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# Adapting network theory for spatial network externalities in agriculture: A case study on hemp cross-pollination

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# Adapting Network Theory for Spatial Network Externalities in Agriculture: A Case Study on Hemp Cross-Pollination

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**Abstract:** Growers have increasingly expressed frustration over the negative externalities created by their neighbor's production practices. These spatial agricultural network problems include issues such as cross-pollination and herbicide drift. We develop novel methods for estimating parameters that allow us to adapt and apply general network diffusion models to these spatial agricultural network problems. Doing so allows us to calculate externality damage within a region and calculate cost-effective policies for alleviating that externality. We empirically illustrate, motivate, and test this approach by applying it to hemp. We find that network structure is an important factor in externality size and cost-effective policy response for spatial agricultural network problems. We also find that policies that are implemented early and proactively are more likely to be successful and cost-effective than policies implemented retroactively. Finally, we find that in our application of limiting the cross-pollination damage experienced by growers of feminized hemp from non-feminized hemp growers, the most cost-effective policy is to establish a regional quota on non-feminized production combined with intertemporal cultivar spacing. This policy response will likely change across time and region as economic and network variables evolve.

**Keywords:** externality, hemp, network diffusion, tipping point

**JEL Codes:** C63, C73, C93, O33

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As agricultural producers gain access to more options for inputs (e.g., seed, fertilizer, herbicide) and respond to changes in consumer tastes, their production practices become less uniform. As these practices fragment, the potential for one grower's actions to negatively affect their neighbors increases. Herbicide drift, voided organic certifications, and degraded cannabinoid concentration (e.g. CBD, THC) from cross-pollination represent a few examples of this problem. The damage associated with these spatial agricultural network externality problems (henceforth, "SANEPs") is often substantial. Because of this, better understanding SANEPs is a top priority of growers, researchers, and policy makers. However, SANEPs contain unique temporal and spatial complexities that make them difficult to model. A damaged grower may switch to the damaging crop the subsequent season, reinforcing the externality. A neighbor growing a damaging crop in an adjacent field poses more risk than one growing it far away.

Fully understanding SANEPs requires a generalizable framework capable of estimating damage, making predictions, and informing policy. We seek to develop a generalizable model and parameter estimation technique capable of handling different SANEPs. We subsequently apply this model to one specific empirical application to provide concrete illustrations of a complex problem, that is, cross-pollination in the hemp production sector.

After its de-classification as a controlled substance in the 2018 Farm Bill, hemp received attention from growers due to its relatively high price at the time. Hemp cultivars are optimized for various end uses including fiber for textiles, grain for food, seed for improved genetics, and floral material for cannabinoid extraction and smokeable flower. During the timeframe under consideration, cultivars optimized for cannabinoids generally provided the highest expected returns.

Hemp production practices vary by cultivar, having both dioecious (both male and female) and monoecious types. Cannabinoids such as THC and CBD are found predominantly in the flowers of unpollinated female cannabis plants (Stack et al. 2021; Yang et al. 2020).[1] Thus, growers of floral hemp typically use expensive feminized seeds or cloned female plants.[2] In contrast, pollination does not harm fiber hemp and is necessary for grain cultivars, so fiber and grain growers use cheaper, non-feminized seed. The problem is that pollen from fields of fiber and grain (henceforth, "non-feminized") hemp can cross-pollinate nearby fields of feminized floral (henceforth, "feminized") hemp.[3] This decreases cannabinoid concentration, increases seed content in feminized hemp fields, and can make the harvested floral material unsellable. Breeders of seed for premium cultivars are also at risk of cross-pollination. Hemp pollen's long travel distance exacerbates this problem (Small and Antle 2003; Smart et al. 2018; Stack et al. 2018). Thus, sufficiently high levels of cross-pollination damage within a region could destroy the viability of high premium feminized hemp production in that area.

There is also considerable concern about cannabis cross-pollination among regions in which marijuana is produced legally. Because cross-pollination diminishes THC, several states

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[1] Recent work, after the period of our study, developed pollen-immune or "triploid" cultivars of *Cannabis sativa* L. Crawford et al. (2021) reviews the details of pollination on these new strains.

[2] This process requires monitoring to cull rogue male plants or removing plants which were feminized clones but hermaphrodized from environmental stress (Gerlach 2019; Place 2019a,b).

[3] We define "feminized" solely with floral hemp. While this excludes specialty seed production, the acres devoted to seed were minuscule during the years considered. However, the model we develop herein generalizes to the case for both seed and floral material.

where marijuana production is legal have implemented legislation to curb cross-pollination between hemp and marijuana. For instance, Washington implemented a four-mile buffer zone between industrial hemp and outdoor marijuana growers, which it later repealed in 2019. Humboldt County, California banned production of all low-THC cultivars in 2018. The Colorado legislature launched a working group to study cannabis cross pollination in 2021.

Network diffusion models can accommodate the aforementioned spatiotemporal complexities associated with SANEPs, but require novel techniques of parameter estimation and model specifications unique to these problems. We develop these techniques and specifications herein, then use this re-parameterized, refined network diffusion model to estimate the cost-effectiveness of various policies aimed at curbing negative network externalities in SANEPs. We empirically motivate, illustrate, and test this framework by examining the case of industrial hemp.

Our research makes three key contributions:

1. We develop estimation techniques that adapt network diffusion models to fit SANEPs.
2. We use a parameterized model to estimate pollen damage and tipping dynamics for hemp.
3. We identify the policies most effective for mitigating hemp pollen damage.

We accomplish this by parameterizing and solving a network diffusion model developed by Jackson and Yariv (2005). The data are from the Kentucky Department of Agriculture (KDA) and a Cornell University hemp extension study (L.B. Smart, personal communication, November 3, 2020). This study is the first to utilize such data. While the timeframe and context of the data are limited to hemp for cannabinoid extraction as the "premium" crop, our parameter estimation and method apply to other SANEPs including herbicide drift and organic certification.

The network literature explores how social network externalities influence individual agent payoffs to a given action. The structure that ties all agents together is referred to as the network.

