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RESEARCH ARTICLE

Modeling Soybean Planting Decisions with Network Diffusion: Does Herbicide Drift Affect Farmer Profitability and Seed Selection?

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Abstract

U.S. soybean farmers are currently grappling with dicamba herbicide drift. Using a network diffusion framework that accommodates key features of soybean farmer networks, we estimate the damages incurred from dicamba drift across different regions. Under our baseline assumptions, we estimate an average yield loss of 3% and predict sizable levels of forced switching to dicamba-resistant seed in response to drift. The relative importance of drift on damage and seed choice holds across a range of economic and network assumptions. In the absence of policy, this damage may cause regional adoption rates of dicamba-resistant soybean seed to increase.

Keywords: herbicide drift; network diffusion; soybeans; tipping points

JEL classifications: C73; C93; C63; O33

1. Introduction

Herbicide resistance is an inherited or engineered trait that allows plants to survive herbicide applications. For crops, this trait is typically developed within a lab with the aim of being paired with a specific herbicide such as glyphosate or dicamba. Herbicide-resistant crops allow farmers to spray herbicides over the crop without injuring or killing plants. These crops provide an efficient and economical weed management tool for farmers (Dintelmann et al., 2020; Fernandez-Cornejo, Klotz-Ingram, and Jans, 2002; Fernandez-Cornejo, Hendricks, and Mishra, 2005; Solomon and Bradley, 2014). However, this procedure contributes to weeds developing herbicide resistance over time. Agricultural input suppliers are in turn incentivized to develop additional herbicide-resistant traits to pair with herbicides to which weeds are not yet resistant. This cycle creates problems when herbicide sprayed in a resistant crop field drifts into a neighboring non-resistant field.

U.S. soybean farmers are currently facing this very issue with the herbicide dicamba. Dicamba is an effective herbicide for killing weeds that have become resistant to glyphosate (Behrens et al., 2007; Dintelmann et al., 2020; Shergill et al., 2018). Bayer recently developed soybean varieties that are resistant to dicamba for this reason. Dicamba, unfortunately does not always stay in one place once it is sprayed (Bish, Oseland, and Bradley, 2021; Oseland et al., 2020). This off-target movement (OTM) drifts into neighboring soybean fields that do not have the dicamba-resistant (DR) trait and injures the non-resistant (NR) soybeans, which can significantly reduce yield (Kniss, 2018; Meyeres et al., 2021; Solomon and Bradley, 2014).[1] OTM resulted in 2,708 dicamba-related injury investigations by state departments of agriculture in 2017 (Oseland et al., 2020). Reported dicamba injuries in 2017 were estimated to cover about 3.7 million acres of soybeans in the U.S. (Bradley, 2017). Over time, OTM could force soybean farmers in some regions to adopt DR soybean varieties to avoid the externality, which in turn would intensify the externality as more farmers spray dicamba.

Deciding whether, or in what cases, dicamba OTM is severe enough to warrant policy intervention, requires accurate estimation of the size of OTM damage at a regional level. This requires a framework capable of handling the spatial and temporal complexities inherent within OTM. This research aims to make two primary contributions. We seek to develop a framework capable of estimating the regional soybean yield loss resulting from dicamba OTM. We also seek to use this framework to estimate how a given regions adoption of DR seed could be affected through farmer exposure to the OTM externality. We accomplish this task through the modification and parameterization of a network diffusion model.

1.1. Network Diffusion

We draw insight into the dicamba OTM problem from the game theory literature on network diffusion. When a sufficient number of agents within a region adopt a particular technology with negative externalities, neighbors who incur loss from that technology in the current period may switch to that same technology in the next period. Their neighbors, in turn, suffer the negative externality in the next season and switch as well. This starts a cascade that continues until the new technology is widely adopted in the market or region. In addition to OTM reducing yields in NR soybean fields, it could also exacerbate market concentration for soybean seed. As of 2020, it was estimated that about 86% of all US soybean acres were planted with two herbicide-resistant traits: dicamba resistance and 2,4-D resistance, functionally a duopoly (Polansek and Nickel, 2020). If dicamba OTM forced enough farmers to adopt DR varieties, the market could shift from this duopoly to a monopoly. This would further exacerbate input supplier market power.

Any potential policy aimed at efficiently addressing this problem would need to be able to first quantify OTM externalities and what conditions lead to a shift to a functional DR soybean monopoly. We adopt and parameterize a network diffusion model to accommodate herbicide drift and soybean seed selection. We parameterize this model with soybean price, yield, and novel agronomic field trial OTM data. This allows us to estimate the spatial relationship between dicamba application and OTM damage to yields in neighboring fields. We use that to characterize the nature of the soybean seed networks and compute the resulting Nash equilibrium market structure likely to result as this externality diffuses across a regional network.

Network diffusion models are a popular tool for applications involving epidemiology and technology adoption (Abdulai and Huffman, 2005; Coomes et al., 2015; Genius et al., 2014; Maertens and Barrett, 2013; Wang et al., 2009; Zhang et al., 2010). The use of network diffusion models for spatially based agricultural network problems, however, is quite recent. McCarty and Young (2020) describe cross-pollination between hemp growers. They find theoretical evidence consistent with grower accounts of switching from the pollen-sensitive hemp to the pollen-shedding crop as a result of having the prior year's crop ruined. Kolady et al. (2021) study the impact of spatially close peers make on individual conservation tillage adoption decisions. They find a positive but small impact of spatial peer effects on conservation tillage adoption.

[1]Two types of drift are associated with dicamba OTM. Primary drift occurs during application when wind moves the herbicide droplets. Primary drift typically results in the largest injury occurring to plants nearest the herbicide application. Secondary drift occurs after application. It is influenced by many factors, mostly beyond the applicator's control. There is often no obvious pattern associated with secondary drift (Bish, Oseland, and Bradley, 2021).

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Soybean farmers also are connected via spatial networks. How the structure of these networks impact OTM damage and seed selection decisions has meaning for policy, marketing, and management. This requires a framework capable of estimating regional network structure and its effect on OTM damage. Our framework is adapted from a general Spatially based Agricultural Negative Externality Problem diffusion model developed by Young and McCarty (2022), parameterized for the problem of dicamba OTM. We also draw insight from a general network diffusion model developed by Jackson and Yariv (2006). The structure of the network externality OTM model we parameterize can be used in a variety of other herbicide drift cases in future work, allowing for benefit-cost analysis of various herbicide drift mitigation policies, or of management decisions for marketing new releases of herbicide-resistant seed genetics.

2. Model

2.1. Farmer's Individual Strategy

In our network diffusion model, a finite set of soybean farmers choose between a DR seed and a seed that is NR. Since spraying dicamba creates a negative externality for nearby fields that adopt NR seed, each farmer's seed choice has the potential to affect their neighbor's profitability. If two farmers' soybean fields are adjacent, then they are considered neighbors. The amount of neighbors farmer i has is known as their degree and is denoted d_i. The percentage of farmers within the network with a given degree is denoted $P(d)$, where $P(d) \geq 0$, for $d \in \{0, 1, 2, 3, 4\}$, and $\sum_{d=0}^{4} P(d) = 1$.

