: (i) Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. (ii) Please refer to Table 1 in the manuscript for a detailed description of the variables.

Supplemental Information for Biodiversity Implications

Table S7. Price Effects on Biodiversity Through Neonicotinoid Use and Seeding Rate Choice

		Corn	Soybean
Percentage change in bird population			
	Due to a 100 kg increase in neonicotinoid use per county (which represents a 12% increase on average)	**Due to a 10% tax on seed or 10% decrease in crop price**	
Grassland bird	-2.4%	0.6%	3.9%
Non-grassland bird	-2.0%	0.5%	3.3%
Insectivorous bird	-2.3%	0.6%	3.7%
Non-insectivorous bird	-2.0%	0.5%	3.3%
Percentage change in butterfly population			
	Due to a 1% increase in neonicotinoid seed treatment area	**Due to a 10% tax on seed or 10% decrease in crop price**	
Monarch	-0.22%	0.6%	4.3%

Notes: (i) Li et al. (2020) report the semi-elasticities of bird populations with respect to neonicotinoid use. They estimate that a 100 kg increase in neonicotinoid use per county (equivalent to a 12% average increase) reduces grassland bird populations by 2.4% on average and non-grassland bird populations by 2.0%, holding all else constant. Using these data alongside the seed own-price elasticities for corn (-0.29) and soybean (-1.96), we estimate that a 10% tax on corn seed (or a 10% decrease in corn price) would lead to a 0.6% decrease in grassland bird populations. Similarly, a 10% tax on soybean seed (or a 10% decrease in soybean price) would result in a 3.9% decrease in grassland bird populations. These calculations are derived as follows: for corn, -0.29%×10×(-2.4%/12%)≈0.6%; for soybean, -1.96%×10×(-2.4%/12%)≈3.9%. Similar calculations can be applied to estimate the impacts on insectivorous and non-insectivorous bird populations. (ii) Van Deynze et al. (2024) use a generalized linear model (negative binomial) to analyze the effects of neonicotinoid-treated areas on butterfly populations in the U.S. Midwest. Their findings indicate that a 1% increase in neonicotinoid seed treatment area is associated with a 0.22% decrease in county-wide monarch butterfly abundance. By combining this result with seed price elasticities, we estimate that a 10% tax on corn seed (or a 10% decrease in corn price) would reduce monarch abundance by 0.6% (-0.29%×10×(-0.22)≈0.6%). Similarly, a 10% tax on soybean seed (or a 10% decrease in soybean price) would lead to a 4.3% reduction in monarch abundance (-1.96%×10×(-0.22)≈4.3%).

Focus Group Responses

Focus Group Meeting Data

We implemented three focus group meetings with corn and soybean growers and consultants in August 2018, during which participants were asked about factors influencing their opinions about seeding rate choices. Three meetings were held: one on August 13 in East Lansing, Michigan; another on August 20 in Wauseon, Ohio; and the third on August 21 in Columbus, Ohio. The meetings were held at university or state extension service meeting rooms and respondents generally resided within 30 miles of the meeting place. Each meeting lasted about 3.5 hours, and about 1.5 hours were required to complete paper-format survey instruments. A Michigan State University extension educator with a precision agriculture background led a presentation to help participants work through the instrument.

We received 14 responses from East Lansing attendees, 21 from Fulton attendees, and 14 from Columbus attendees. Of the 49 respondents who completed the questionnaire, 37 were operators and 12 were either crop consultants or suppliers.[1] The average operated acres in our sample were about 1,100 acres in Wauseon, 1,800 acres in Columbus, and 3,200 acres in East Lansing. These acreages were much higher than the average operated acres (441 acres) in the United States (USDA-NASS, 2019). The 2017 Agricultural Census data reveals that the largest 8% of farms in the United States (1,000 or more acres) operated 71% of all farmland (USDA-NASS, 2019) while most farms in the United States are not commercially viable (Hoppe et al., 2010).

The focus group meetings provided information about how farmers adjust corn and soybean seeding rate choices when faced with changes in tillage type, planting date, soil moisture, soil quality, chemical treatment, and genetic technology. Moreover, the meetings also explored how much impact different market or human influences had on seeding rate choices and what the most important factors were.