Through this network, an agent's individual payoffs to a given action are influenced by the actions of those geographically (or socially) close to them, their "neighbors." This approach is popular in research exploring epidemiology and adoptions of new technology (Wang et al. 2009; Zhang et al. 2010). Such studies routinely find that the size of an externality experienced by a given agent is increasing in the number and/or percentage of their neighbors who engage in whatever activity produces the externality (Jackson and Yariv 2005; 2007). The network literature matters for feminized hemp production because an individual grower's expected payout to growing feminized hemp is influenced by their neighbors' planting decisions.

Certain social or physical phenomena (e.g., fads, epidemics, technological adoption) can lead to tipping: unstable equilibriums that shift dramatically in a short amount of time. The idea behind tipping is that if an agent switches from action A to action B, then the agent's new action choice affects their neighbors who had been following action A. Tips occur when a relatively small number of B adopters shifts a proportion of the network to a higher level of B adoption. Tipping is an important concept in hemp production since growers who choose to cease feminized production to avoid cross-pollination may adopt non-feminized hemp cultivars. This decision then affects any of their neighbors who grow feminized hemp. The potential exists for a cascade of decisions leading to dramatically reduced feminized hemp production over time.

Using network effects to explain agricultural technological adoption has gained popularity in the agricultural economics literature. Studies about the diffusion of new agricultural technology find that producer decisions are affected by those socially or geographically close to them (Abdulai and Huffman 2005; Bazzana et. al 2022; Coomes et al. 2015; Genius et al. 2014; Maertens and Barrett 2013; Varshney et. al 2022; Yoo and Chavas 2022). These studies focus on the impact of neighbors learning from one another. A grower changes their own profitability from adopting new technology by observing or interacting with neighbors who have already. While social learning is a valuable tool for explaining the decision to switch from traditional practices to improved, it does not fully capture SANEPs where switching occurs to avoid a negative externality.

To our knowledge, only one existing economic study has leveraged the strengths of networks and tipping points to model SANEPs.[4] McCarty and Young (2020) conceptually examined how hemp externalities could be modeled using network theory and qualitatively measured how network structure influences hemp cultivar selection. They highlighted the advantages of using network diffusion to model SANEPs, but could only examine these problems qualitatively as they lacked the approaches and data to estimate the network structure for SANEPs.

We find that under our parameter assumptions and during the period studied, multiple Kentucky counties were at risk of tipping to non-feminized production. We find the most cost-effective solution for preventing this tip would be a quota system aimed at limiting the amount of non-feminized production within a given region combined with intertemporal cultivar spacing. We also find, more generally, that earlier actions make it cheaper and easier to solve SANEPs.

## Theory

When possible, we follow the notation and formulas laid out by Jackson and Yariv (2005) and McCarty and Young (2020) that define network diffusion models. In these models, agents are connected to one another through a network. Each agent (henceforth, "grower") has a given

[4] In this article, we refer to "tipping points" in the context of network diffusion. Some branches of the behavioral and sociological literature use this same term to refer to the point of inflection in a nonlinear regression curve or to estimate a point of diminishing marginal returns.

number of neighbors whose choices affect their individual payouts to a given action, A or B. The starting action is defined as A, and a grower has the option of switching to action B. The benefits or costs of switching to B are influenced by both grower $i$'s unique private payouts to action B and the decisions of grower $i$'s neighbors. In our problem, action A denotes feminized hemp production. A grower has the option of switching to action B, non-feminized hemp production, to avoid the negative social externality of cross-pollination. Degree, denoted $d_i$, defines the quantity of neighbors grower $i$ has. The percentage of agents within the network that have $d$ neighbors must be $P(d) \geq 0$ and the probability density function of $d$ must sum to one.

We assume that all growers within the network are price-taking profit maximizers. There is a cost, $c_i$, and benefit, $b_i$, to adopting action B. We define cost to be the decrease in private profit associated with growing a less valuable crop: $c_i = \pi_A - \pi_B$. The forgone private profit from feminized hemp is $\pi_A$, and the private profit of growing non-feminized is $\pi_B$. The benefit the grower receives from choosing B is the forgone expected revenue loss from having their feminized hemp crop cross-pollinated is defined in Equation 1 as

(1) $$b_i = v_i g(d_i, \lambda_i)$$

where parameter $v_i$ denotes the loss in feminized hemp revenue that occurs if a field experiences sufficient pollination to experience a total loss. The function $g$ transforms grower $i$'s degree, $d_i$, and percentage of neighbors who have adopted non-feminized hemp, $\lambda_i$, into the expected proportion of pollinated flowers in grower $i$'s field. Grower $i$ then chooses to switch from feminized to non-feminized production whenever $R_i = \frac{v_i g(d_i, \lambda_i)}{\pi_A - \pi_B} = \frac{b_i}{c_i} \geq 1$.

Equation 2 denotes the percentage of all growers within the network that have adopted non-feminized production at time $t$ as $x_t$:

(2) $$x_t = \sum_d \frac{x_{td} d P(d)}{\bar{d}}$$

where parameter $x_{td}$ denotes the percentage of growers of degree $d$ that have adopted non-feminized hemp at time $t$. Parameter $\bar{d}$ denotes the average degree of a grower within the network. To solve this problem, we exogenously define a given percentage of non-feminized adopters at time 0, $x_0$. In the following period, each grower responds to this level of adoption and makes their planting decision accordingly.[5] If $x_0$ is sufficiently small, the social externality will be small and the behavior will reduce over time. If $x_0$ is sufficiently large, then non-feminized adoption will increase over time, leading to a new steady state of reduced feminized output.

