Seeding Rate Responses to Markets, Resources, and Technologies

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Abstract

Corn and soybean seeding rates in the United States have moved in opposite directions over recent decades, with the former trending upward and the latter trending downward. Such different trends provide interesting opportunities to better understand how farmers' seeding rate choices respond to market, resource, and technological factors. We develop a theoretical model of seeding rate choices by incorporating a resource budget trade-off between seeds and resources allocated to each seed. With a large and detailed U.S. farm-level market dataset over twenty years, we find the soybean seeding rate choice to be more price elastic than that for corn. Specifically, the seeding rate for soybean would decrease by 15% more than that for corn in response to a 10% increase in seed price or 10% decrease in crop price. Furthermore, more land-embodied inputs (e.g., soil nutrients) increase both corn and soybean seeding rates; while more seed-embodied inputs (e.g., genetically engineered treatment) increase corn rates but decrease soybean rates. The difference in price elasticities across crops due to different plant architectures has consequential implications, including for division of economic surplus arising from innovations and for the outcomes of policy incentives intended to mitigate the negative ecological impacts from seed use.

Keywords: Crop yield per plant, genetic technology, land-embodied technical change, plant architecture, seed price elasticity, seed-embodied technical change

JEL Codes: Q11, Q12, Q16, Q57

1. Introduction

Seeds are an essential input in crop production and generally constitute a significant portion of the 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 the production costs of each crop in the U.S. Midwest (Plastina, 2023). Seed markets are oligopolies (Ciliberto et al., 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. Furthermore, genetically modified seeds may carry additional expenses (Hyde et al., 2003). Technology trait endowed seeds sell at large premiums, suggesting that growers will seek to carefully evaluate and select seeds as well as economize on seeding rates while still availing of the embedded technology (Larson et al., 2007).

The selection of seeding rates gives rise to considerable environmental concerns due to the widespread use of chemical coatings on seeds. Neonicotinoids are the most widely used insecticides that are applied to the surface of seeds. Specifically, neonicotinoids are 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 from seed-applied neonicotinoid insecticides persist in the soil and water and pose a threat to many non-target plants. These chemicals can also have adverse effects on bird (Eng et al., 2019; Li et al., 2020), butterfly (Gilburn et al., 2015; Forister et al., 2016; Van Deynze et al., 2022), bee (Rundlöf et al., 2015), and general pollinator insect species (Wei et al., 2020) abundance. Due to these negative environmental consequences, neonicotinoids have been banned in some regions around the world. Some U.S. states are considering proposals to banning their use (Nargi, 2022) while the U.S. Environmental Protection Agency is presently reviewing their registration status (EPA, 2023). 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 that enter the environment.

Corn and soybean are major crops in the United States and so their seeding rate choices have great 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 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, we show that the same tax rate will lead to different seeding rate adjustments for corn and soybean.

Due to the importance of seeding rate choices, a large agronomic literature investigating the relationship between crop yield and seeding rates has emerged, where emphasis has been placed on agronomically optimal seeding choices for corn (Assefa et al., 2016; Assefa et al., 2018; Lindsey et al., 2018; Schwalbert et al., 2018; Fromme et al., 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). Few studies have investigated farmers' seeding rate choices from an economic perspective, although some have examined seed industry structure (e.g., Ciliberto et al., 2019).

One study by Perry et al. (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, but do not explicitly examine the optimal seeding rate choices or how different resources, such as land quality and weather factors, affect these choices.

Our primary objective is to examine how farmers' seeding rate choices for two major crops, 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 U.S. 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 price elastic than corn. Second, higher levels of land-embodied inputs increase corn and soybean seeding rates while higher levels of seed-embodied inputs increase corn seeding rates but decrease soybean seeding rates.

Our paper 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 best knowledge, no existing work has systematically examined farmers' seeding rate choices both in theory and empirics, 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 where we highlight the roles of two important factor attributes: seed-embodied factors and land-embodied factors.

Second, we empirically investigate the price elasticities of seeds across different crops, controlling for variations in plant architecture. Specifically, our analysis adds to the work by Ciliberto et al. (2019), who estimate a larger absolute value of seed own-price elasticity for aggregate corn seed products than for soybean and also find that the seed industry extracts more surplus from corn products than from soybean products. However, they do not provide reasons behind the above difference in elasticities. Our analysis gives insights in this regard by providing evidence on the different elasticities of crop yield to seeding rate, where these elasticities are important in explaining how economic surplus is divided. 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 (or corn) seed tax or a 10% decrease in soybean (or corn) price contributes to about a 3% (or 0.6%) increase in the bird population and a 4% (or 0.7%) increase in the 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 a longer time-series coverage. Most agronomic studies only focus on seeding rate issues and are typically conducted only for particular field locations and only for shorter time periods. 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.

2. Background on Seeding Rates

The seeding rate input is a distinctive choice. While more seed on unlimited land resources should increase yield output, as with other inputs, 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 can 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 at varying seeding rates.

Corn and soybean seeding rates in the United States have 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. These trends are also reflected in the cumulative distribution function (CDF) for seeding rates in some representative years as given in Figure 2.[1] The CDF lines for corn seeding rates shifted rightward from 1996 to 2016 while those for soybean seeding rates shifted leftward. The temporal pattern at the nation-wide level is also reflected at the state level even though different states have different seeding rates.[2] In addition to temporal differences, seeding rates differ geographically because higher latitude locations need short-season varieties, more arid locations need drought-

[1] Detailed about cumulative distribution functions of seeding rates can be found in the Supplemental Materials (SM), Section A.
[2] Seeding rate time trendlines in selected states can be found in SM, Figure B1.

tolerant varieties and varieties perform differently on different soils. Corn and soybean seeding rates are known to vary considerably, even in a locality. As depicted in Figure 3, which provides the seeding rates distribution by crop reporting district (CRD)[3] in 2000 and 2016 for both corn and soybean, corn seeding rates in most districts were higher in 2016 when compared with 2000. For a given year, corn seeding choices varied spatially, generally being highest in the Cornbelt 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 Cornbelt and Northern Great Plains than in the Western Cornbelt.

Seeding rate choices have played a critical role in enhancing productivity. For corn, increased seeding rates have provided a large proportion of yield gain due to modern hybrids (Tollenaar and Lee, 2002; Tokatlidis and Koutroubas, 2004; Duvick, 2005; Assefa et al., 2016; Assefa et al., 2018; Gonzalez et al., 2018; Fromme et al., 2019). 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 has been the primary driver of increased yield per acre (Gonzalez et al., 2018; Fromme et al., 2019). In contrast, soybean seeding rates are lower in higher yield environments (Carciochi et al., 2019). A decrease in seeding rates produces greater yield from individual plants (Epler and Staggenborg, 2008; Cox et al., 2010; Luca and Hungria, 2014).

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

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

genome to express desirable traits. Two sets of attributes, herbicide tolerance in both corn and soybeans 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, and 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 U.S. seed market.[4] We examine the different effects of GE traits on corn and soybean seeding rates in a later section.

3. 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.

Yield per seed is given generically as a bounded function $y(s, \tau, \theta)$ with $\lim_{s \to 0} y(s, \tau, \theta) < \infty$, that is decreasing in s and 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.[5] This yield function is assumed to be twice

[4] Figure B2 in SM presents diffusion patterns for GE varieties over 1996-2016.
[5] 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.

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.

3.1 Price Effects

Given price per seed as *w* and output price as *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 or minimum point. Consequently, there can be only one interior solution s^* to (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) $$y(s,\tau,\theta)|_{s=s^*}\left[1 + \frac{y_s(s,\tau,\theta)|_{s=s^*}\, s^*}{y(s,\tau,\theta)}|_{s=s^*}\right] = y(s^*,\tau,\theta)\left[1 + \frac{d\ln[y(s,\tau,\theta)|_{s=s^*}]}{d\ln(s)}\right] = \frac{w}{p},$$

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

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

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'. 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 (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.

For this technology,

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

and we have optimal seeding rate as

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

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.

Thus, we have our first hypothesis,

Hypothesis 1: H1) For given prices and seeding rate, the more space elastic the plant, the more elastic the seed own-price demand curve.

This perspective then 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 and, in addition, farmers cannot respond at the intensive margin to higher prices by spreading seed over larger areas.

3.2 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

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

and cross derivatives

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

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

Derivative (9*a*) asserts that an increase in per acre resources complements seed use and so optimal seed use should increase with an increase in this form of endowments, $ds^*/d\tau > 0$. Derivative (9*b*) cannot be so readily signed. 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 seeding rate. An example where the two resources are likely to substitute is when resources per plant come in the form of genetics to protect against drought and the endowment per acre is soil moisture. Then the drought tolerance trait would provide confidence to the farmer that sharing water endowments over more seed will be beneficial. An example where two resources are likely to complement is when herbicide tolerant seed releases nutrients, sunlight and other land resources that would have been consumed by weeds for use by the plant.