Focus Group Participants' Opinions about Seeding Rate Choices

Table S9 presents how farmers' seeding rate choices respond to land-embodied and seed-embodied inputs across market estimation results and focus group meeting responses. Focus group participants in Ohio and Michigan differ in some regards to what market data convey. For land-embodied inputs, farmers indicate that corn seeding rates should increase when soil quality is better, soil moisture is higher, and soil variability is smaller. Soybean seeding rates should increase with higher soil moisture. These seeding rate responses are consistent with Hypothesis 2A in the conceptual model. However, stated views on how soybean seeding rates respond to soil quality and variation are not as expected. Turning to land-embodied inputs, corn seeding rates would decrease were either above ground or below ground insect protection trait altered from yes to no, but seeding rates would still increase when chemical treatment changes from yes to no. For soybean, as expected seeding rates would increase when chemical treatment changes from yes to no and would decrease when treatment changes in the opposite direction.

Figure S9 presents the most important factors that affect corn and soybean seeding rate choices from focus group participants' view, results that are also discussed by Hennessy et al. (2022). Farmers rely most heavily on their own experience when making seeding rate choices. The second-order important information sources are dealer, agronomy consultant, and university or extension recommendations. Peer farmer experience has little influence on seeding rate choices. Although price changes affect seeding rate choices, surveyed farmers claim that seed prices and crop expected prices are not major drivers in the decision process.

[1] In Table S8 we compare the mean values for each surveyed grower response with average values for growers in the corresponding CRD.

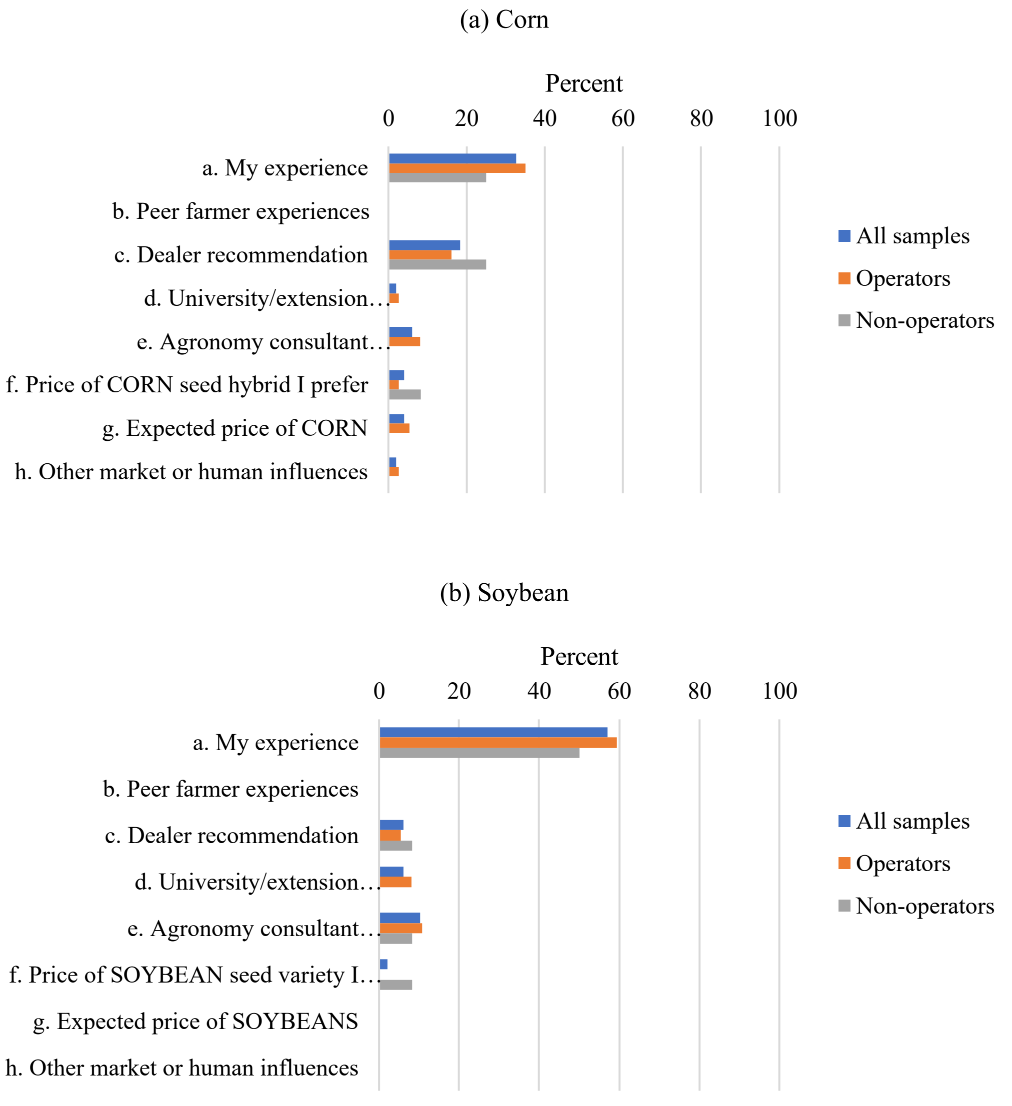


Figure S9. The Most Important Factor That Affects Seeding Rate Choices from the Focus Group Participants' Viewpoint
Notes: Fifteen participants did not answer the questions for corn, and ten participants did not answer the question for soybean.