Grower actions in time $t-1$ affect $x_t$. Equation 3 denotes the percentage of non-feminized adopters of degree $d$ by period $t$:

(3) $$x_{td} = 1 - F[\frac{1}{g(d,x_{t-1})}]$$

Each grower has a unique ratio $\frac{v_i}{c_i}$, and $F$ denotes the cumulative distribution function of this ratio for all growers within the entire network. We derive the percentage of non-feminized adopters at time $t$ across the entire network in response to non-feminized adopters at time $t-1$ by substituting Equation 3 into Equation 2, resulting in Equation 4

(4) $$x_t = \frac{1}{\bar{d}} \sum_d dP(d) \left(1 - F\left[\frac{1}{g(d)x_{t-1}}\right]\right) = 1 - \frac{1}{\bar{d}} \sum_d dP(d) F\left[\frac{1}{g(d)x_{t-1}}\right]$$

[5] We follow Jackson and Yariv's (2005) assumption that each grower in the population is exposed to is constant percentage of non-feminized adopters. The percentage of each grower's neighbors who have adopted non-feminized cultivars, $\lambda_i$, is equal to the percentage of non-feminized hemp adopters within the entire population, $x$. This assumption enhances the tractability of our problem with little loss in generality.

which captures the relationship of whether the action producing non-feminized becomes more prevalent or fades over time. There will exist a unique ${x_0}^*$ for which $x_0 < {x_0}^*$ will cause behavior B to decrease over time and for which $x_0 \geq {x_0}^*$ increases the adoption of non-feminized hemp over time until the equilibrium converges to a new steady state, $ss^*$. The ${x_0}^*$ causing a tip to the new equilibrium is referred to as the tipping point. This tipping point and its resulting steady state matter because a tip to increased non-feminized production (via reduced feminized production) represents a loss in grower surpluses. More importantly, any policy aimed at preventing this tip from occurring must recognize the structure of the network to understand how policy affects it.

**Methods and Data**

Accurately parameterizing Equation 4 requires estimating the function $g$, the distribution of $\frac{v_i}{c_i}$, and the network's distribution of $d_i$. Some of these estimations require novel techniques not present in the precursory game theory literature. In this section, we develop the procedure needed to estimate these key primitives and report their estimated levels.

Pollination of female hemp plants reduces their cannabinoid concentration, which makes the harvested material less valuable and processing more expensive. Pollination also increases the quantity of seeds within each flower. Floral processors follow varying acceptance criteria for floral material but typically reject it if it contains too many seeds. We use the fact that seed count is increasing in percentage of flowers pollinated and assume processors reject material that contains at least 20% pollinated flowers. Parameterizing $g$ requires taking feminized processors' seed criteria into account. Recall from Equation 1 that $g$ maps the effect of $d_i$ and $\lambda_i$ onto $b_i$, in the context of our problem, $b_i = v_i g(d_i, \lambda_i)$.

Parameter $v_i$ denotes the damage associated with a total loss from pollination for grower $i$, $g$ is the mapping, $d_i$ denotes grower $i$'s degree (distance-weighted number of neighbors), and

$\lambda_i$ denotes the percentage of grower $i$'s neighbors who produce non-feminized hemp. Grower $i$ counts any nearby hemp growers as neighbors if they are close enough to cross-pollinate. Degree, $d_i$, is increasing in number of neighbors and decreasing in distance between neighbors. Function $g$ maps the expected percentage of flowers within a field that get pollinated, denoted as $d_i\lambda_i$, and scales the damage into one of two categories: no loss, 0, and total loss, 1. This creates two possible outcomes in which either $b_i = 0$ or $b_i = v_i$. The assumed functional form of $g$ is

(5) $$g(d_i, \lambda_i) = \begin{cases} 0, for\ d_i\lambda_i < 0.20 \\ 1, for\ d_i\lambda_i \geq 0.20 \end{cases}$$

Network diffusion models require an accurate estimation of the network structure that links growers (the distribution of all individual degrees within the network). To recover this, we first estimate each individual grower's degree. Grower $i$'s degree, $d_i$ dictates the size of the network externality to which they will be exposed. The expected damage grower $i$ receives from cross-pollination is increasing in their degree, $\frac{\partial b_i}{\partial d_i} \geq 0$. An individual neighbor of $i$ is denoted as $j$. Grower $i$'s total number of neighbors is denoted $J_i$. Euclidean distance from neighbor $j$ to grower $i$ is denoted $E_{ji}$. These parameters dictate $d_i$, where $\frac{\partial d_i}{\partial J_i} \geq 0$ and $\frac{\partial d_i}{\partial E_{ji}} \leq 0$.

Parameter $J_i$ is determined by pollen's maximum travel distance, $E_{max}$. Grower $j$ is a neighbor to grower $i$ if the distance between their fields is such that $E_{ji} \leq E_{max}$. How heavily grower $j$ contributes to grower $i$'s degree is determined by their individual contribution to $i$'s feminized pollination percentage if they grow non-feminized hemp is denoted as $\Delta d_{ji}$. If grower $j$ is capable of pollinating 100% of grower $i$'s flowers within their field at $E_{ji}$, then grower $j$'s marginal contribution to grower $i$'s degree is $\Delta d_{ji} = 1$. If grower $j$ is far enough away that they could only pollinate 20% of $i$'s flowers, then $j$'s marginal contribution to $i$'s degree is $\Delta d_{ji} = 0.2$. Grower $i$'s total degree is

(6) $$d_i = \sum_{j=1}^{J_i} \Delta d_{ji} \, (E_{ji})$$

To estimate the number of neighbors and their respective weights in relation to grower $i$, we first use the Cornell extension data to estimate distances effect on cross-pollination between fields (L.B. Smart, personal communication, November 3, 2020). These field trials measured seeds per plant as a function of distance from a pollen source, denoted as $S(E_{ji})$, where $E_{ji} = 0$ corresponds to field adjacency. We use these estimates to calculate grower $j$'s marginal contribution to grower $i$'s degree, where $\Delta d_{ji} \in [0,1]$.

Hemp is wind-pollinated. While pollinators collect pollen from male hemp plants, they are not attracted to female plants (Flicker, Poveda, and Grab 2020). How far wind carries hemp pollen remains under debate. Previous research claims that cannabis pollen travels more than 150 km (Cabezudo et al. 1997). Conversely, Small and Antle (2003) claim only 0.2% of pollen captured in their traps traveled 400 m. Cannabis produces as much as 350,000 pollen grains per flower (Faegri, Kaland, and Krzywinski 1989). With hundreds of male flowers on a plant and potentially thousands of male plants in a field, even 0.2% of pollen could amount to millions of pollen grains.