Our second hypothesis is then

Hypothesis 2: H2*i*) The optimal seeding rate will increase with an increase in per acre endowments for any plant architecture. **H2*ii*)** Whenever the marginal value of resources per plant is elastic (respectively, inelastic) with respect to resources per acre, then optimal seeding rate will decrease (respectively, increase) in response to an increase in resources per plant.

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

4. Data Description

We first collect trial data on crop yield, seed treatment, and seeding rate from seed trial reports or extension reports by land grant universities.[6] We then combine data from several sources to construct a unique field-year panel dataset that we focus on, covering information about seeding rates, locations, prices, soil conditions, agricultural practices, and genetic technologies.

4.1 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 a market research company, Kynetec USA, Inc., whose business is to collect data from annual surveys from randomly sampled farmers in the United States. The sampled farmers

[6] 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 February 18, 2024. Table B1 in SM reports the mean values of yield and area per plant by crop and region in the trial datasets.

were designed 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 twelve most commonly planted varieties only account for about 6% and 7% of corn and soybean varieties, respectively.[7]

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 another dataset AgroTrak®, which is also assembled by Kynetec. Each plot is identified as using one of three alternatives: "Conventional Tillage", "Conservation Tillage", or "No-Till".[8]

At the time when farmers make seeding rate choice decisions, post-harvest-time market crop prices are not yet realized and each crop's futures prices are used to represent farmers' expected postharvest prices (Gardner, 1976). To be specific, monthly average pre-planting 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.[9]

[7] Table B2 in SM provides summary statistics for the twenty most commonly planted varieties.
[8] Details on data screening are available in SM, Table B3.
[9] Futures prices for commodities are downloaded from https://www.quandl.com/.

4.2 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 U.S. 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[11] provide monthly PZ values for climate divisions in the conterminous United States. We calculate the intersection area between climate divisions and each county, and then calculate area-weighted PZ values for each county. Since PZ values have been normalized to zero 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, the time when farmers begin to make seeding rate decisions.

4.3 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

[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 February 18, 2024.

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 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 shows descriptive statistics for the corresponding variables for corn and soybean.

5. Empirical Methods

5.1 Plant Architecture Estimation

Based on our measures of plant elasticity and rigidity in the conceptual model, we further explore whether corn and soybean present different plant architectures by examining crop yield responses to area per plant with seed trial data. 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

$$\text{(10)} \qquad \ln(y_{c,t}^{l}) = \alpha_0 + \alpha_1 \ln(a_{c,t}^{l}) + \psi_t + b_c + d_v + \xi_{c,t},$$

where c denotes county, t denotes year, l denotes crop (i.e., corn or soybean) and v denotes

[12] Details on median planting dates are included in SM, Section C.

variety. The term ψ_t represents year-fixed effects, included to capture the influence in the 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 as discussed earlier. Having introduced variety fixed effects, the estimated yield response can be interpreted as pertaining to a fixed technology. The term $\xi_{c,t}$ is the error.

5.2 Market Estimation

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

$$\begin{aligned}(11)\qquad s_{i,t}^{l} &= \beta_0 + \beta_1 PR_{i,t}^{l} + \beta_2 LE_{i,t}^{l} + \beta_3 SE_{i,t}^{l} + \beta_4 AG_{i,t}^{l} + \beta_5 t + \beta_6 LOC_{i,t} + \beta_7 t * LOC_{i,t} \\ &\quad + \delta_f^{l} + h_v^{l} + \varepsilon_{i,t}^{l}\end{aligned}$$

where each field is denoted as i, each farmer who may own 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 $s_{i,t}^{l}$, 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_f^{l}, variety-fixed effects denoted by

h_v^l, and error term denoted by $\varepsilon_{i,t}^l$. The presence of farmer-fixed effects is intended to control for unobserved factors, idiosyncratic to a farmer, and so to account for any omitted variables such as education, age, and other personal characteristics, that are correlated with seeding rate choices. The presence of 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.

6. Results and Discussions

6.1 Plant Architecture

Table 3 shows equation (10) regression estimates for per plant yield responses to area per plant in some representative states. 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. This finding is consistent with the intuition that soybeans are short and space elastic and can readily branch laterally, while corn is tall and rigid. 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. We also test the hypothesis that coefficients of area per plant in the log form equal one so that seeding rate does not affect yield within a seeding rate range. The null hypothesis is rejected for corn in Ohio and Colorado and for soybean in Michigan at 1% significance level, and for soybean in Ohio at 10% significance level.

6.2 Price Effects on Seeding Rate Choices

Table 4 reports equation (11) 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 with an expected negative coefficient value. Recall that sample average price ratio values are approximately 40.4 and 3.8 for corn and soybean, respectively. Hence, a 10% increase in seed price or 10% decrease in corn price, given the estimated coefficient in column 2, would reduce corn seeding rate by less than 3% of the average seeding rate. By contrast, soybean seeding rate would decrease by 18% of the average seeding rate in response to a 10% increase in seed price or 10% decrease in soybean price, given the estimated coefficient in column 4. Thus, on average, the seeding rate for soybean would decrease by 15% more than that for corn in response to a 10% increase in seed price or 10% decrease in crop price. These estimates support hypothesis H1 in our conceptual model, namely that the demand for soybean seed is more price elastic than that for corn.[13]

6.3 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 4, for land-embodied inputs, we find that corn seeding rates are higher on better quality land (i.e., LCC higher), but 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 does not have much impact on soybean seeding rates.

Conventional tillage usually incorporates most crop residue into soil, and so more nutrients per acre are released into soil when compared 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

[13] The seed own-price elasticities by year are presented in SM, Table D1.

resources and help to warm springtime soils, among other effects on increasing land resources available to the crop. Consistent with our H2*i*), 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, while 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 H2*ii*) in the conceptual model, namely 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.

6.4 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 et al., 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 et al. (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 genetically engineered varieties has favored the seed industry over farmers for corn but farmers over the seed industry for soybeans. 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 acres changes due to a tax on seeds. In addition, we also assume that the potential tax does not differentiate among different types of seeds, and is applied on general 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 et al. (2020). They report the percentage impact of a 100kg increase (which represents a 12% increase on average) in neonicotinoid use on bird populations in the United States, measured by the number of birds observed. Then we draw on negative binomial regression estimates regarding how changes in neonicotinoid area treatments affect specific butterfly populations (measured by hourly counts by county-year during June, July, and August) in the U.S. Midwest as reported by Van Deynze et al. (2022).

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 3.6% increase in the grassland bird population and a 3.0% increase in the non-grassland bird population. This tax or price change also increases the insectivorous bird population by 3.4% and the non-insectivorous bird population by 3.0%. In addition, the tax or price change also leads to an increase in the population of two groups of butterflies. More specifically, a 10% tax on soybean seed or 10% decrease in soybean price causes about 4% increase in each of monarch and silver-spotted skipper populations. A 10% tax on corn seed or 10% decrease in corn price can also improve the monarch and silver-spotted skipper populations, but the magnitude of effects is smaller than that for soybean.

7. Conclusions

Seeding rate choices are a critical decision in crop production, playing a vital role in both farm 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 paper 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 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 (Rees 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.[14] Discrepancies between market estimations and surveyed farmers' responses suggest that farmers may not be fully rational. Some economic inquiries have found evidence that farmers misjudge their choices in many contexts including crop insurance, pesticides and nitrogen use. These misjudgments lead to inefficiency (i.e., farmers forego profits) and so a deeper understanding of these behavioral factors could help improve policy design and enhance efficiency.

[14] 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 SM, Section E.

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: 817–849. https://doi.org/10.1007/s00122-019-03306-3.

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. https://doi.org/10.2135/cropsci2016.04.0215.

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. https://doi.org/10.1038/s41598-018-23362-x.

Brester, G.W., J. Atwood, M.J. Watts, and A. Kawalski. 2019. "The influence of genetic modification technologies on US and EU crop yields." *Journal of Agricultural and Resource Economics* 44(1): 16–31. https://www.jstor.org/stable/26797541.

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. https://doi.org/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. https://doi.org/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." *The RAND Journal of Economics* 50(3): 615–644. https://doi.org/10.1111/1756-2171.12290.

Corassa, G.M., T.J. Amado, M.L. Strieder, R. Schwalbert, J.L. 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. https://doi.org/10.2134/agronj2018.04.0239.

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. https://doi.org/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. https://doi.org/10.2134/agronj2010.0047.

Duvick, D.N. 2005. "The contribution of breeding to yield advances in maize (Zea mays L.)." *Advances in Agronomy* 86: 83–145. https://doi.org/10.1016/S0065-2113(05)86002-X.