We assume that because the DR trait is a relatively recent development, the NR seed is the default seed choice. Farmer i's payout from using NR seed is their expected externality-free profit from NR, $\pi_{i,\mathrm{NR}}$, minus their expected externality damage from OTM, $E_{i,\mathrm{NR}}$, denoted

$$V_{i,\mathrm{NR}} = \pi_{i,\mathrm{NR}} - E_{i,\mathrm{NR}} \tag{1}$$

The externality damage farmer i receives from NR seed, $E_{i,\mathrm{NR}}$, is a function of d_i, and the percentage of these neighbors growing DR soybeans, λ_i, and their externality-free profit, $\pi_{i,\mathrm{NR}}$. The model parameter g estimates the percentage loss in yield based upon number of neighbors using DR seed, $g(d_i, \lambda_i)$, while the parameter f estimates the percentage loss in NR profit as a function of yield loss, $f(g(d_i, \lambda_i))$. The percentage loss in profit is multiplied by expected externality-free profit to calculate total OTM damage,[2] giving us the final form,

$$E_{i,\mathrm{NR}} = f\big(g(d_i, \lambda_i)\big)\pi_{i,\mathrm{NR}} \tag{2}$$

Farmer i could instead receive a payoff for using DR seed, $V_{i,\mathrm{DR}}$. This payoff is free from externalities since DR seed is by definition resistant to dicamba and thus is unaffected by neighbors' actions and is simply the expected profit to growing DR seed, $\pi_{i,\mathrm{DR}}$.

$$V_{i,\mathrm{DR}} = \pi_{i,\mathrm{DR}} \tag{3}$$

Finally, a farmer compares the two options and chooses the one that provides the highest expected profit.[3] They will switch from NR seed to DR seed once the payoff of adopting DR, $V_{i,\mathrm{DR}}$ surpasses the opportunity cost of NR, $V_{i,\mathrm{NR}}$. Hence, farmer i will adopt DR whenever $\frac{V_{i,\mathrm{DR}}}{V_{i,\mathrm{NR}}} \geq 1$.

[2] We discuss the empirical details of mapping d_i and λ_i onto g, and g onto f in Sections 3.2 and 3.3.

[3] While our framework could account for risk aversion, it is beyond the scope of this study. The goal of this research is to adapt a network diffusion model to the problem of herbicide drift and quantify OTM damage in a variety of network structures. Focusing on risk aversion would add considerable complexity while adding little to our main contribution.

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2.2. Modeling Spatial Network Effects

As mentioned, payouts for each farmer's decision within the network are influenced by the actions of others within their network. The social externality experienced by an NR seed grower, $E_{i,\mathrm{NR}}$, is 0 if no one in the network grows DR, but it can become quite high if enough farmers within the network adopt DR seed. Due to this spatial externality tying together all farmers within the network, we must model how DR adoption rates within a network, x_t, evolve over time, t.

$$x_t = \sum_{d=0}^{4} \frac{x_{t,d} dP(d)}{\bar{d}} \tag{4}$$

Parameter $x_{t,\,d}$ captures the percentage of farmers with degree d, that have chosen DR seed, at time t. Parameter $\bar{d}$ denotes the average degree of a farmer within the network. Diffusion of DR seed technology is modeled by exogenously establishing a given percent of DR seed adoptors at $t = 0$, x_0. Each farmer responds to this x_0 and its expected effect on their payouts from each seed choice by altering or keeping their original planting choice in the following period, $t = 1$, this new level of DR adoption is defined as x_1. This new level of adoption in time 1 will then subsequently affect planting decisions in time 2, and so on. These changes will continue until the market hits a new steady state, x_{SS}, where neither NR or DR growers want to change technology in the subsequent period.

Farmer adoption decisions in the previous period x_{t-1} will affect adoption this period. Equation (5) computes the percent of DR adopters of a given degree[4] in time t.

$$x_{td} = 1 - C[1 - f(g(d, x_{t-1})] \tag{5}$$

Each farmer will have unique ratio of externality-free payouts between DR and NR adoption, denoted $K_i = \frac{\pi_{i,\mathrm{DR}}}{\pi_{i,\mathrm{NR}}}$. When considering all farmers within a network, K captures the distribution of all K_i within the network. Parameter C in Equations (5) and (6) captures the CDF of K. Equation (6) shows the calculation of DR adaptors at time t for the entire network and is derived by substituting the right-hand side of Equation (5) into Equation (4) for $x_{t,\,d}$,

$$x_t = 1 - \frac{1}{\bar{d}} \sum_{d=0}^{4} dP(d) C\big[1 - f(g(d, x_{t-1})\big] \tag{6}$$

The result from Equation (6) captures whether DR adoption becomes more prevalent, less prevalent, or remains constant over time. This allows us to characterize what levels of x_0 create a sufficiently large negative externality across the network to drive increased DR adoption. It also estimates what the new Nash Equilibrium level of DR seed adoption resulting from an externality for a given adoption rate. Details on steady-state characterization are found in Appendix A.

3. Data and Model Parameterization

3.1. Relative Profitability DR Seed Adoption (Parameter K)

While a farmer can choose between soybean varieties, the reality of this highly concentrated market is that they will likely be choosing between two companies. As previously noted, about 86% of all 2020 soybean acres in the U.S. were planted with seed possessing genetic traits owned either by Bayer or Corteva (Reuters, 2020). However, only Bayer provides the gene for dicamba resistance. Thus, we make the simplification that there is one DR variety and one NR variety. This streamlines the problem with little loss in generality. While companies guard their yield data, talks with soybean farmers revealed that there is little perceived difference if any between the two seed

[4]Note that consistent with Jackson and Yariv (2006) and McCarty and Young (2020), we have substituted x for λ for the calculation of profit loss as a percent, f. This means that each farmer within the network is modeled to be in contact with a constant percentage of DR adaptors. This assumption allows our model to provide tractable results.

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types as long as fields remain unimpacted by OTM. This perception is corroborated by an agronomic study testing performance of various Xtend (that is, from Bayer, or "DR" in our notation) and Enlist (Corteva, "NR") varieties across the state of Arkansas. Researchers found an average yield of 71.3 bu/acre for Xtend varieties and 71.0 bu/acre for non-Xtend (primarily Enlist) varieties (Carlin, Morgan, and Bond, 2022).[5]

Selling prices and production costs should also be comparable across these two different seed types. Midland, a soybean seed dealer, listed its suggested retail price for both Xtend and Enlist soybean seed to be \$56.60 per 140,000 seeds for the 2021 season (Midland, 2020). Herbicide applications to Xtend soybean are typically a little more expensive than those to Enlist soybean, because additional volatility- and drift-reduction agents must be included in dicamba applications (\$36.53/acre vs. \$20.00/acre) (Kansas State Research and Extension, 2022).[6] We use a soybean crop budget to estimate the impact of yield losses on profitability (University of Missouri Extension, 2021).

While the aforementioned snapshots of various soybean seed yields and costs do not provide a definitive profit for each seed likely to be experienced by every farmer in all scenarios, they do suggest that the externality-free profit of DR and NR soybeans should be on average similar. Individual farmer experiences will vary depending upon production practices, seed- and herbicide-specific discounts retailers apply, as do fluctuating herbicide costs. To accommodate the fact that different traits could create slight differences in the yields, seed prices, or other intangible costs individual farmers experience, we model the ratio of these expected benefits experienced by everyone within a network to follow a distribution for the random variable K. To accomplish this, we assume a normal distribution with an expected value of this ratio equal to unity and a 10% standard deviation. We also run comparative statics on the mean of the distribution of K at 0.9 and 1.1. While we expect both seeds to provide similar externality-free payouts on average, it could be possible that DR seed provides higher expected average returns due to superior weed management with dicamba (mean $K = 1.1$). It would also be possible that NR seed provides a higher average externality-free return due to lower herbicide cost or fewer application rules (mean $K = 0.9$). Testing the distributional assumptions of K enriches the results of our baseline analysis ($E[K] = 1$, $\mathrm{SD}[K] = 0.1$) and provides detail on the impact of economic factors in influencing OTM damage and soybean seed adoption.