Previous studies in multiple plant species found that, as distance from a pollen source increases, pollen abundance decreases rapidly but persists at low levels over long distances (Ramsay, Thompson, and Squire 2003; Saeglitz, Pohl, and Bartsch 2000; Small and Antle 2003; Weekes et al. 2005). These relationships are routinely modeled with exponential and logarithmic curves in which pollen level or pollination rate is a function of distance from pollen source. We fit the field trial data in Excel. Of the exponential, linear, logarithmic, polynomial and power structural forms, the exponential form fit best. We estimated the relationship between seeds count per plant and distance between fields as $S(E_{ji}) = 19{,}998 * e^{-0.00049 * E_{ji}}$. The $R^2$ was 0.32.

We then use the estimation of $E_{ji}$'s effect on seed count to calculate grower $j$'s marginal contribution to grower $i$'s degree (Figure 1). Recall that $\Delta d_{ji}$ is defined as the additional percentage of $i$'s flowers that go to seed if neighbor $j$ starts growing non-feminized hemp $E_{ji}$ feet away. An adjacent field creates an average seed count of 19,998 seeds per plant. We assume this number approximates the field of feminized hemp having 100% of its flowers pollinated. This means that $\Delta d_{ji} = \frac{S(E_{ji})}{19{,}998}$. A neighbor in an adjacent field would increase grower $i$'s degree by 1 and a neighbor 1,500 feet away would increase $i$'s degree by about 0.5. We plot and calculate this relationship between $\Delta d_{ji}$ and $E_{ji}$ in Figure 1. Under our baseline assumptions ($E_{max} = 2$ miles), $\Delta d_{ji}$ is best approximated with the function $e^{-0.00049*E_{ji}}$. We then take the sum of $\Delta d_{ji}$ for each of $i$'s neighbors to calculate $i$'s total degree using the formula in Equation 7

(7) $$d_i = \sum_{j=1}^{J_i} \Delta d_{ji}\,(E_{ji})$$

Building a distribution of $d$ for all growers requires estimating the degree of each grower in the network. In addition to the number of growers in a network, spatial correlation between growers affects each grower's degree. Our prior is that there is positive correlation between hemp growers due to high costs of transporting harvests, which would incentivize growers produce hemp closer to processing plants. Butsic et al. (2017) argued that cannabis cultivation sites within Humboldt County, California, are most likely to locate near other cannabis cultivation sites. McCarty (2019) suggested that there are mutual benefits for hemp processors and growers co-locating. Spatial correlation would increase the average degree within the network by increasing the density of hemp growers in that area. This would magnify the effect of the network externality.

Here, we utilize plot-level data from the KDA over 2017–2019. The dataset contains each field's acreage, planted cultivar(s), operating costs, sales revenue, yield, unsold harvest and identifiers for county, field, and grower. All GPS hemp field coordinates are kept private by government regulators, so we cannot measure grower degree directly. However, the dataset contains hemp acres within a county, hemp processors' county level investment, and other individual field level variables. Figure 2 shows processor investment ($M) and planted hemp acreage (per thousand acres of cropland) per county. While this suggests hemp clustering, we can test for it formally.

We use spatial econometric methods on this county-level data to test the size and importance of spatial patterns of hemp planting and processing in Kentucky. The results of these county-level tests offer a lower bound for within-county spatial correlation: if there is spatial dependence between counties, one would expect it to be at least as pronounced within counties. We test for global and local spatial autocorrelation by estimating the respective Moran's I and Geary's C test statistics, using a row-standardized, "queen" contiguity spatial weights matrix (SWM).[6] The calculated values of both statistics are significant and large: 0.24 for Moran's I, 0.74 for Geary's C. Both reject the null hypothesis of random hemp planting at the 1% significance level.[7] While both suggest significant global and local autocorrelation in 2019 relative planted hemp acres in Kentucky, neither provides a meaningful estimate of spatial autocorrelation's magnitude. If our assumption holds and growers prefer locating near processors, we can test for it

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[6] Queen contiguity denotes spatial units as neighbors if they share a contiguous edge or are diagonal to one another. The $n \times n$ SWM will have a "1" if "row" is a neighbor of "column." Row standardization divides the elements in each row of the SWM by that row's sum to ensure that rows all sum to 1; spatial lags of a variable, $x$, are interpreted as a weighted average of the neighbor's $x$-values; and the spatial autocorrelation coefficient is bounded between -1 and +1.

[7] Inferences are drawn from a bootstrap with 1,000 iterations.

empirically. We estimate this structural model using a regression with a spatial autoregressive lag[8] taking the form seen in Equation 8

$$(8) \qquad \boldsymbol{y} = \alpha + \rho \boldsymbol{W} y + \beta \boldsymbol{x} + \boldsymbol{\epsilon},$$

The variable $\boldsymbol{y}$ denotes relative planted acres of hemp, $\boldsymbol{x}$ is the cumulative capital investment of processors at the beginning of the year ($millions), $\boldsymbol{W}$ is the same (standardized) SWM used previously, and $\boldsymbol{\epsilon}$ is a normally distributed residual. Parameter $\rho$ measures the size of spatial autocorrelation in the dependent variable. Table 1 shows the maximum likelihood estimation (MLE) point estimates with their inferences, the average effects of processor capital investment, the regression fit statistics, and, most importantly, the magnitude and significance of $\rho$.

Spatial autocorrelation matters, even at the county level. The spatial autocorrelation coefficient, $\rho$, is large and statistically significant. This means that a county's relative hemp acreage is correlated with neighboring counties' relative hemp acreage.[9] Processors' role in planting decisions also matter. All marginal effects are highly significant, and the magnitudes are noteworthy: the average total effect an additional million dollars of capital invested prior to 2019

[8] We fail to reject the Lagrange multiplier test for spatial serial correlation (autocorrelated errors) and therefore do not estimate a spatial ARAR (lagged dependent variable and residuals, or "double-autoregressive") model.