Egli, D.B. 1988. "Plant density and soybean yield." *Crop Science* 28(6): 977–981. https://doi.org/10.2135/cropsci1988.0011183X002800060023x.

Eng, M.L., B.J. Stutchbury, and C.A. Morrissey. 2019. "A neonicotinoid insecticide reduces fueling and delays migration in songbirds." *Science* 365(6458): 1177–1180. https://doi.org/10.1126/science.aaw9419.

Environmental Protection Agency (EPA). 2023. "Schedule for review of neonicotinoid pesticides." Available online at https://www.epa.gov/pollinator-protection/schedule-review-neonicotinoid-pesticides [Assessed February 24, 2024].

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. https://doi.org/10.1094/CM-2008-0925-01-RS.
Fernandez-Cornejo, J. 2004. *The seed industry in US agriculture: An exploration of data and information on crop seed markets, regulation, industry structure, and research and development* (No. 786). US Department of Agriculture, 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. https://www.jstor.org/stable/30139472.
Ferreira, A.S., A.A. Balbinot Junior, 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: 362–370. https://doi.org/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. https://doi.org/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: 3589768. https://doi.org/10.1155/2019/3589768.
Gardner, B.L. 1976. "Futures prices in supply analysis." *American Journal of Agricultural Economics* 58(1): 81–84. https://doi.org/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. https://doi.org/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. https://doi.org/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. https://doi.org/10.2135/cropsci2016.06.0547.
Heim Jr, 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. https://doi.org/10.1175/1520-0477-83.8.1149.
Hurley, T., and P. Mitchell. 2017. "Value of neonicotinoid seed treatments to US soybean farmers." *Pest Management Science* 73(1): 102–112. https://doi.org/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): 15–33. https://www.jstor.org/stable/40987170.
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 Climate and Applied Meteorology* 77–86. https://www.jstor.org/stable/26182460.
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): 383–401. https://www.jstor.org/stable/40987370.
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. https://doi.org/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. https://doi.org/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. https://doi.org/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. https://doi.org/10.2134/agronj2018.07.0426.
Luca, M.J.D., ad M. Hungría. 2014. "Plant densities and modulation of symbiotic nitrogen fixation in soybean." *Scientia Agricola* 71: 181–187. https://doi.org/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. https://doi.org/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. https://doi.org/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. https://doi.org/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?" Available online at https://ambrook.com/research/legislation/states-ban-neonic-pesticides-neonicotinoids-new-york-california [Assessed on December 24, 2023].
Perry, E.D., and G. Moschini. 2020. "Neonicotinoids in US maize: insecticide substitution effects and environmental risk." *Journal of Environmental Economics and Management* 102: 102320. https://doi.org/10.1016/j.jeem.2020.102320.
Perry, E.D., D.A. Hennessy, and G. Moschini. 2022. "Uncertainty and learning in a technologically dynamic industry: Seed density in US maize." *American Journal of Agricultural Economics* 104(4): 1388–1410. https://doi.org/10.1111/ajae.12276.
Plastina, A. 2023. "Estimated costs of crop production in Iowa – 2023." Available online at https://www.extension.iastate.edu/agdm/crops/html/a1-20.html. [Assessed on February 24, 2024].
Rees, J., L. Thompson, S. Stepanovic, J. Luck, and N. Mueller. 2019. "Soybean seeding rates." Nebraska Institute of Agriculture & Natural Resources. Available online at https://cropwatch.unl.edu/2019/soybean-seeding-rates [Assessed on February 24, 2024].
Rundlöf, M., G.K. 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. https://doi.org/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. https://doi.org/10.3390/agronomy11030605.

Schwalbert, R., T.J. Amado, T.A. Horbe, L.O. Stefanello, Y. Assefa, P.V. 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. https://doi.org/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. https://doi.org/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. https://doi.org/10.1038/ng.746.

Tokatlidis, I.S. 2013. "Adapting maize crop to climate change." *Agronomy for Sustainable Development* 33: 63–79. https://doi.org/10.1007/s13593-012-0108-7.

Tokatlidis, I.S., and S.D. 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. https://doi.org/10.1016/j.fcr.2003.11.013.

Tollenaar, M., and E.A. Lee. 2002. "Yield potential, yield stability and stress tolerance in maize." *Field Crops Research* 75(2-3): 161–169. https://doi.org/10.1016/S0378-4290(02)00024-2.

Torshizi, M., and J. Clapp. 2021. "Price effects of common ownership in the seed sector." *The Antitrust Bulletin* 66(1): 39–67. https://doi.org/10.1177/0003603X209857.

Van Deynze, B., S.M. Swinton, D.A. Hennessy, and L. Ries. 2022. "Adoption of modern pest control systems associated with declines in butterfly abundance across Midwestern monitoring network." *bioRxiv* 2022-07. https://doi.org/10.1101/2022.07.29.502042.

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. https://doi.org/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. https://doi.org/10.22004/ag.econ.302462.

Xu, Z., D.A. Hennessy, K. Sardana, and G. Moschini. 2013. "The realized yield effect of genetically engineered crops: US maize and soybean." *Crop Science* 53(3): 735–745. https://doi.org/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: 289–301. https://doi.org/10.1002/agj2.21509.

Figures and Tables

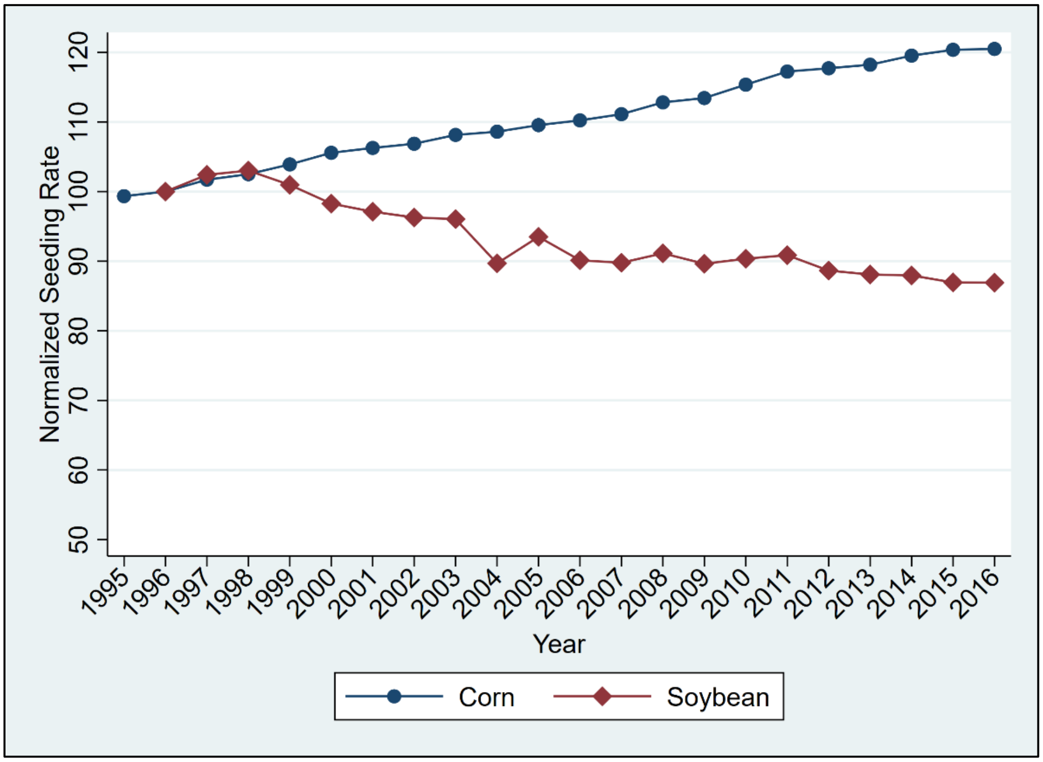
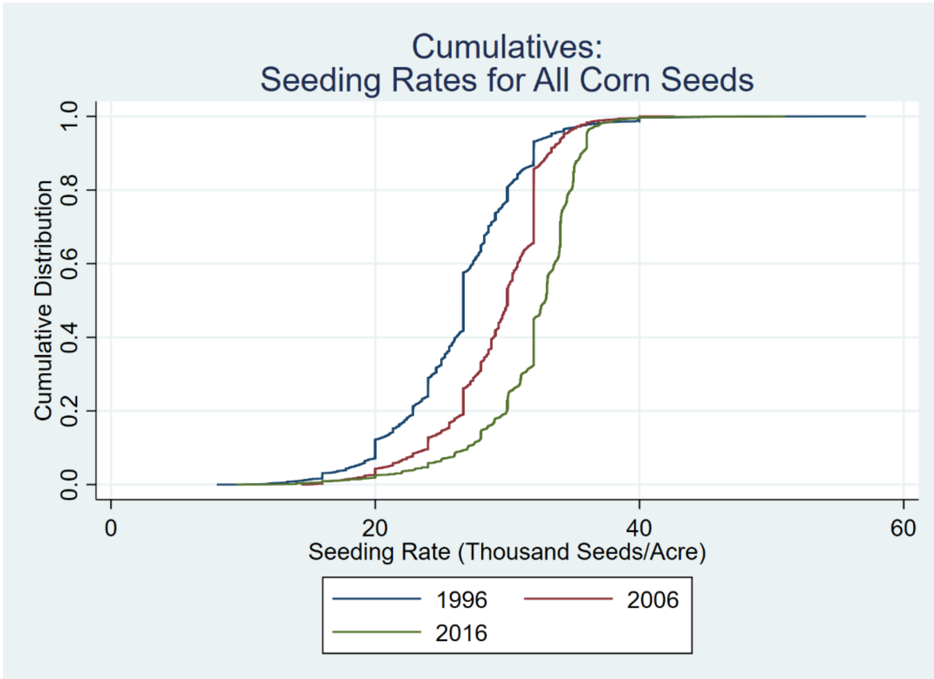
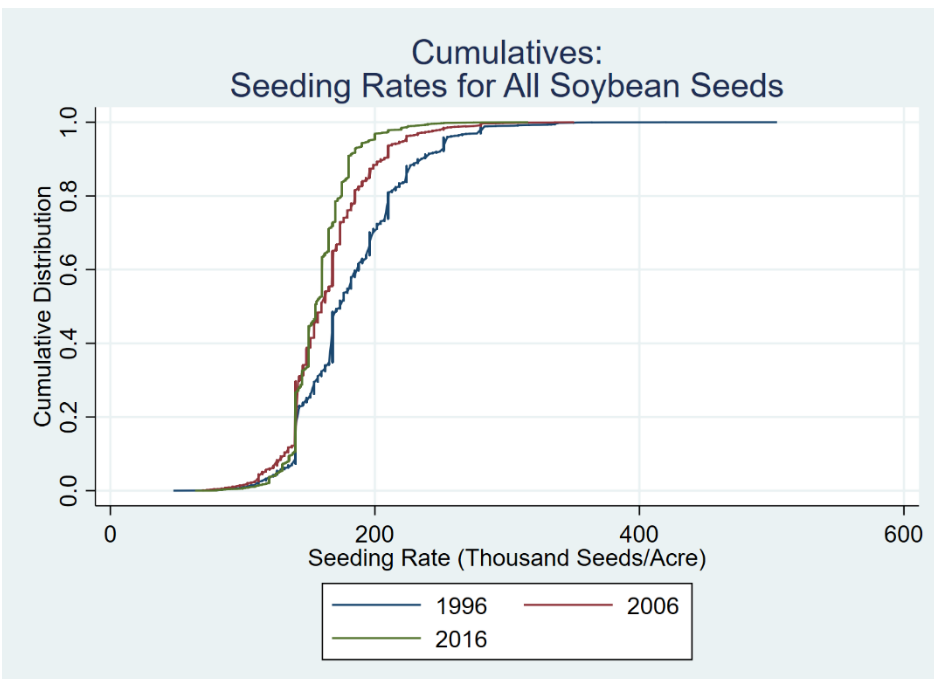