3.2. Dicamba Damage as a Function of Distance (Parameters f and g)

We used data from two experiment fields in Chariton and Dunklin Counties in Missouri between 2016 and 2017 to estimate yield damage as a function of distance from herbicide source. Soybeans in these fields were NR and were injured by dicamba OTM. The patterns of dicamba injury within the fields are consistent with primary dicamba drift, which occurs at the time of the herbicide application. Studies were designed at the sites specifically to quantify the impact of dicamba OTM on NR soybeans across various distances. Yield loss was estimated at 25-m intervals from the dicamba application area. We then estimated the damage for each field as a function of distance by fitting a curve to the data.

Figure 1 shows predicted soybean losses are high within 500 ft of herbicide application, but drop off quickly. Adjacent fields will be subject to considerable loss, but far enough away from DR plantings we would expect damages from OTM to be minimal. This result suggests that regions with high densities of soybean acreage ("dense networks") are more likely to experience substantial losses from dicamba OTM. It is important to note that these field trials do not account for secondary drift, which occurs sometime after the herbicide application. Secondary drift covers a wider area, and it can be impossible to determine from whence the herbicide moved. This means

[5]Yields were compared across a total of 86 plots. All plots where either 2 or 4 rows wide and 20–21 ft long.

[6]Prices were from citation where then multiplied by quantity requirements using author calculations.

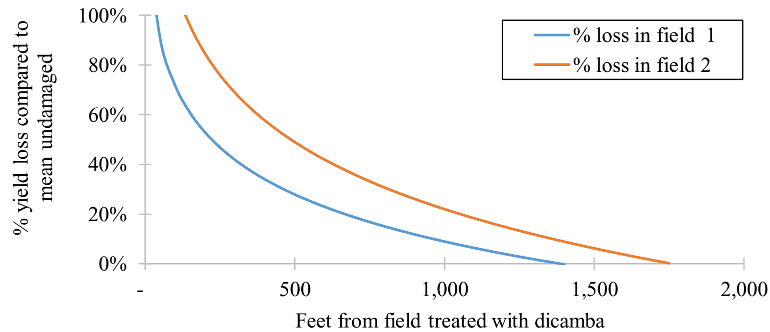

Figure 1. The loss in soybean yield of non-dicamba-resistant varieties as a function of distance. Field 1: ($R^2 = 0.4549$, $n = 419$). Field 2: ($R^2 = 0.1711$, $n = 201$). Data in Appendix B.

our estimated losses are conservative: they do not include secondary drift damage, nor any damage to non-soybean plants (Dintelmann et al., 2020).

From here, we take the estimated relationship of yield loss as a function of distance and calculate the losses we expect a NR farmer with an 80-acre field (approximately 1,867 ft × 1,867 ft) would experience if one of the edges was adjacent to an 80-acre field of DR soybean treated with dicamba. We then summed damage as a function of distance for every square foot from the source to the edge of the field. Next, we multiplied that number by how many feet across a given field was. Finally, we averaged the yield loss for every 1 × 1 foot cell within the 80-acre model. This gives us the estimated yield loss associated with one neighbor using DR seed. We are able to estimate the loss for two or more neighbors by using the same process but adding in additional calculation for joint probabilities, which allows us to avoid double-counting OTM damage.

3.3. Estimating Network Structure for Soybean Farmers

One final factor that required estimation was the network structure of soybean farmers. We took county-level data for three representative counties within Missouri: Pemiscot, Cooper, and St. Genevieve. They represented high density, median density, and low density of soybean production within the state, with 55%, 17%, and 7% of respective total acreage for each county dedicated to soybean production (National Agriculture Census Data, 2021). This planting density influences network structure. We estimated the network structure of a given county using a Monte Carlo simulation which we explain in detail in Appendix C. The network structure influences the size of the externality farmers are exposed to, which in turn influences how many farmers switch to DR soybeans.

The number of neighbors bordering a field and the corresponding OTM damage varied considerably depending upon county-level grower density. Table 1 shows this impact of grower density on network structure and network induced damage on NR soybean growers if OTM follows the first field trial results. Results were similar but even more pronounced when we modeled after the second field trial (Appendix D). A quick comparison across yield losses and percent of a regional network with neighbors close enough for dicamba OTM to cause injury to NR varieties shows how much the magnitude of this problem can vary even within a given state.

Once yield loss as a function of neighbors using DR seed was calculated (the parameter g), we applied these yield losses to the aforementioned crop budget to estimate the losses in profit resulting from a given yield loss (the parameter f). This means that the externality damage that each farmer growing NR seed is exposed to can be calculated for their given number of neighbors and the percentage of the network that has adopted DR seed.

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Table 1. Network structure of soybean farmers under different planting densities (1st field trial)

Neighbor count (d)	NR farmer's % yield loss if all neighbors grew DR (g)	% of network with a given neighbor count (low density)	% of network with a given neighbor count (median density)	% of network with a given neighbor count (high density)
0	0.00%	73.90%	47.00%	4.00%
1	18.50%	23.20%	39.00%	19.80%
2	35.20%	2.70%	12.20%	36.70%
3	48.50%	0.10%	1.70%	30.20%
4	60.10%	0.00%	0.10%	9.30%

Table 2. Steady-state DR adoption rates, forced switching, and network-wide yield loss from OTM for Field 1 simulations and median grower density assumptions under varying profitability ratio distributions

	$E[K] = 0.9$	$E[K] = 1.0$	$E[K] = 1.1$
Steady-state DR seed adoption percentage (x_{SS})	60.4%	76.5%	92.5%
Percent of network forced to adopt DR due to OTM	44.6%	26.5%	8.4%
Average yield loss across entire network 1st season	1.7%	3.1%	1.7%

4. Results

Table 2 contains results from the first field trial's OTM estimates. These results were calculated for varying levels of farmer profitability ratio distribution, K, where the mean ratio of DR seed to NR seed absent OTM was 0.9, 1, and 1.1. The standard deviation associated with this ratio was 0.1 in all cases.[7] Going left to right across the table shows the effect of making DR seed relatively more profitable.

Table 2 highlights the importance of economic criteria for seed selection decisions and the size of the OTM externality within a given network. In our base case, mean $K = 1$, 50% of the network would adopt DR and the other half would adopt NR seed if there was no OTM. However, DR adoption rates greater than 0% generate OTM damage which pushes farmers into DR adoption. This change in seed adoption results in a new steady state where 76.5% of the network adopts DR seed. No farmer has any incentive to switch after this as the remaining farmers still growing NR seed gain more from growing that seed than they lose from the externality (these are the farmers towards the left tail of the K distribution that also have few to no neighbors). This high steady state suggests that under baseline assumptions for economic and network parameters, OTM could further concentrate the soybean seed sector.