[9] This aligns with some of the work in the peer-effect or reflection literature (see Manski 1993; Munshi 2004; Shikuku 2019; Skallsveen et al. 2020; Takahashi et al. 2020), where there is knowledge diffusion between growers. However, that diffusion is less pronounced in contexts involving high levels of experimentation, which was the case in hemp during our study period.

increases hemp planting in a county by 0.68 acres per thousand acres of cropland. The first quartile of the distribution of county relative hemp acreage is only slightly greater (0.77 acres per thousand acres) which suggests this effect is quite large. While quantifying spatial relationships between neighbors is essential for building an accurate network structure, the causal mechanisms underlying those relationships are beyond the scope of this work.

We then estimate the distribution of neighbor degree using Monte Carlo methods, with the above econometric results as our guide. We estimate three sets of degree distributions in response to three spatial autocorrelation assumptions. Our econometric model establishes a baseline assumption for spatial autocorrelation $\rho$, specifically, $\hat{\rho} = 0.47$, indicating moderate spatial clustering. Because this effect is likely an underestimate, we also consider a case of strong spatial clustering: $\rho_{high} = 0.95$. While it is unlikely that $\rho < 0.47$, we do consider a case of random field location, $\rho_{low} = 0$, for sake of completeness. Having this set of values for $\rho$ allows us to recover three separate degree distributions or network structures and analyze the implications for tipping points, steady states, and policies aimed at curbing pollination. This enhances the generalizability of our work and acts as a robustness check for policy analysis. When computing degree, we also consider three regional grower densities and three maximum travel distances for pollen.

The initial step in our Monte Carlo is to construct a symmetric grid representing a large area. This grid can represent a county or region spanning multiple counties, thereby avoiding the problems of arbitrarily defined county borders and therefore ecological fallacy (see Dall'Erba and Domínguez 2016; Bae and Dall'Erba 2021) and possible cross-county pollination. Kentucky's median county size is 201,222 acres. Due to computational dimensionality constraints, we modeled a proportional area of 100,489 acres. We populated this grid with a random uniform variable of length $n = 317^2 = 100{,}489$ consisting of zeroes and ones in quantity proportional to grower density. Ones ("1") denote acres planted with hemp, and zeroes ("0") anything else.

Using the Kentucky county-level hemp data, we parameterize a range of hemp planting densities. The county level quantiles of hemp acreage are the first quartile, 0.77 acres per thousand acres of cropland; the median, 2.1 acres per thousand; and the third quartile, 5.6 acres per thousand. Under the median county, every 1,000 cells in our simulated grid should have about two cells with a value of "1", and 998 with "0". Which cells receive a "1" in a given draw of our Monte Carlo can be either random (left panel of Figure 3) or spatially correlated (right panel of Figure 3) [10].

Once we have simulated our grid, we estimate the distance between all growers (green squares, or those with a "1") to recover the $\Delta d_{ji}$ each grower has on one another. We then calculate each grower's degree. To estimate distance between each grower we compute the Euclidean distance from the centroid of that cell and count the number of cell centroids falling within that radius as neighbors. The marginal effect growers can have on one another is affected by pollen's maximum travel distance, $E_{max}$. Using the previously described relationship of seed count and distance from a pollen source, we determine that pollination between fields falls rapidly. It approaches zero marginal effect at about two miles. Because factors like topography, weather, and field size all can affect hemp pollen's travel distance, we consider two other scenarios: We use the same functional form to fit $\Delta d_{ji}$ to maximum pollen travel of one mile and three miles. Using the

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[10] We consider feminized and non-feminized together. Neighbor status does not distinguish between the two in network diffusion models. This abstraction makes the model solvable. A limitation of this assumption is that it does not directly account for fiber and grain fields typically being larger than an acre. This reinforces the need to include spatial correlation between fields.

estimated negative exponential or weighted degree function for each qualified neighbor located at a distance $E_{ji}$ away from the populated cell, we compute the degree for that cell as $d_i = \sum_{j=1}^{J_i} \Delta d_{ji}$:

(9) $$\Delta d_{ji}(E_{ji}) = \begin{cases} (e^{-0.00098E_{ji}} \big| E_{max} = 1\ mile) \\ (e^{-0.00049E_{ji}} \big| E_{max} = 2\ miles). \\ (e^{-0.00033E_{ji}} \big| E_{max} = 3\ miles) \end{cases}$$

We calculate individual degree for all growers in a network (simulated grid) for the previous planting densities, spatial correlations, and pollen travel distances. Visualized in Figure 3, $E_{max}$ affects the number of growers in a grid that are close enough to be counted as neighbors, grower density affects the total number of growers within the grid (marked as green cells), and $\rho$ influences the location decisions of growers (whether green cells are dispersed or clustered). Online Supplementary Appendix A details an empirical implementation of degree calculation across various levels of $\rho$.

Once we have the total degree for each grower within the network, we estimate the network's distribution of degree. We use the distribution fitting function in the @RISK software for this. Best fit is based upon the Akaike Information Criterion. We estimate seven network structures. Our baseline network is $E_{max}$= 2 miles, $\rho = 0.47$, and grower density = 210 acres of hemp per 100,000 acres of cropland. We then run comparative statics for higher and lower levels of $E_{max}$, $\rho$, and grower density. Figure 4 demonstrates the effect of these parameter levels on network structure.

Figure 4A shows the effect of spatial autocorrelation, $\rho$, on network structure. Average degree and variability in degree are both increasing in $\rho$. Spatial clustering pulls neighbors into closer proximity which increases degree. The increased proximity raises the degree for growers within the center of the network. It also leaves growers on the spatial periphery with fewer neighbors than they would otherwise have. Figures 4B and 4C have similar results where degree averages and variability are increasing in grower density and $E_{max}$ (see Online Supplementary Appendix A for details).