Figure 1. Normalized seeding rates for corn (1995-2016) and soybean (1996-2016) in the United States (Kynetec data)

Notes: In the TraitTrak® dataset, prior to 2010, soybean units are reported in 50 lb bag units, while all soybean units are converted to 140,000 seed bag units since 2010. We convert soybean planting rates prior to 2010 by multiplying 2,800 seed/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 value of 100 represents 26,467 seeds per acre for corn and 181,252 seeds per acre for soybean, respectively.

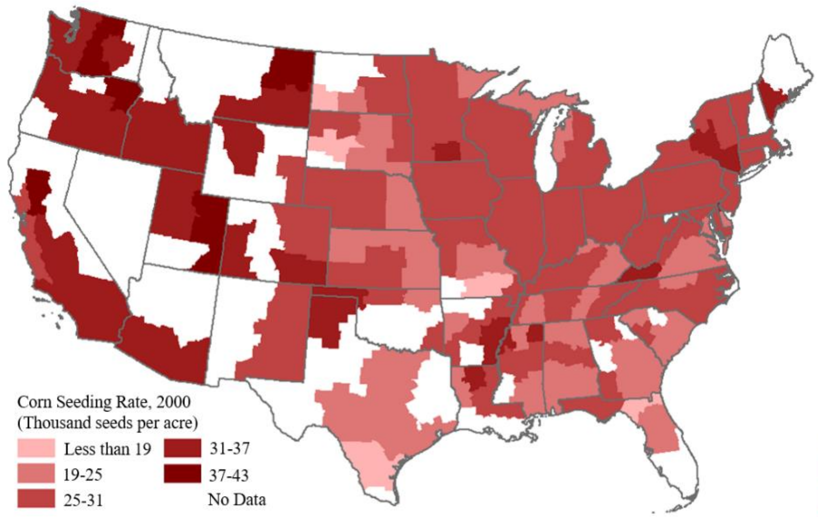


(a) Corn

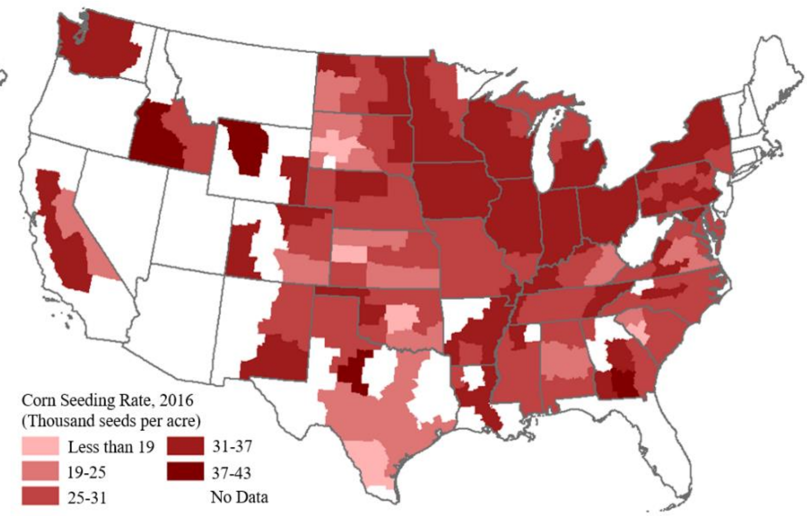


(b) Soybean

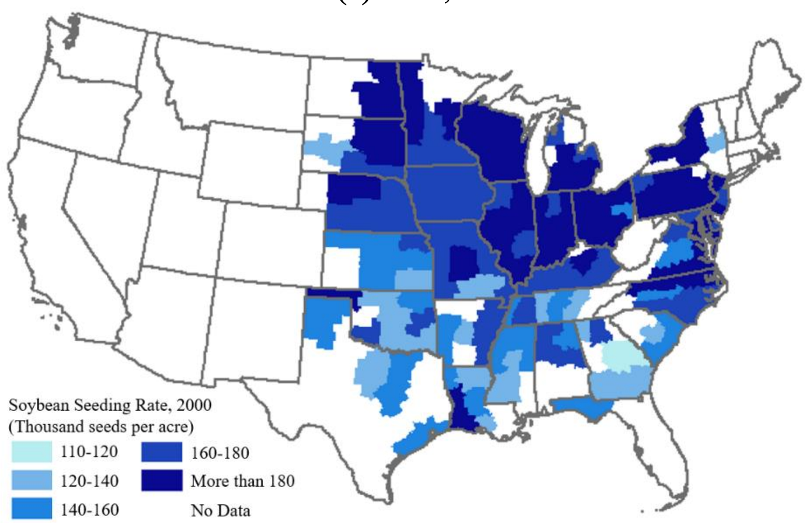
Figure 2. Cumulative distribution for corn and soybean seeding rates in representative years