Table S8. Grower Characteristics by Location

	East Lansing, MI	CRD 80, MI	Wauseon, OH	CRD 10, OH	Columbus, OH	CRD 50, OH
Mean years as grower	19	25	22	26	26	24
Mean age	46	57	45	57	45	57
Share who farm as principal occupation	0.75	0.41	0.60	0.38	0.50	0.39

Notes: In "mean years as grower", we record 15 years for one operator in East Lansing who reported "15+" years, and 12.5 years for another in Wauseon who reported "10-15" years. Area comparisons are from the 2017 Agricultural Census. Although surveyed growers were younger and had operated farms for fewer years than is typical in the area, a greater share operated farms as their principal occupation.

Table S9. How Seeding Rates Choices Are Affected by Different Environmental Changes or Agricultural Practices

		Corn		Soybean	
	Environmental Changes or Agricultural Practices	**Market Regression**	**Focus Groups**	**Market Regression**	**Focus Groups**
Land-embodied inputs	Soil quality better.	R^{a}	R^{a}	L	L^{a}
	Soil moisture higher.	L^{a}	R^{b}	L^{a}	R^{b}
	Soil moisture lower.	R^{a}	L^{b}	L^{a}	R^{c}
	Soil variability greater.		L^{a}		R^{a}
	Tillage choice change to being more intensive.	R^{a}	L	R^{a}	L^{a}
	Tillage choice change to being less intensive.	L^{a}	R^{b}	L^{a}	R^{a}
Seed-embodied inputs	Chemical treatment change from Yes to No.		R^{c}		R^{a}
	Chemical treatment change from No to Yes.				L^{b}
	Insect protection above ground trait choice change from Yes to No.		L^{c}		
	Insect protection above ground trait choice change from No to Yes.		E		
	Insect protection below ground trait choice change from Yes to No.		L		
	Insect protection below ground trait choice change from No to Yes.		R		
	GT	R^{a}		L^{a}	
	Bt	R^{a}			
Other agricultural practices	Planting date change to earlier.	R	R^{a}	L	L
	Planting date change to later.	L	L^{a}	R	R^{a}
	The share of irrigated acres in harvested acres greater.	L^{a}		L	
	Tile drained change from Yes to No.		L		R
	Tile drained change from No to Yes.		R^{b}		L^{b}

Notes: L denotes farmers would like to lower seeding rates; R denotes farmers would like to raise seeding rate; E denotes farmers would not change seeding rates. Red color indicates that the responses are consistent with our hypotheses. Standard errors are at the significance levels: ^{a} $p<0.01$, ^{b} $p<0.05$, ^{c} $p<0.1$.

Table S10. The *t*-Test Results for Changes in Corn Seeding Rates Choices When Faced with Different Environmental Changes or Agricultural Practices

Corn	Environmental Changes or Agricultural Practice Changes	All Samples		Operators	
		Mean	Pr(T > t)	Mean	Pr(T > t)
Land-embodied inputs	Soil quality better.	0.872	0.000	0.889	0.000
	Soil moisture higher.	0.128	0.016	0.111	0.052
	Soil moisture lower.	-0.106	0.971	-0.111	0.978
	Soil variability greater.	-0.192	0.999	-0.194	0.997
	Tillage choice change to being more intensive.	-0.021	0.839	N/A	N/A
	Tillage choice change to being less intensive.	0.149	0.035	0.083	0.162
Seed-embodied inputs	Chemical treatment change from Yes to No.	0.106	0.067	0.139	0.048
	Chemical treatment change from No to Yes.	N/A	N/A	N/A	N/A
	Insect protection above ground trait choice change from Yes to No.	-0.081	0.908	-0.077	0.837
	Insect protection above ground trait choice change from No to Yes.	0.000	0.500	0.000	0.500
	Insect protection below ground trait choice change from Yes to No.	-0.048	0.667	0.000	0.500
	Insect protection below ground trait choice change from No to Yes.	0.111	0.297	0.125	0.299
Other agricultural practices	Planting date change to earlier.	0.426	0.000	0.361	0.000
	Planting date change to later.	-0.128	0.994	-0.111	0.978
	Tile drained change from Yes to No.	0.079	0.237	0.069	0.286
	Tile drained change from No to Yes.	0.444	0.017	0.571	0.015

Notes: To test whether 'raise' exceeds 'lower', we set 'lower' = -1, 'same' = 0 and 'raise' =1. Then we test whether the mean exceeds 0. The table shows the mean value and the one-tailed p-value for the difference from zero. "N/A" denotes no responses.