Another important baseline result is the percentage of a network forced to adopt DR due to OTM. We calculate this as the difference between the steady state (76.5%) and how many farmers would have adopted DR without the externality (50%). This means that 26.5% of the entire network was sufficiently damaged from OTM that they were forced to adopt a seed that, absent of any externality, would have provided a lower return. Finally, we estimate the average network-wide loss associated with OTM within the first growing season. This is calculated as the weighted loss each farmer would receive if they grew NR soybeans based upon their number of neighbors, starting DR adoption rates, and the percentage of NR adaptors who would choose NR seed without the externality. This result captures loss in efficiency generated by the externality. Under baseline assumptions, we calculate average loss for each farmer within the network to be 3.1%.

[7]When we increase the standard deviation from 10% to 100%, the steady state decreases by a few percentage points, and the share of NR growers forced to switch to DR soybean production reduces slightly. Further discussion is in Appendix E.

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Even a small percentage loss is problematic for soybean growers since margins for commodity crops are often thin (University of Missouri Extension, 2021).

Going left to right across the Table 2 shows the impact the mean value of K has on network dynamics and associated externality damage. We find that the number of farmers forced into switching is greater in scenarios where NR seed is on average a better choice ($K = 0.9$). This results from a small number of farmers who would prefer to grow DR absent the externality, 15.9%, but a high number of farmers who adopt DR in the steady state, 60.4%. This means that almost 45% of the entire network switches due to OTM. This is less of a problem for $K = 1.1$, as most farmers would prefer to grow DR even without the externality. Interestingly, there is a non-linear response of average yield loss as a function of K. Under our modeling assumptions, yield losses are greatest when the externality-free return of each seed is most similar ($K = 1$). NR being on average more attractive ($K = 0.9$) has a relatively large number of farmers that are damaged and forced to switch. However, this damage per farmer is low due to a low percentage of initial DR adaptors ($x_0 = 0.159$). DR being on average more attractive ($K = 1.1$) creates a much larger damage per farmer due to a higher starting adoption rate ($x_0 = 0.841$) but damages relatively few farmers for this same reason, most are already growing DR seed.[8]

Table 3 highlights the importance of network structure (soybean production density) in determining whether dicamba OTM is a serious issue or not. These results were calculated for the high, low, and median county densities of soybean production in Missouri, respectively, 55%, 7%, and 17% of total acreage dedicated to soybean production (USDA, 2021).

In the low-density situations, the steady state is only slightly greater than the 50–50 mix we would expect absent OTM. In high-density scenarios, the steady state is almost 100% DR soybean adoption. This means network density has a large effect on farmer's seed adoption decisions. Increasing density also forces a greater percentage of growers within a network to adopt DR seed as it exposes each farmer to more neighbors and subsequently greater levels of OTM damage.

Density also matters a great deal for yield loss and the overall relevance of OTM as a problem. A 1% yield loss in a low-density region may not be even worth addressing through any type of policy when accounting for monitoring and implementation costs. However, a 9% loss in a high-density county would certainly warrant attention, especially considering that commodity crops typically have a tight margin and a 9% yield loss would be enough in many years to turn profits negative. It is also worth noting that this effect across planting densities is even larger than the percent suggests, since dense counties have more total soybean growers, which implies the total damage could be an order of magnitude greater in a high-density than low-density network (e.g. 1% loss for 100 farmers vs. 9% loss for 300 farmers). Additionally, observations in regions with high adoption rates of DR soybean indicate these regions are subject to more secondary dicamba drift. The term "landscape-level effects" has been adopted to describe the dicamba injury observed in high adoption regions due to secondary movement (Bish et al., 2019).

Tables 2 and 3 highlight that economic factors and network factors can both have a considerable effect on seed selection and OTM damage. With this understanding, the dicamba OTM problem should be viewed on a regional level where local prices and network structures can be accounted for. Due to the especially large effect planting density has on this problem, regions with high soybean grower density should be acutely aware of this issue. We conduct the same

[8]Yield loss being the same for both mean $K = 0.9$ and $K = 1.1$ is no accident. We assumed that a given starting percentage of DR adoption, x_0, would be the percentage of farmers within a network who would choose DR without any OTM and then ran the simulation from there, determined by K. We felt this was the most realistic assumption as farmers may have an idea about a given seed cost and yield ex ante, but may not learn about the scale of OTM damages until after harvest. Parameter K does not change network structure so average yield loss conditional on number of neighbors can be calculated as a constant, C, times x_0 times $(1-x_0)$. For mean $K = 0.9$, x_0 was 0.159 and the corresponding $(1-x_0)$ was 0.841. For mean $K = 1.1$, x_0 was 0.841 and the corresponding $(1-x_0)$ was 0.159. This leads to the same solution for yield loss for both $K = 0.9$ and 1.1. Solutions are unique when we did not move K by the same percentage in both directions. Note $(1-x_0)$ is incorporated because only NR can be damaged by dicamba OTM. Yield loss is 0.8% for both mean $K = 0.85$ and mean $K = 1.15$.

Table 3. Steady-state DR adoption rates, forced switching, and network-wide yield loss from OTM for Field 1 simulations and baseline K assumptions, under varying county-level soybean grower densities

	Low density	Median density	High density
Steady-state DR seed adoption percentage (x_{SS})	63.0%	76.5%	98.0%
Percent of network forced to adopt DR due to OTM	13.0%	26.5%	48.0%
Average yield loss across entire network	1.3%	3.1%	9.2%

Note: the corresponding results for Field 2 and other robustness checks can be found in Appendix E.

Table 4. Steady-state DR adoption rates, forced switching, and network-wide yield loss from OTM for Field 1 simulations and baseline K assumptions, under varying assumptions for reductions in OTM due to updated federal label

	0% yield loss prevention (baseline)	50% yield loss prevention	90% yield loss prevention
Steady-state DR seed adoption percentage (x_{SS})	76.5%	76.5%	63.0%
Percent of network forced to adopt DR due to OTM	26.5%	26.5%	13.0%
Average yield loss across entire network	3.1%	1.5%	0.3%

comparative statics for economic and network factors using OTM estimations from Field 2 (OTM was stronger than in Field 1) as a robustness check, shown in Appendix E. Results were similar for steady-state adoption and forced switching and larger for yield loss.

These results of economic losses occurring in the face of unregulated and uncoordinated agricultural production are consistent with other studies that look at negative externalities or Tragedy of the Commons problems within agriculture more generally. Work by Heal et al. (2004) showed farmers left to their own devices will choose an amount of crop diversity that is less than socially optimal when considering pathogen resistance. Livingston et al. (2015) find that managing glyphosate resistance in crops such as corn and soybeans is more cost effective if farmers coordinate weed management decisions with one another. The seminal work by Ostrom et al. (1994) also highlights what can occur when individuals exploiting a common pool resource such as grazing land will have better outcomes if they coordinate production decisions.

Our field data were collected in 2016 when federal label regulations governing dicamba spraying primarily focused on keeping Dicamba out of irrigation ditches and other water sources (EPA, 2016). The current federal "label" regulations, adopted in 2020, state that the latest Dicamba can be applied for soybeans anywhere in the country is June 30$^{\text{th}}$. Certain states such as Illinois, Indiana, Minnesota, South Dakota, and Iowa have all implemented earlier dates in June than the federal label date (Tindall et al., 2021). This additional regulation may reduce the size of the externality, $E_{i,\mathrm{NR}}$. While there is insufficient agronomic data to quantify the impact constraining application timing will have on OTM damage, we ran a sensitivity analysis for 0%, 50%, and 90% lower rates of yield loss occurring from following the updated federal label in Table 4.