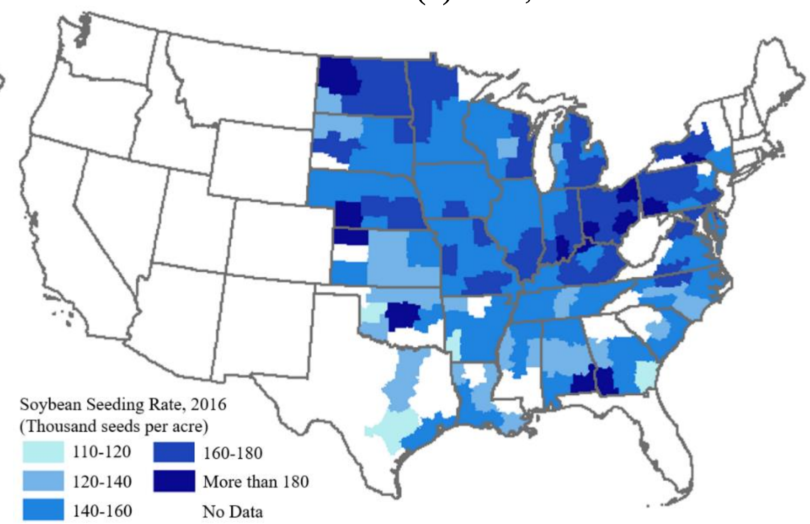
(a) Corn, 2000



(b) Corn, 2016

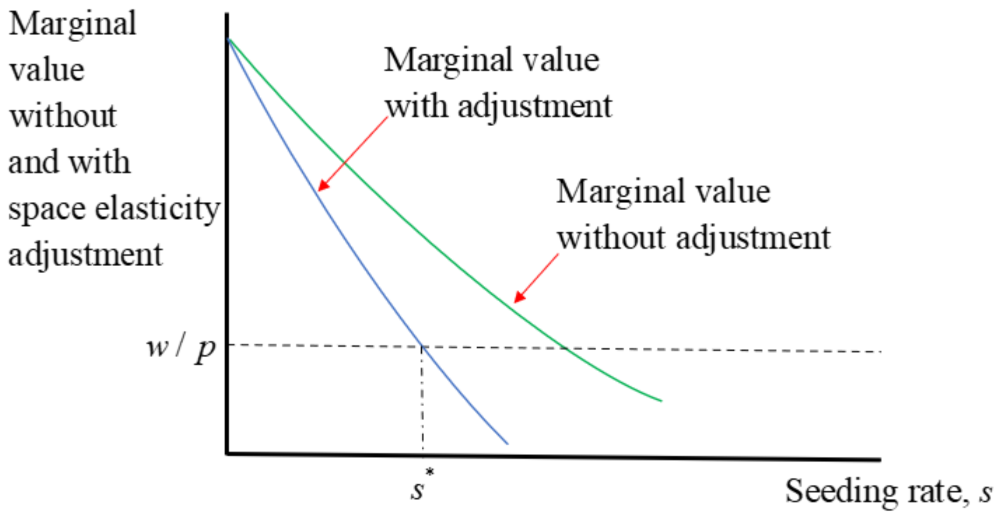


(c) Soybean, 2000

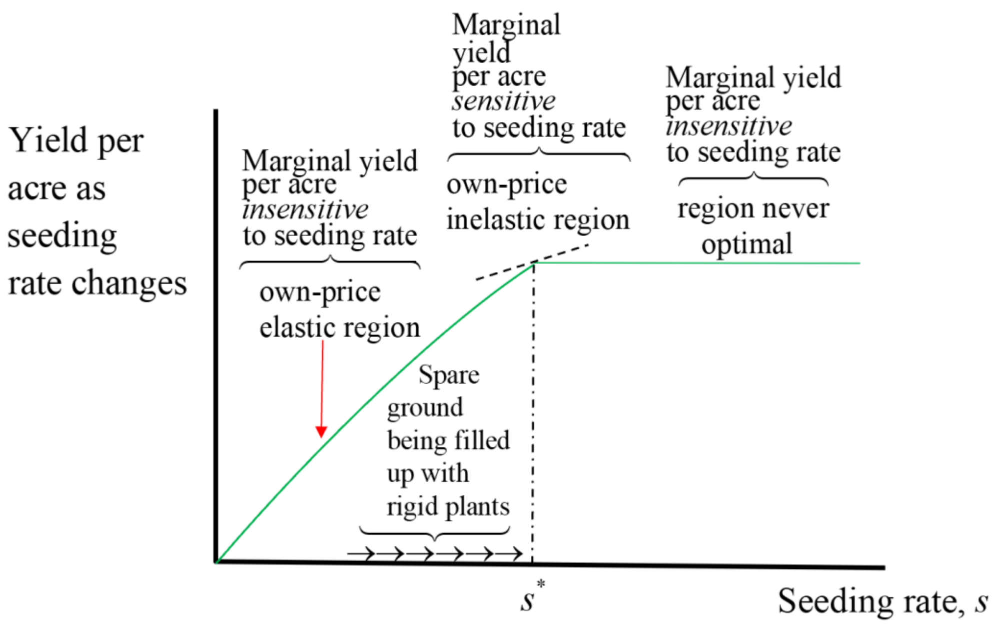


(d) Soybean, 2016

Figure 3. Seeding rates (thousand seeds/Acre) for corn and soybean by crop reporting district (CRD) in 2000 and 2016 (Kynetec data)



(a) Optimal seeding choice and plant architecture



(b) Yield as a function of seed under rigid plant architecture

Figure 4. Seeding rate and plant architecture

Table 1. Variable definitions

Category	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 Z in March	NOAA
	DRY	Negative value of the minimum among 0 and the Palmer 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	TraitTrak®
	BT	An indicator function for corn seed where BT=1 whenever seed trait is either rootworm resistant or cornborer resistant or both	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

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

Table 2. Variable descriptive statistics

Crop	Variable	Obs	Mean	Std. Dev.	Min	Max
Corn	*s*	403,262	29.532	4.509	8.000	57.143
	PR	403,262	40.405	14.909	0.000	114.490
	LCC	402,807	0.490	0.229	0.000	0.935
	WET	403,262	0.539	0.998	0.000	9.240
	DRY	403,262	0.842	0.960	0.000	5.890
	TI	360,529	0.406	0.187	0.000	1.000
	GT	403,262	0.499	0.500	0	1
	BT	403,262	0.503	0.500	0	1
	IR	401,949	0.121	0.212	0.001	1.430
	PD	383,073	0.097	1.263	-3.053	6.674
	t	403,262	-0.577	6.237	-12	9
	LAT	403,262	41.422	2.699	26.083	48.831
	LON	403,262	91.235	6.365	68.722	124.148
Soybean	*s*	187,776	168.761	34.446	14.000	504.000
	PR	187,776	3.818	1.381	-0.938	9.566
	LCC	187,721	0.506	0.221	0.000	0.935
	WET	187,776	0.521	1.030	0.000	9.240
	DRY	187,776	0.857	0.950	0.000	5.290
	TI	172,829	0.360	0.178	0.000	1.000
	GT	187,776	0.744	0.436	0	1
	IR	187,059	0.070	0.145	0.000	0.822
	PD	181,043	-2.635	1.091	-5.164	1.065
	t	187,776	-0.712	6.110	-11	9
	LAT	187,776	40.879	3.185	28.288	48.828
	LON	187,776	90.864	5.274	73.656	106.352

Table 3. Regression of yield per plant on area per plant with fixed effects

	Corn, Ohio	Corn, Colorado	Soybean, Ohio	Soybean, Michigan
Variable	Log (Yield per Plant)			
Log (Area per Plant)	0.896***	0.335**	0.970***	0.943***
	(0.0198)	(0.131)	(0.0153)	(0.0108)
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***
	(0.210)	(1.203)	(0.187)	(0.127)
Observations	113	193	191	513
R-squared	0.981	0.921	0.985	0.964
	H_0: coefficients of log (Area per Plant) equal to 1			
F statistics	27.89	25.69	3.86	27.61
Prob>F	0.000	0.000	0.051	0.000

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

Table 4. Regression results with fixed effects for corn and soybean (Kynetec data)

	Corn		Soybean	
	(1)	(2)	(3)	(4)
Variable	*s* (thousand seeds per acre)			
PR	-0.000962**	-0.00203***	-1.106***	-0.758***
	(0.000387)	(0.000470)	(0.0590)	(0.0714)
LCC	1.643***	1.383***	-2.414	0.214
	(0.216)	(0.224)	(3.527)	(3.751)
WET	-0.0148***	-0.0118**	-0.506***	-0.456***
	(0.00535)	(0.00569)	(0.0719)	(0.0779)
DRY	0.0386***	0.0218***	0.0123	0.0659
	(0.00556)	(0.00606)	(0.0826)	(0.0897)
TI	0.589***	0.538***	6.564***	3.373***
	(0.0545)	(0.0579)	(0.807)	(0.866)
GT	0.208***	0.312	-3.742***	-4.941***
	(0.0146)	(0.293)	(0.190)	(1.431)
BT	0.156***	0.329		
	(0.0101)	(0.218)		
PD	0.0162***	0.000469	0.356***	0.557***
	(0.00388)	(0.00428)	(0.0694)	(0.0756)
IR	-0.832***	-0.999***	-5.843	-1.431
	(0.266)	(0.284)	(3.999)	(4.483)
t	0.647***	0.313***	-6.605***	-7.145***
	(0.0261)	(0.0338)	(0.351)	(0.519)
LAT	0.0274	0.0744**	0.776	0.319
	(0.0332)	(0.0346)	(0.525)	(0.571)
LON	-0.0858***	-0.102***	-1.407***	-1.015***
	(0.0157)	(0.0171)	(0.289)	(0.312)
*t**LAT	0.00478***	0.0142***	-0.138***	-0.100***
	(0.000529)	(0.000712)	(0.00700)	(0.0109)
*t**LON	-0.00665***	-0.00751***	0.121***	0.110***
	(0.000244)	(0.000279)	(0.00397)	(0.00471)
Farmer FE	Yes	Yes	Yes	Yes
Variety FE	No	Yes	No	Yes
Constant	35.34***	35.02***	272.0***	254.4***
	(1.573)	(1.703)	(29.02)	(31.94)
Observations	342,794	333,237	163,316	157,225
R-squared	0.775	0.796	0.636	0.678