After matching individual growers with their counter-factual payoffs using Propensity Score Matching (see Online Supplementary Appendix D for details), we estimate the payoff distributions for switching to non-feminized hemp. Table 2 reports summary statistics from the matched samples. Average payoff to feminized hemp is higher, but so is the potential for large losses. Our estimated mean revenue, operating cost, and profit of both crops are comparable to those in enterprise budgets developed by various extension offices. We then use these figures from the matched samples for operating cost, revenue, and profit in order to estimate the individual ratio of $\frac{v_i}{c_i}$ for grower $i$ and subsequently fit the distribution of that ratio for all growers in the matched samples using @RISK. The functional form that best fit the distribution of the benefit-cost ratio was an exponential distribution with a mean of 1.4910 and a shift parameter of 1.2595.

**Results**

We use our estimated network structures to calculate the tipping point ${x_0}^*$, the steady state after the tip $ss^*$, and the total pollination damage at the regional level. Recall that the tipping point is the percentage of non-feminized adopters required to tip the network to a new equilibrium (i.e., the steady state of increased non-feminized production).

Figure 5 illustrates the mechanics of tipping points and steady states. The horizontal axis denotes the percentage of non-feminized adopters in time 0 and the vertical axis denotes the percentage of non-feminized adopters resulting in period 1. The blue line captures the relationship between $x_0$ and $x_1$ under our baseline network assumptions. The orange curve is a 45º line. Whenever the blue line is higher than the orange line, adopters of non-feminized increase between periods. When blue is lower, they decrease. The points where the blue and orange curves intersect are the areas of interest. The first intersection point, ${x_0}^*$ , denotes the percentage of non-feminized adopters that causes a tip. If $x_0 > 0.045$, there will be more non-feminized adopters in period 1 than in period 0. If $x_0 = 0.10$, then $x_1 = 0.35$ and $x_2 = 0.86$. One can project over time by taking $x_1$ in response to $x_0$ and plugging it back in for $x_0$ to see what would happen in period 2. The second intersection point denotes the steady state occurring after a tip. Once the network reaches a steady state, no grower wants to change crops.

Tables 3-5 contain tipping points, steady states, and long-term network damage occurring across various network structures. These network diffusion results identify the adoption thresholds necessary to stay below in order to prevent large-scale damage, and can estimate the cost of failing to enact timely policy. It is therefore unsurprising that the tipping point and steady state get reported in all other applications of network diffusion. Their interpretations are by construction longer term in nature. When applied to the volatile hemp markets, they do not provide a complete picture by themselves.

Consequently, we also calculate and report "single-season" results in Tables 3-5. This includes both single-season damage and switching. We also include years required to reach$ss^*$. These enrich the network diffusion results by disentangling how much damage, switching, and tipping is likely to occur after the first growing season. Predictions for the first growing season or two will be more important and qualitatively useful for hemp than those made many more years into the future. We conducted single-season comparative statics under the assumption the initial adoption rate of non-feminized hemp in time 0 was 7% and network changes progressed from there (KDA 2019). Seven percent was the average non-feminized adoption rate in Kentucky in 2019. This differs from the network diffusion results which calculate a unique tipping point and steady state.

Parameter $T|(x_0 = 0.07)$ denotes the number of years required to reach a stable Nash Equilibrium in a given network structure with a 7% non-feminized hemp adoption rate at time 0. This elucidates what a steady state means in a hemp application. A steady state level occurring two years in the future may be qualitatively useful, especially if most of the switching occurs in the first year, but one occurring four years in the future would be less meaningful for hemp markets. We also estimate non-floral adoption rate after one season, $x_1|(x_0 = 0.07)$ , and the associated damage over that first season, $FSD|(x_0 = 0.07)$.

Table 3 displays the tipping points, steady states, single-season changes, years to steady state, and both short- and long-term pollination damages that occur under various levels of spatial autocorrelation, $\rho$. Tipping occurs at low thresholds of non-feminized adoption rates in all cases, but further decreases when $\rho$ increases. It is easier to prevent a tip when $\rho$ is low. However, once a tip begins, non-feminized adoption occurs at a level just short of a corner solution for all $\rho$ levels. These similar steady states lead to similar damages. While pollination damage is similar in all cases, it follows a nonlinear response to $\rho$. Low levels of $\rho$ guarantee the grid is sufficiently full that very few growers have no neighbors, but $\rho$ being very high forces all neighbors in the grid to be close; $\rho$ = 0.47 meanwhile pulls most neighbors close together but creates a large area where a small number of growers are sufficiently remote to remain undamaged. This is why the steady state and resulting damage are slightly lower for $\rho$ = 0.47.

Spatial autocorrelation has a more pronounced effect on single-season results. The associated damage and switching occurring over a season varies dramatically across $\rho$. In the uncorrelated case, $x_0 = 7\%$ was insufficient to cause a tip and non-feminized adoption was predicted to fall to 0% over two seasons – pollination damage was not an issue. Conversely, when

$\rho = 0.95$, almost 40% of the network was sufficiently damaged to switch in the first season. Over 99% of the network adopted non-feminized in just three seasons.

Table 4 displays the comparative statics associated with grower density. As growers become denser, tipping points decrease and steady states increase. Tips are easier to prevent in a low-density situation, though preventing them has a lower payoff. Grower density in some regions may change over time as more growers enter or leave hemp markets.[11] This creates a moving target for policy makers, which means that policies will need to be adjusted over time. This highlights the benefits of enacting policy early and proactively to prevent tips.

Results were even starker across densities for the single-season parameters. Under a 7% initial non-feminized adoption rate, non-floral adoption died out in the low-density network, but non-feminized adoption rates jumped from 7% to 71.5% in one season under the high-density network. Including single-season parameters also enriches baseline density results. While the steady state after a tip was an estimated 97.5% non-feminized hemp adoption, the first season damage switching would be low when $x_0 = 7\%$. Moreover, it would take four years to reach that steady state. Pollination would still be a serious issue under baseline assumptions, but less so if one only looked at steady state and associated damage.