Table 4 displays how steady state, forced switching and average yield losses are influenced if spraying policy reduced baseline assumption losses by 25% and 50% across all distances from the spray zone (e.g. a 50% loss reduction reduces a 19% yield loss across a field associated with having one neighbor growing DR to an 9.5% loss).

The results in Table 4 show that forcing farmers to follow best management practices for application would have a mixed effectiveness for preventing suboptimal outcomes, under the parameters considered. Unsurprisingly, if spraying restrictions are efficacious in reducing damage, then we would expect average yield loss to fall considerably under these restrictions. On the other

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hand, they are not likely to be effective at preventing a forced DR adoption. A 90% reduction in OTM yield loss only reduces forced switching from 26.5% to 13% and does not reduce it at all for a 50% reduction in yield loss. The damage is large enough that the only farmers who do not switch for 0% loss prevention and 50% loss prevention is the farmers with no neighbors who would prefer NR absent an externality (23.5% of a median density soybean network).

5. Conclusions

The damage from dicamba OTM can be quite large for soybean farmers. This damage affects soybean seed technology adoption decisions within a network. The size of this OTM externality and its effect on seed adoption will vary with network structure and economic factors. Grower density has a large effect on average OTM damage caused by DR adoption. While relative profitability of DR to NR has important effects on individual OTM damage, the average effect of OTM on the network structure is more modest. Both grower density and the ratio of expected payoffs between DR and NR seed have large effects on adoption decisions. Our results suggest that without policy aimed at curbing this network externality, many soybean producing regions will experience considerable OTM damage that will drive increased DR seed adoption over time. This would be problematic because it reduces total soybean yields and could serve to further concentrate the soybean seed market.

OTM damage will be particularly problematic in regions with large soybean acreages. Indeed, some larger producing counties grow well over 100,000 acres. A 3.1% average yield loss per acre occurring for 100,000 soybean acres would create an expected county-level[9] loss of over \$1.5 million (\$15.35 per acre $\times$ 100,000). This loss only captures the loss from injury and could be greater when one considers the resulting losses in efficiency from additional market consolidation for seed supply. NASS estimates that 88 million acres of soybeans were planted in the U.S. during 2022 (NASS). Even a relatively small percentage of OTM-induced yield loss could cause hundreds of millions of dollars in damage.

To focus on the impact of economic and network criteria on OTM damage and seed adoption, this study modeled farmers as being profit maximizers. In the real world, risk is an important consideration to many farmers (Sydorovych and Marra, 2008). Thus, farmers would increase DR seed adoption even more if we included risk aversion. All else equal, NR seed would provide a riskier expected return than DR seed since NR can be damaged by dicamba OTM. Adjustments to farmer risk aversion would enter the problem through parameter K. We also focus our analysis on responses to economic and network parameters while abstracting away from constantly evolving EPA federal label regulations. These regulations would affect parameters K and g. Our baseline results are taken under 2016 federal regulation assumptions, which are less stringent than they currently are. If these regulations reduce OTM, yield losses as a function of distance could be less today than it was in 2016. Although as Table 4 points out, forced switching may still be quite high. A comparison to observed OTM damage as a function of distance and resulting seed adoption decisions under the newer federal label regulations would be beneficial.

Our result that the network damage associated with dicamba OTM is important appears to mirror empirical reality. OTM resulted in 2,708 dicamba-related injury investigations by state departments of agriculture in 2017 (Oseland et al., 2020). Reported dicamba injuries in 2017 were estimated to cover about 3.7 million acres of soybeans in the U.S. (Bradley, 2017). A survey recently posted on the website for the Association of American Pesticide Control Offices reported numerous dicamba complaints from various soybean producing states. Illinois, Minnesota, Missouri, Indiana, and Nebraska reported 151, 116, 102, 73, and 63 complaints, respectively

[9]Damage per acre is under median growing density and baseline profitability ratio ($K = 1$) assumptions. Counties that have high soybean acreage will also likely have higher farmer densities as well. High soybean farmer density assumptions lead to revenue losses of \$45.54/acre. Original revenue estimates are from University of Missouri Extension (2021).

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(AAPCO, 2020). The EPA received 3,300 incident reports of OTM in 2019 and 3,461 incidents OTM in 2021 (Tindall et al., 2021). These cases are likely all underreported, and OTM has become more common as the market share for DR soybeans has grown since the survey was given (AAPCO, 2020; Bradley, 2019).

We also find our result that OTM drift affects DR seed adoption to be consistent with reality. DR seed was first available to farmers in 2016 and not widely used that year (Wechsler et al., 2019). Dicamba OTM first appeared in areas with higher adoption rates for this technology, where the extent of injury to NR soybeans became noticeable (Bradley, 2017; Hager, 2017; Loux and Johnson, 2017; Steckel, 2017). Additional reports of injury to sensitive, non-target crops were extensively documented in the following years (2020b; Bradley, 2018, Hager, 2019; Hartzler, 2020a; Johnson and Ikley, 2018; Steckel, 2018, 2019; Zimmer et al., 2019; Zimmer and Johnson, 2020). Along with these increasing injury reports, DR seed adoption rates increased to 55% in the United States in 2021. While we applied our model at a county level our take-away that under a variety of cases, adoption rates for DR increase to above 50% still holds when we zoom out to the national level.

While identifying an optimal policy response is beyond the scope of this study, it does appear that the size and scope of dicamba OTM damage could warrant policy intervention. This intuition holds even when average externality-free returns are greater for DR seed ($K = 1.1$). The Environmental Protection Agency continues to update dicamba label restrictions and regulations annually, which is not typical. As noted in Table 4, these policies may be effective at reducing damage but are likely insufficient to reduce consolidation within the soybean industry. Other potential interventions aimed at curbing OTM could include timing restrictions on application, zoning laws banning certain chemicals in certain areas, or increasing the buffer zone between neighboring crops. Current herbicide labels require a 240-ft downwind buffer, which according to Figure 1 would be insufficient to minimize yield loss in NR soybeans. Due to the large heterogeneity in outcomes associated with different regional network structures, it may be beneficial to craft policy targeted towards regions to account for unique network characteristics that will greatly affect the size of the problem and optimal solution.

Future work could build upon this research by quantifying the impact that OTM-induced seed adoption decisions have on market consolidation. For instance, a tip to 98% dicamba-resistant adoption would effectively mean a monopoly for soybean seed in the US. The long-term losses from such a shift could even outweigh the short-term losses from the OTM damage. This future work has a recent policy issue to motivate it: the Minnesota state legislature quite recently considered two policies, an increased tax on gross sales of dicamba, and a Coasian bargaining framework between those whose soybeans were damaged by dicamba and those who applied it to their own crop (MDA, 2020; ML, 2021). Whether these policies aimed at curbing OTM damage to soybeans should be enacted together or separately (and which policy is more cost effective) extends into the sphere of antitrust and market power—exacerbated regional tipping can lead to de facto monopolies for parent companies supplying DR seed in certain areas. The implications of such a policy study for Minnesota would have value for policy makers.