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

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%	3.6%
Non-grassland bird	0.5%	3.0%
Insectivorous bird	0.6%	3.4%
Insectivorous bird	0.5%	3.0%
Percentage change in butterfly population		
Monarch	0.6%	4.0%
Silver-spotted skipper	0.7%	4.2%

Supplemental Materials for

“Seeding Rate Responses to Markets, Resources, and Technologies”

A. 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.

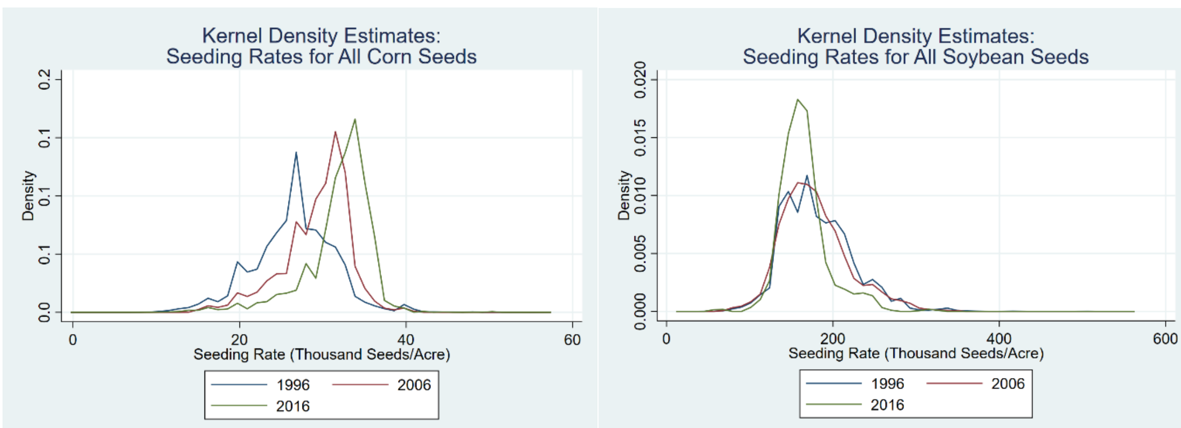


Figure A1. Kernel density estimates for corn and soybean seeding rates

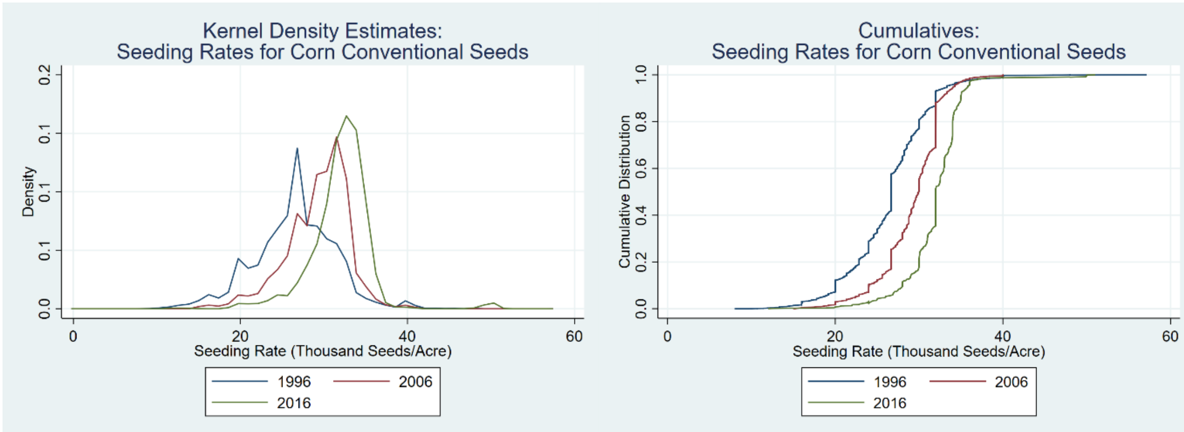


Figure A2. Kernel density estimates and cumulative distributions for the seeding rates of corn conventional seeds

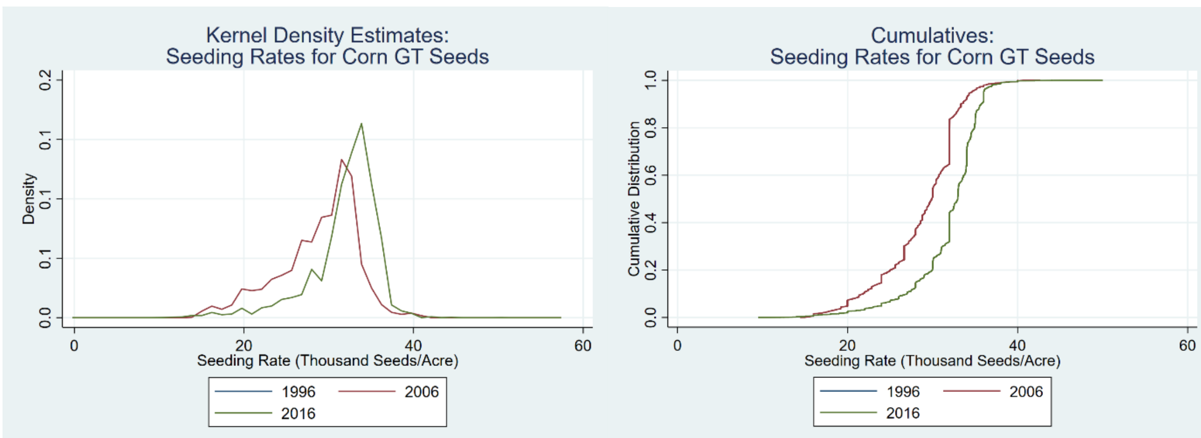


Figure A3. Kernel density estimates and cumulative distributions for the seeding rates of corn seeds with the glyphosate tolerant (GT) trait

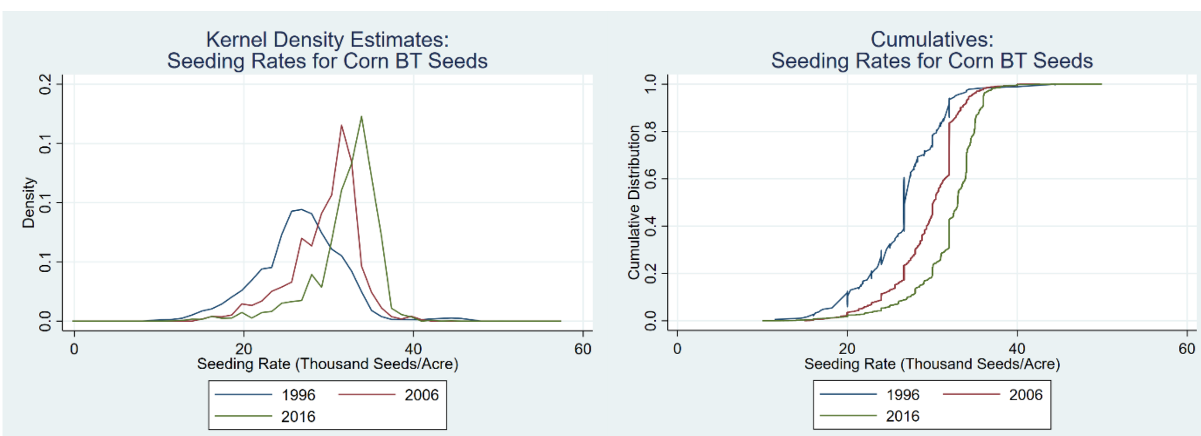


Figure A4. Kernel density estimates and cumulative distributions for the seeding rates of corn seeds with the *Bacillus thuringiensis* (*Bt*) trait