Table S11. The *t*-Test Results for Changes in Soybean Seeding Rates Choices When Faced with Different Environmental Changes or Agricultural Practices

Soybean	Environmental Changes or Agricultural Practice Changes	All Samples		Operators	
		Mean	Pr(T > t)	Mean	Pr(T > t)
Land-embodied inputs	Soil quality better.	-0.604	1.000	-0.622	1.000
	Soil moisture higher.	0.163	0.016	0.135	0.048
	Soil moisture lower.	0.082	0.052	0.108	0.022
	Soil variability greater.	0.204	0.001	0.216	0.002
	Tillage choice change to being more intensive.	-0.286	1.000	-0.216	0.995
	Tillage choice change to being less intensive.	0.225	0.000	0.162	0.006
Seed-embodied	Chemical treatment change from Yes to No.	0.364	0.000	0.406	0.000
	Chemical treatment change from No to Yes.	-0.750	0.971	-0.750	0.971
Other agricultural practices	Planting date earlier.	-0.041	0.656	-0.135	0.872
	Planting date later.	0.408	0.000	0.460	0.000
	Tile drained change from Yes to No.	0.108	0.162	0.185	0.067
	Tile drained change from No to Yes.	-0.364	0.981	-0.333	0.960

Notes: To test whether 'raise' exceeds 'lower', we set 'lower' = -1, 'same' = 0 and 'raise' =1. Then we test whether the mean exceeds 0. The table shows the mean value and the one-tailed p-value for the difference from zero.

References

Cox, W.J., J.H. Cherney, and E. Shields. 2010. "Soybeans Compensate at Low Seeding Rates but Not at High Thinning Rates." *Agronomy Journal* 102(4):1238–1243. doi: 10.2134/agronj2010.0047

Deng, X., B.J. Barnett, and D.V. Vedenov. 2007. "Is There a Viable Market for Area-Based Crop Insurance?" *American Journal of Agricultural Economics* 89(2):508–519. doi: 10.1111/j.1467-8276.2007.00975.x

Egli, D.B. 1988. "Plant Density and Soybean Yield." *Crop Science* 28(6):977–981. doi: 10.2135/cropsci1988.0011183X002800060023x

Hennessy, D.A., A.J., Lindsey, Y. Che, L.E. Lindsey, M.P. Singh, H. Feng, E.M. Hawkins, S. Subburayalu, R. Black, E.A. Richer, and D.S. Ochs. 2022. "Characterizing the Decision Process in Setting Corn and Soybean Seeding Rates." *Journal of Extension* 60(1):3. doi: 10.34068/joe.60.01.03

Hoppe, R.A., J.M. MacDonald, and P. Korb. 2010. *Small Farms in the United States: Persistence Under Pressure*. USDA Economic Research Service Economic Information Bulletin EIB-63.

Lee, C.D., D.B. Egli, and D.M. TeKrony. 2008. "Soybean Response to Plant Population at Early and Late Planting Dates in the Mid-South." *Agronomy Journal* 100(4):971–976. doi: 10.2134/agronj2007.0210

Li, Y., R. Miao, and M. Khanna. 2020. "Neonicotinoids and decline in bird biodiversity in the United States." *Nature Sustainability* 3(12):1027–1035. doi: 10.1038/s41893-020-0582-x

Salgado-Ugarte, I.H., M. Shimizu, and T. Taniuchi. 1994. "Exploring the Shape of Univariate Data Using Kernel Density Estimators." *Stata Technical Bulletin* 3(16).

US Department of Agriculture. 2019. *2017 Census of Agriculture Publication Highlights: Farms and Farmland.* USDA National Agricultural Statistics Service. Available online at https://www.nass.usda.gov/Publications/Highlights/2019/2017Census_Farms_Farmland.pdf

Van Deynze, B., S.M. Swinton, D.A. Hennessy, N.M. Haddad, and L. Ries. 2024. "Insecticides, More Than Herbicides, Land Use, and Climate, Are Associated with Declines in Butterfly Species Richness and Abundance in the American Midwest." *PLoS One* 19(6):e0304319. doi: 10.1371/journal.pone.0304319