Another potentially valuable vein of future work is further exploring additional complexities within network structure between farmers. This study focused on farmer's playing a game to maximize their own financial payoff. We know from the game theory literature that individual agent's sometimes care about what happens to others playing the game. Factors such as playing a repeated game, social values, or reputation may push some agent's away from actions that harm their neighbors (Mailath and Samuelson, 2006, Van Lange et al., 1997). This means that if a farmer has preferences for not damaging a neighbor's crop, they may be less likely to adopt DR technology in the first place. This could be accommodated through the use of an additional parameter (of the same type as g) applied to DR payoffs. Having two simultaneous network externalities (OTM drift damage and damage to one's social circle) could lead to unstable equilibriums where different regions may adopt mostly DR or NR seed.

Author contributions. Conceptualization, S.L. and M.B.; Methodology, J.S.Y. and T.J.M.; Formal Analysis, J.S.Y. and T.J.M.; Data Curation, M.B., S.L., and T.J.M.; Writing – Original Draft, J.S.Y. and T.J.M.; Writing – Review and Editing, J.S.Y., T.J.M., S.L., and M.B.

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Appendix A: Characterization of Steady-State "Nash Equilibrium"

As mentioned in Section 2.2, the steady state occurs when the percentage of DR adopters stays constant across time periods. Recall Equation (6):

$$x_t = 1 - \frac{1}{\bar{d}} \sum_{d=0}^{4} dP(d)C\left[1 - f(g(d, x_{t-1})\right] \tag{6}$$

This equation shows the percentage of DR adopters at time t (left-hand side of the equation) resulting from a given percentage of DR adopters at time $t-1$ (right-hand side of the equation). The point where $x_t = x_{t-1}$ can be thought of as the steady state. This point is recovered through numerical simulation in which we tested 200 values for x_0 between 0 and 1 (intervals of .005) and the resulting x_1 for each. The point at which the absolute value of the difference between x_1 and x_0 was minimized (arbitrarily close to zero) was our steady state.

The blue line in Figure A1 shows the DR adoption rate in time 1 "x_1" resulting from a given adoption rate in time 0 "x_0." Figure A1 shows relationship under baseline assumptions (field trial #1 OTM distance, median grower density and mean $E[k] = 1$). The orange line is a 45 degree line used to demark increasing or decreasing levels of DR adoption over time. When the blue line is above the orange line, DR adoption is increasing between periods. When the blue line falls below, the orange line DR adoption is decreasing between periods. The intersection of these two lines denotes the steady state. The steady state can be interpreted as a Nash Equilibrium in which DR adoption is constant between periods and no farmer within the network has any incentive to change seed choice. This point is marked with the black dot and labeled accordingly. Figure A1 shows that for $x_0 = 76.5\%$ that the resulting $x_1 = 76.5\%$, and thus, the steady state $x_{ss} = 76.5\%$. Under baseline assumptions, initial DR adoption below 76.5% (x_0 to the left of the dotted line) will eventually rise until the steady state is reached. Additionally, DR adoption rates above 76.5% (x_0 to the right of the dotted line) will fall until the steady state is reached.

Also notice that even at $x_0 = 0$ that x_1 jumps to 50%. This occurs because under our assumption of $k = 1$ that even without the externality, half of the farmers in a given network would be better of adopting DR soybeans. Finally, Figure A1 can be generalized to periods beyond $t = 1$ by simply plugging in x_1 for x_0 and interpreting the resulting x_1 from that exercise as x_2. For example, $x_0 = 0$ leads to $x_1 = 0.5$. If we then plug in 0.5 for x_0, we then get $x_1 = 0.765$ which would mean that an $x_0 = 0$ ultimately leads to $x_2 = 0.765$.

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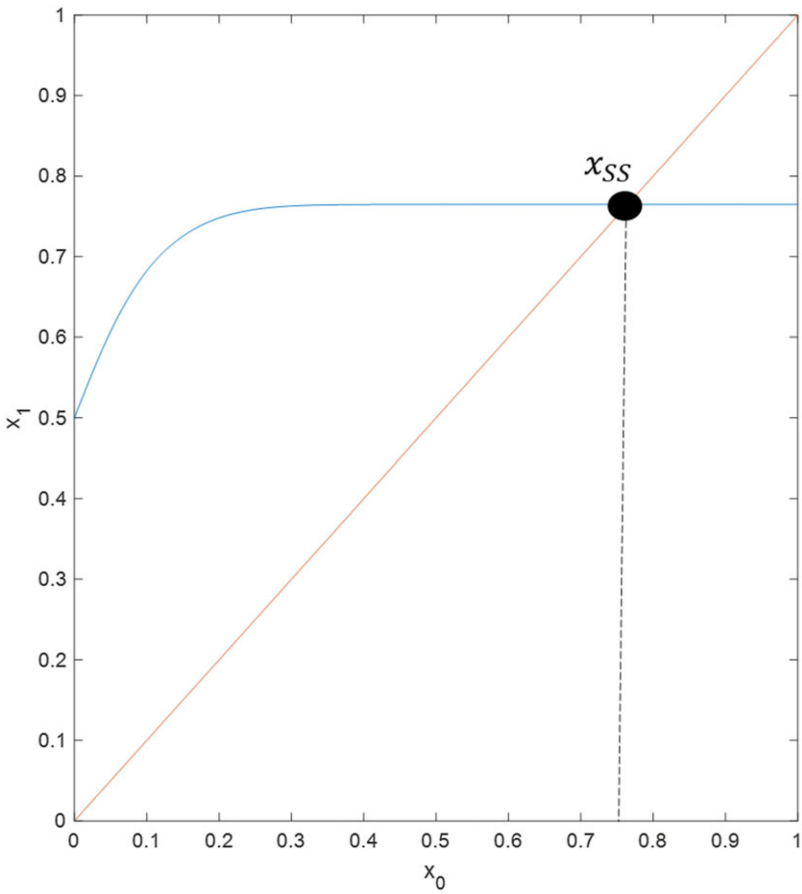

Figure A1. Recovery of the steady state.

Appendix B: Calculations for OTM Damage as a Function of Distance from Spray Site

The following section displays the raw data used to estimate Figure 1 (yield loss as a function of distance from spray area) for both field trials. We fit the observations using the trend line option in excel, with the logarithmic trend providing the best fit in both cases.

The % yield loss was calculated on a per-acre basis compared to production on an average acre of undamaged soybeans. Negative yield losses can be attributed to areas exhibiting higher than average yields compared to the unaffected areas. Idiosyncrasies in soil, climate, topography, and even individual soybean plants have unique yield impacts, and thus, even some affected areas can still show higher yields despite the damage, not because of it.

Additionally, for our modeling, we stopped predicting yield loss when the estimated loss reached 0%. It would not make sense that yields would be higher than the average once a certain distance threshold was passed. Furthermore, this is consistent with our assumptions of 80-acre plots for soybean growers. These results illustrate our reasoning for using field trial #1 as our baseline assumption. Not only was using this trial a more conservative assumption for OTM damage than field trial #2, but it also has a much richer data set and better corresponding fit in estimating the relationship between distance and yield loss.