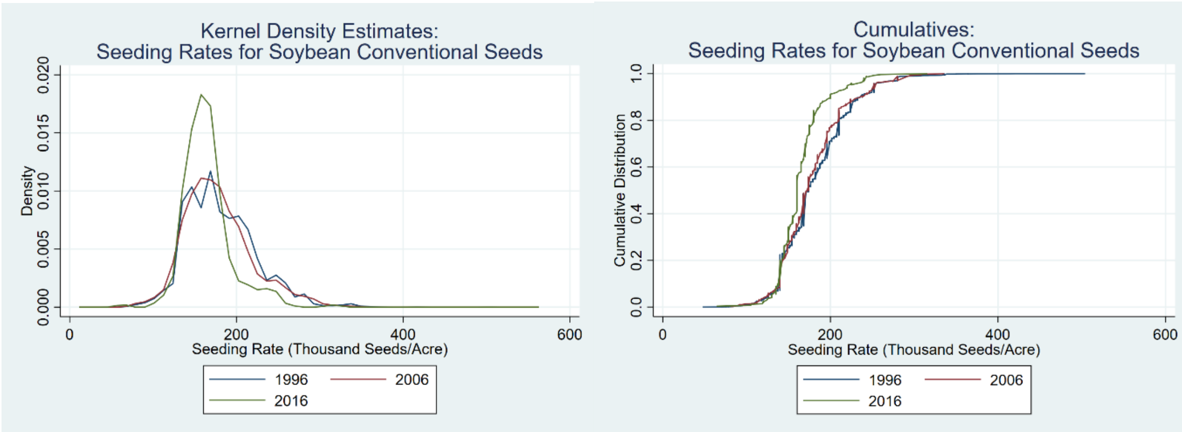


Figure A5. Kernel density estimates and cumulative distributions for the seeding rates of soybean conventional seeds

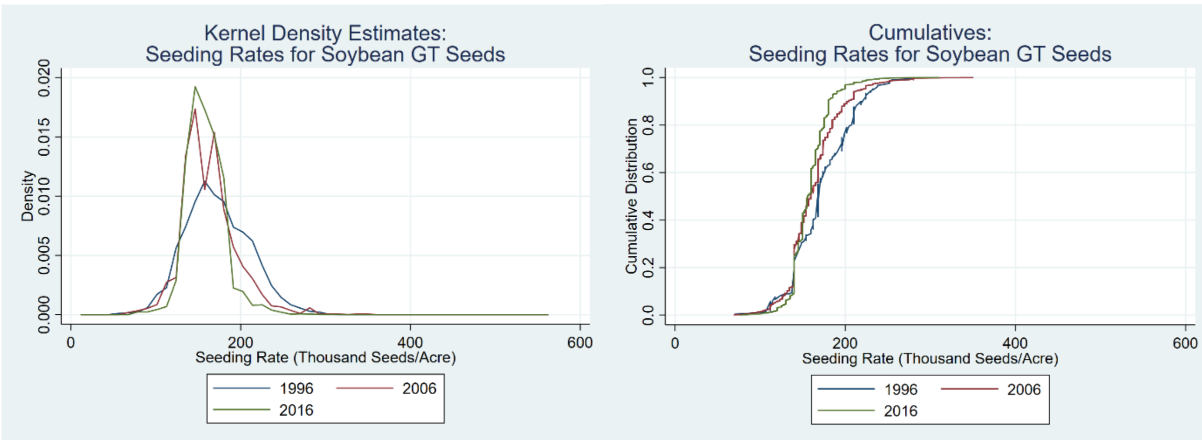


Figure A6. Kernel density estimates and cumulative distributions for the seeding rates of soybean GT seeds

B. Supplemental Information for Seeding Rate Data

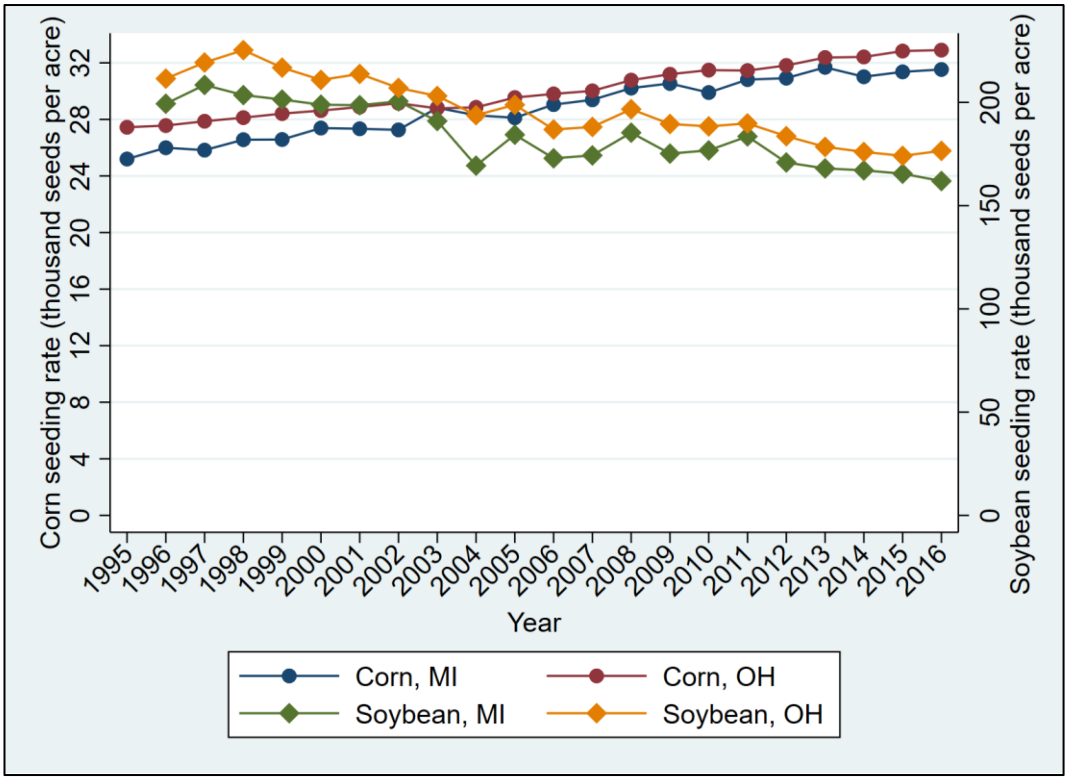


Figure B1. Average seeding rates for corn (1995-2016) and soybean (1996-2016) in Michigan and Ohio (Kynetec data)

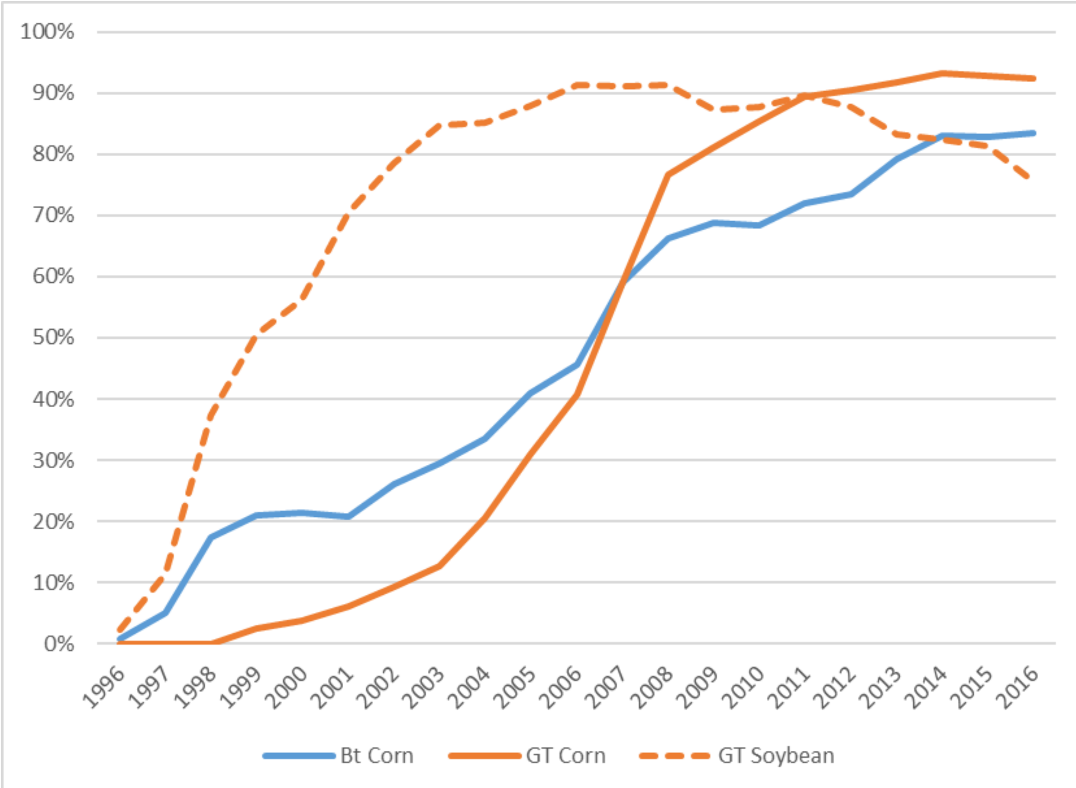


Figure B2. Area percentages of genetically engineered corn and soybean in the United States, 1996-2016

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 B1. The mean of yield and area per plant by crop and region (seed trials data)

Variable	Corn OH	Corn CO	Soybean OH	Soybean MI
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]
Obs	113	193	191	516

Table B2. Summary statistics for the twenty most commonly planted varieties

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%
3,335	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%	

Note: Hutcheson is a Group 5 variety developed by Virginia Tech and released in 1987. It is resistant to soybean mosaic virus, peanut stunt virus, and stem canker.