[11] We relax the assumption of constant network structure over time and test the effect of grower "attrition" in Online Supplementary Appendix E. Modeling 50% of damaged growers leaving the network after reduced grower density over time reduced steady state adoption rates and increased the years it took to reach a steady state. It did not affect the qualitative results that once a tip occurs the externality becomes more difficult to stop.

Table 5 shows the effect of maximum pollen travel distance, $E_{max}$, on tipping points and steady states. Factors like topography, forestation, and wind speed all affect how far hemp pollen travels. Interestingly, there is a clear diminishing marginal effect associated with $E_{max}$. Moving from $E_{max}$ = 1 to $E_{max}$ = 2 dramatically lowers the tipping point and increases the resulting steady state. Changing from $E_{max}$ = 2 to $E_{max}$ = 3 has a smaller effect. Single-season results follow a similar pattern to those in Tables 3 and 4. Under $E_{max} = 1$, non-floral production dies out when $x_0 = 0.07$. When $E_{max} = 3\, miles$, adoption rates jump from 7% to 58.3% in the first season, and the steady state is hit after two years. Hemp pollination would be especially problematic in scenarios where pollen travels further. Without legislation, it is possible to envision a scenario where regions of natural pollination barriers (low wind and diverse topography) and/or greenhouse infrastructure are the only viable places to grow feminized hemp in the future.

Tables 3–5 show that four of the seven considered networks would receive large amounts of pollination damage under Kentucky's average non-feminized adoption rate in 2019. If a tip occurs, the damage associated with pollination becomes large in all seven cases. This damage becomes more difficult to prevent under higher spatial correlation, higher grower density, and higher maximum pollen travel distance. Damage increases with higher grower density and higher pollen travel distance.

While many counties in Kentucky grew only feminized hemp in 2019, we identified 20 counties where observed levels of non-feminized hemp adoption rates and grower densities at the county level would put feminized growers at risk of damage and the network at risk of tipping (Table 6). Based upon these at-risk counties and the damage associated with hemp cross-pollination in 2019, policy may have been warranted in some regions. In the following section, we discuss the likely effectiveness of various public and private tools aimed at reducing pollen damage.

It would be possible to separate non-feminized and feminized growers into different geographic zones to limit pollination damage. In all seven cases, marginal pollination rates followed exponential decay functions with respect to distance. By ensuring feminized and non-feminized fields were spatially separated, a tip could be avoided. However, this would be politically difficult. It forces some growers who prefer growing one cultivar to grow the other. This is unlikely to be an attractive policy to either grower type and was a factor for the 2019 repeal of geographic spacing in Washington State.

Researchers have discussed temporally spacing various cultivar planting dates, to stagger when these crops enter their reproductive cycles. There has also been research to develop hemp strains that flower asynchronously to achieve these same ends. We would expect temporal spacing of cultivars to have a similar effect on network structure as reducing the hemp grower density (Table 4). Neighbors only count as neighbors if they can pollinate one another. This would raise tipping points and reduce pollen damage. The drawback to this policy is the lack of data available to quantify its effectiveness. Hemp genetics that dictate photoperiod sensitivity and/or duration from planting to flowering further complicate this problem. Due to the low implementation cost, it should be worth pursuing even for modest pollination reduction.

Taxes levied upon non-feminized producers affect the distribution of the payoff ratio for switching to non-feminized hemp, $R$. Having to pay a tax to grow non-feminized hemp makes it less attractive and should increase tipping point and reduce steady state levels. We tested taxes imposed on non-feminized producers of \$100 per acre and \$200 per acre in our tipping model, under all seven network structures. Taxes had no meaningful effect on tipping dynamics or pollination damage.[12] This is surprising because taxes are often touted as an effective tool for reducing externalities. The damage from pollination is much higher than any tax level that allows non-feminized hemp production to continue.

Provided non-feminized hemp is more profitable than commodities, a $200 per acre tax does not affect grower decisions because the damage from pollination would be over $10,000 per acre. Growers produce feminized hemp until they become sufficiently pollinated to switch to non-feminized hemp. The tax changes the magnitude of payoffs between the two crops but not the cultivar choice (e.g., $R_i = \frac{b_i}{c_i}$ changes from 1.4 to 1.3). Taxes are unlikely to be effective for reducing cross-pollination damage. They also directly harm one set of producers to protect another, making them unlikely to be politically attractive.

If a state government established a regional quota for percentage of total growers allowed to grow non-feminized just below the tipping point, the tip would be avoided. Quotas would cap the $x_0$ allowed within a region, $\hat{x}_0 < {x_0}^*$ for that region. For the quota system to be successful, quota levels should be crafted at the county or regional level each growing season to capture unique economic and network structure variables of that area. A quota system should be effective in times and regions in which externality damage is high, the current $x_0$ is low, and data is reliable.

Currently, Kentucky has no legislation governing hemp pollination. This means that in practice, non-feminized hemp producers retain the right to emit pollen. Policy could re-establish

[12] Margins on pollen-shedding hemp in 2019 were on average more attractive than row crops but were still thin. We did not consider higher taxes as they would effectively mean a ban on pollen-shedding hemp and force growers back into row crops. While outright bans are theoretically possible, we did not consider them due to numerous economic and political drawbacks.

this right, giving feminized producers the right to not be pollinated, by mandating non-feminized growers plant windrows around their fields. This would reduce maximum pollen travel distance. It also would reduce $R_i$ by increasing the cost of growing non-feminized hemp. This policy is risky, and no one has quantified the effect of windrow crops on reducing $E_{max}$. Windrows impose additional cost on non-feminized growers in terms of actual cost and reduced acreage available for agriculture. This policy would likely be unattractive due to its potentially high cost and uncertain payout. If future research finds windrows effectively reduce $E_{max}$, then it could become viable.