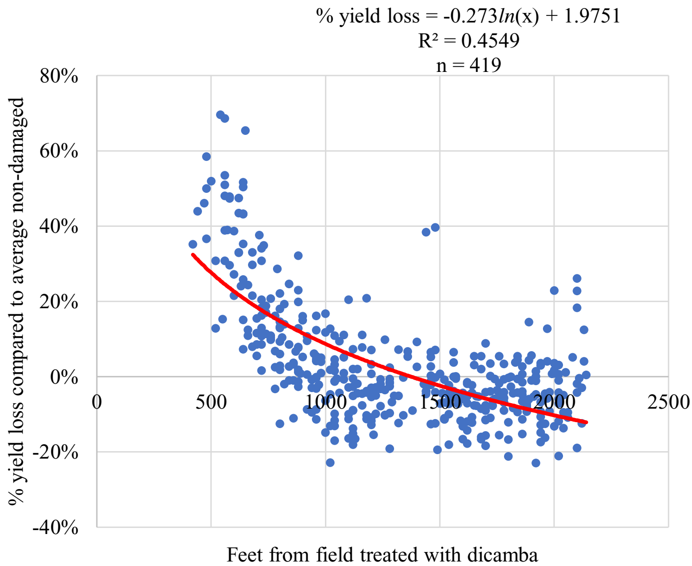

Figure B1. OTM yield loss estimates for field trial #1.

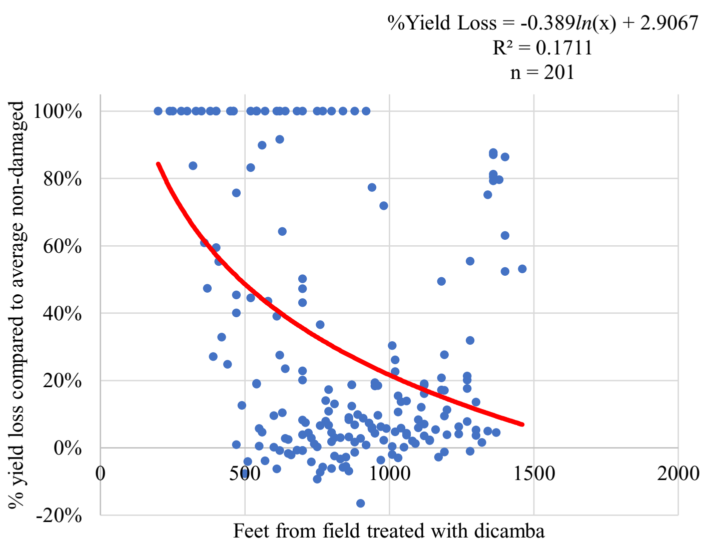

Figure B2. OTM yield loss estimates for field trial #2.

Appendix C: Simulating County Planting Patterns

In this section, we illustrate the county planting patterns described in the data and methods sections of the manuscript. Because site-specific coordinate data for soybean growers (much less choice of genetic strands) are infeasible to collect on such a large scale, we use county proportions from our sample counties in Missouri, namely Pemiscot (where 7.3% of the acreage is planted to soybeans), Cooper (17.3%), and St. Genevieve (55.5%) counties. To do this, we randomly populate an $n \times n$ grid (simulated region of arbitrary size, without any loss of generality) with a binary planting choice of "soybeans" or "not soybeans." We then compute the field-to-field distance, plug those distances into the yield loss or degree function estimated in Figure 1 of the manuscript, and then utilize that distribution of degree for our network diffusion model.

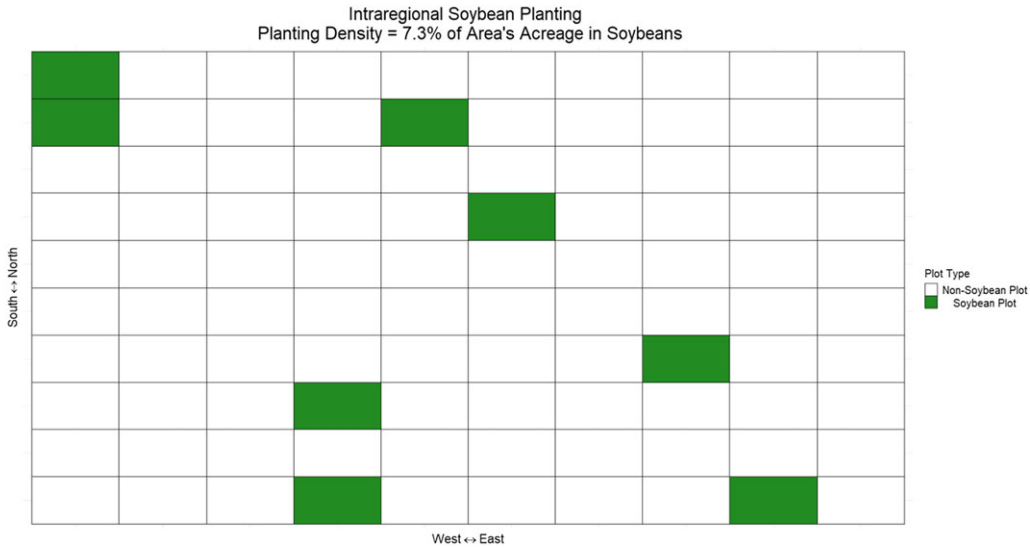

Figure C1. Random network with 7.3% of region's acres planted to soybeans.

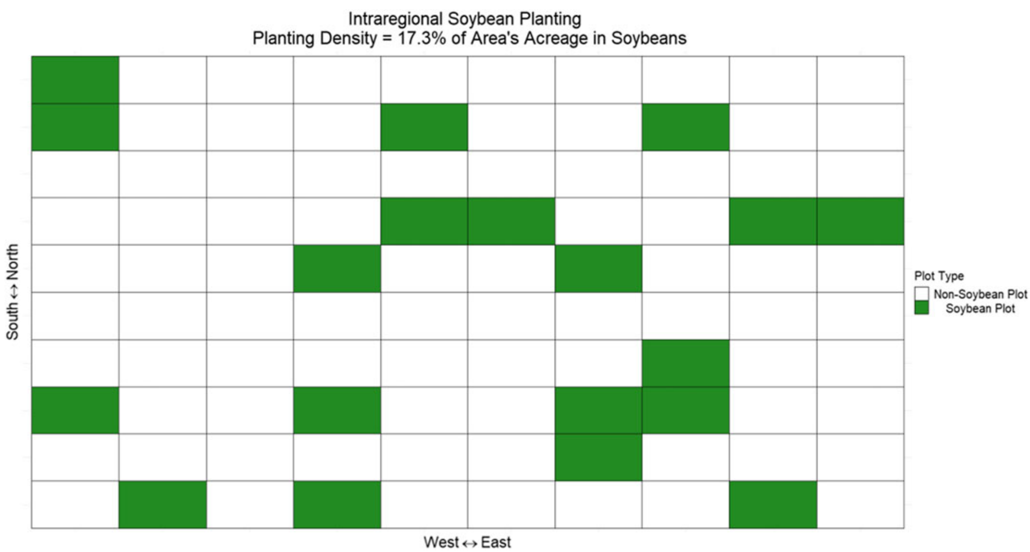

Figure C2. Random network with 17.3% of region's acres planted to soybeans.

The following 3 figures (Figures C1, C2, and C3) illustrate how, assuming the same starting value, soybean plots can be randomly distributed throughout a region.

It should come as no surprise that the green cells out in the open space have degree zero (they are neighborless). It is also expected that those in a cluster have extremely high degree, that is, high potential for OTM damage from neighboring growers. Thus, as planting density in a region intensifies, the risk for OTM in that region is amplified to the point of triggering a tip.