Table B3. Data screening

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 with zero seeding rate	For corn we remove 66 observations with zero seeding rate. There are no soybean observations with zero seeding rate.
Remove observations with 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 of 360,999 for corn and 173,056 for soybean.

C. 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):

(C1) $$d_{c,t} = \lambda_0 + \lambda_1(2017 - t) + \phi_{ct},$$

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

(C2) $$d_{c,t}^D = \frac{d_{c,t}}{\hat{d}_{c,t}} \times \hat{d}_{c,2017},$$

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 of detrended median planting date $d_{c,t}^D$ from its mean value across the study period to use as an explanatory variable in our seeding rate estimation.

D. Supplemental Information for Seed Price Elasticities

Table D1. How seeding rate changes with a 10% increase in seed price or a 10% decrease in crop price

Year	Corn	Soybean
1998	-2.15%	-9.74%
1999	-2.53%	-13.76%
2000	-2.41%	-14.09%
2001	-2.50%	-17.14%
2002	-2.69%	-18.99%
2003	-2.66%	-16.87%
2004	-2.40%	-16.01%
2005	-2.98%	-21.20%
2006	-2.92%	-20.41%
2007	-1.98%	-15.86%
2008	-1.93%	-10.47%
2009	-3.19%	-20.72%
2010	-3.41%	-21.12%
2011	-2.28%	-14.51%
2012	-2.65%	-17.42%
2013	-2.87%	-18.31%
2014	-3.62%	-21.46%
2015	-3.97%	-25.90%
2016	-4.20%	-28.00%

E. 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) controlled 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

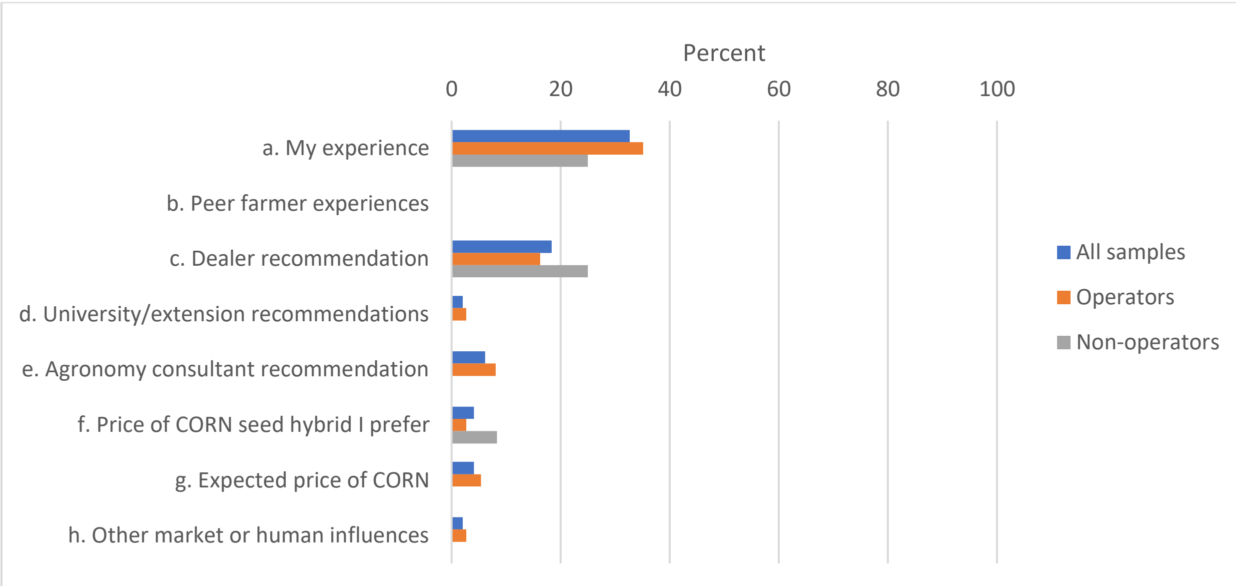
[1] In Table E1 we compare the mean values for each surveyed grower response with average values for growers in the corresponding CRD.

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.

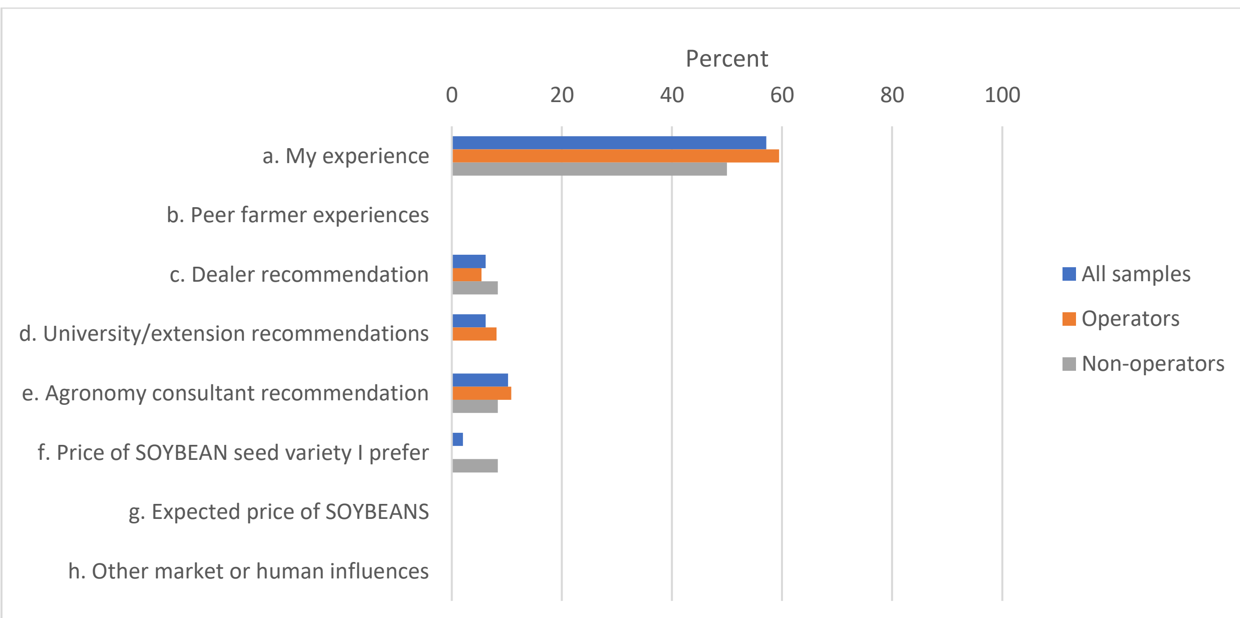
Focus Group Participants' Opinions about Seeding Rate Choices

Table E2 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 our hypothesis H2*i*) 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 insect protection above and below ground 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 E1 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 factors 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.



(a) Corn



(b) Soybean

Figure E1. The most important factor that affects seeding rate choices from the focus group participants' viewpoint.

Note: Fifteen participants did not answer the questions for corn, and ten participants did not answer the question for soybean.

Table E1. 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 E2. How seeding rates choices are affected by different environmental changes or agricultural practices

	Environmental changes or agricultural practices	Corn		Soybean	
		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 = farmers would like to raise seeding rate; E = 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 E3. 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 E4. 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 inputs	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.

SM References

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. https://doi.org/10.1111/j.1467-8276.2007.00975.x.

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. *The Journal of Extension* 60(1): 3. https://doi.org/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*." EIB-63, U.S. Department of Agriculture, Economic Research Service. Available online at https://www.ers.usda.gov/publications/pub-details/?pubid=44463 [Assessed February 24, 2024].

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). Available online at http://stata-press.com/journals/stbcontents/stb16.pdf [Assessed February 24, 2024].

United States Department of Agriculture, National Agricultural Statistics Service (USDA-NASS). 2019. *2017 Census of Agriculture publication highlights: Farms and farmland.* Available online at https://www.nass.usda.gov/Publications/Highlights/2019/2017Census_Farms_Farmland.pdf. [Assessed February 24, 2024].