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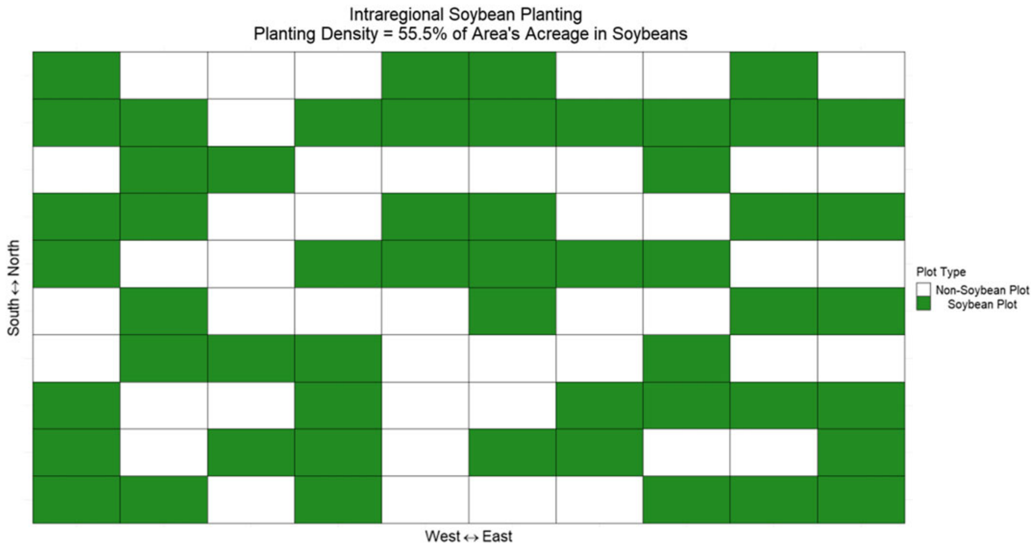

Figure C3. Random network with 55.5% of region's acres planted to soybeans.

Appendix D: Network Structure of Under Different Planting Densities (2nd trial)

Table D1. Network structure under different planting densities (2nd field trial)

Neighbor count (*d*)	NR farmer's % yield loss if all neighbors grow DR (*g*)	% of network with a given neighbor count (low density)	% of network with a given neighbor count (median density)	% of network with a given neighbor count (high density)
0	0.00%	73.90%	47.00%	4.00%
1	33.85%	23.20%	39.00%	19.80%
2	60.05%	2.70%	12.20%	36.70%
3	76.09%	0.10%	1.70%	30.20%
4	86.93%	0.00%	0.10%	9.30%

Note: field trial estimates do not affect how many neighbors a farmer will have within a given network, but they do affect how much damage a farmer is likely to receive conditional on number of neighbors

Appendix E: Results associated with OTM from Field Trial #2 and Other Robustness Checks

Compared to Field 1 assumptions, comparative static results were higher for yield losses when using Field 2 estimations across the board. This is unsurprising since Field 2 had a higher estimation of damage as a function of distance; thus, we would expect the entire network to lose more in soybean yields.

Somewhat more surprising is the constancy of steady state and percent of farmers forced to switch due to OTM. This can be explained by the relatively small difference in K distribution value's relative to the estimated size of the damage (a 10% loss in yield corresponds to a 46% loss in profits, and farmers with two or more neighbors lost over 50% of their yields). Under Field 1 OTM assumptions, the only farmer's not forced to switch to DR traits were those without neighbors. Higher OTM damage just reinforced this result. This constancy for the aforementioned results is a result of the problem's empirics and not the modeling itself. When we increased the standard deviation about K to 1 from 0.1, some farmers with a non-zero amount of neighbors remained in NR production even with OTM. These results are displayed in Table E3.

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Table E1. Steady-state DR adoption rates, forced switching, and network-wide yield loss from OTM for Field 2 simulations and baseline median grower density assumptions under varying profitability ratio distributions

	$E[K] = 0.9$	$E[K] = 1.0$	$E[K] = 1.1$
Steady-state DR seed adoption percentage (x_{SS})	60.4%	76.5%	92.5%
Percent of network forced to adopt DR due to OTM	44.6%	26.5%	8.4%
Average yield loss across entire network 1st season	2.9%	5.5%	2.9%

Table E2. Steady-state DR adoption rates, forced switching, and network-wide yield loss from OTM for Field 2 simulations and baseline K assumptions, under varying county-level soybean grower densities

	Low density	Median density	High density
Steady-state DR seed adoption percentage (x_{SS})	63.0%	76.5%	98.0%
Percent of network forced to adopt DR due to OTM	13.0%	26.5%	48.0%
Average yield loss across entire network	2.4%	5.5%	14.9%

Table E3. Steady-state DR adoption rates, forced switching, and network-wide yield loss from OTM for Field 1 simulations and baseline K assumptions, under varying standard deviations for K

	$SD[K] = 0.1$ (baseline)	$SD[K] = 1.0$
Steady-state DR seed adoption percentage (x_{SS})	76.5%	71.1%
Percent of network forced to adopt DR due to OTM	26.5%	21.1%
Average yield loss across entire network	5.5%	5.5%

Table E4. Steady-state DR adoption rates, forced switching, and network-wide yield loss from OTM for Field 1 simulations and baseline K assumptions (normal distribution with mean $= 1$ and standard deviation $= 0.1$), under varying county-level soybean grower densities

	Low density	Median density	High density
Steady-state DR seed adoption percentage (x_{SS})	63.0%	76.5%	98.0%
Percent of network forced to adopt DR due to OTM	13.0%	26.5%	48.0%
Average yield loss across entire network	1.3%	3.1%	9.2%

Table E5. Steady-state DR adoption rates, forced switching, and network-wide yield loss from OTM for Field 1 simulations under Cauchy K assumptions (x intercept $= 1$ and scale parameter $= 0.0612$), under varying county-level soybean grower densities

	Low density	Median density	High density
Steady-state DR seed adoption percentage (x_{SS})	62.0%	75.0%	96.5%
Percent of network forced to adopt DR due to OTM	12.0%	25.0%	46.5%
Average yield loss across entire network	1.3%	3.1%	9.2%

As an additional robustness check, we tested the distributional form of *K* itself to see if results remained constant. Table E4 displays our baseline results for steady-state adoption, forced switching, and yield loss when parameter *K* follows a normal distribution. Table E5 displays our results when *K* follows a Cauchy distribution. As a reviewer pointed out, a normal distribution over a normal distribution yields a Cauchy distribution, which certainly could be possible if both DR profits and NR profits were normally distributed across a network.

To estimate the appropriate Cauchy distribution to compare to our normal assumptions for *K*, we defined a normal distribution with mean $= 1$ and standard deviation $= 0.1$ (our baseline assumption for *K*), in excel using @risk software. We then ran a simulation with 100,000 iterations generating random points pulled from that distribution. We then fit the simulated observations with a Cauchy distribution. Our estimated Cauchy distribution had an estimated $\times$ intercept of 1 and a scale parameter of 0.0612. We then defined *K* in matlab to follow the aforementioned Cauchy distribution.

Results were remarkably stable across distributional assumptions. Steady states and forced switching were always lower under Cauchy due to the Cauchy distribution having fatter tails than a normal distribution. We attribute this modest decrease in DR adoption to the relatively fatter tails of the Cauchy distribution meaning that more farmers under Cauchy assumptions for *K* would continue to grow NR soybeans, even in the face of a network externality. We also tested the implications of a Cauchy assumption for parameter *K* when networks were low and high density.

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