In a simpler problem, Coasian bargaining could prevail. Feminized growers could compensate non-feminized producers to exit production. Such a solution is likely infeasible in this application, given hemp pollen's travel distance ties numerous growers together. These growers often do not know what every neighbor within a two-mile radius is planning to grow at the time planting decisions are made, making the bargaining cost high. These transaction costs would force feminized growers to either exit production or incur expensive fixed costs to reduce pollen exposure.

Potential technologies capable of this include greenhouses and pollen-resistant triploid cultivars under development (Kurtz et al. 2020; Crawford et al. 2021). These technologies would have an offsetting effect on tipping. They would increase $R$ but reduce the marginal effect of neighbors on $\Delta d_{ji}$. This solution is unlikely to be cost-effective for hemp: over 90% of growers in Kentucky were growing feminized hemp at the time, and cannabinoid prices were high. Greenhouses are costly, and pollen-resistant strains are not yet commercially available. Business as usual could be attractive in situations where most growers are already non-feminized and/or cannabinoid prices are low. Longer-term, sterile triploid cultivars for cannabinoid production could be attractive if they became commercially available for prices at or below current levels.

**Conclusions**

This study set out to develop generalizable estimation techniques that adopt network diffusion models to accommodate Spatial Agricultural Network Externality Problems. It applied these estimation techniques to the hemp cross-pollination problem to both illustrate them and identify cost-effective policy responses to mitigate pollination damage in hemp markets. Changing network structure parameters has large impacts on single season damages and longer-term tipping dynamics for SANEP problems. Additionally, due to the self-reinforcing nature of adoption within networks, alleviating the effects of SANEPs is cheaper and easier to do before a tip has occurred.

Network structure greatly influences pollination damage. Under the state average 7% non-feminized adoption rate, three of the seven considered networks would not have received any meaningful damage and non-feminized adoption would die out. Another three network structures had hemp pollination damage affecting over 90% of growers within the network. We found that a non-floral quota system combined with intertemporal spacing across hemp cultivars was likely to be the most cost-effective policy available for hemp cross-pollination.

While network diffusion can be applied to many SANEPs, it is important to highlight what assumptions must hold. The two relevant crops within a region must be an externality-producing crop and a crop harmed by the externality. The best crop and its opportunity cost will vary across regions and will over time. In 2019, prices were low for commodities, and Kentucky's other chief crop, tobacco. There was interest in all hemp cultivars at the time due to higher expected returns (Cui and Smith 2019; Kime 2019; Mark and Shepard 2019; Place 2019a). Profit estimates for floral hemp now are down from 2019 and commodity prices are up (Cui and Smith 2020; Shepard and Mark 2021), so feminized and non-feminized hemp may no longer be a grower's two best options.

The opportunity cost crop could also vary by individual. Network structure will change over time if a some pollinated growers stop growing any kind of hemp. Farmer attrition dampens the effect of longer-term dynamics such as steady state adoption and steady state damage.

Under our parameters, we found both taxes and the establishment of property rights to be ineffective for managing hemp cross-pollination. This result is unexpected because taxes and establishment of property rights often are touted as useful policy tools for dealing with negative externality problems. Realistic taxes are too small relative to the externality size. Establishing property rights and allowing negotiation is problematic, because the complexities of networks caused by hemp pollen’s long travel distance would raise transaction costs. Conversely, non-floral permitting combined with intertemporal spacing could be quite effective in alleviating hemp cross-pollination: staggered planting dates allows for a larger quota of non-feminized hemp. Moreover, small changes to planting dates should not impose a large cost on non-feminized hemp growers but reducing pollination could benefit feminized hemp growers.

In our analysis, damage only became a meaningful problem after a tip. These results highlight the importance of reliable network parameter estimation for SANEPs. Without a complete understanding of the network for which legislation is being implemented, policies will be inefficient at best and harmful at worst. Agricultural policy passed in the 1930s contributed to hemp irrelevancy in the United States for decades (Malone and Gomez 2019).

Hemp cross-pollination is a relatively new problem in the United States since hemp was not widely grown until after the 2018 Farm Bill. This makes comparing and contrasting our results to existing policy challenging. However, several states had produced marijuana prior to 2018, and experimented with legislation to curb cross-pollination between hemp and marijuana (pollination also reduces THC). Washington State experimented a four-mile buffer zone between hemp and outdoor marijuana growers. While this policy reduced cross-pollination, it was repealed in 2019. This is consistent with our findings that geographical spacing would not be attractive due to the political difficulty of telling farmers where they are allowed to grow crops. Humboldt County, California banned production of all low-THC hemp cultivars in 2018. This policy would be a corner solution associated with quota-based system where the quota for non-feminized hemp production is set to $\hat{x}_0 = 0$. Without localized hemp agronomic data for Humboldt County, there is no way to know whether level of quota or even the quota itself is optimal for that network, but due to the large amount of hemp acreage in Humboldt County and hemp pollen's long travel distance, a low level of legal non-feminized adoption seems reasonable.

Longer term, the commercial rollout of feminized cultivars immune to pollination (called "triploid") would alleviate the problem we analyzed, limiting the need for policy intervention. However, since that technology is not commercially available yet, we require policy to mitigate pollination externalities for the immediate future in hemp production. It is worth mentioning that the direct policy implications in this paper are strictly derived from the premise of Kentucky policy makers in 2019 wanting to cost-effectively reduce hemp cross-pollination. Hemp product prices, network structure, and policy maker goals change over time and space. Thus, our analysis is not suggesting a one-size-fits-all static policy for the ever-changing domestic hemp market. Instead, we seek to use a timely and interesting empirical example to highlight the ability of our approach to parameterize, model, and find cost-effective solutions for alleviating SANEPs.

The ability to estimate the parameters necessary to model SANEPs has numerous applications. This tool will grow in importance in the future as agricultural producers continue to segment into increasingly specialized niches that rely on uncompromised crop attributes to create value. An obvious extension of our framework is to explore the cases of other types of non-floral feminized hemp production. Hemp growers looking to optimize seed genetics or produce marijuana would also be negatively affected by their neighbors growing non-feminized cultivars. This framework could also be useful for modeling the impact of chemical runoff on neighboring organic certifications or herbicide drift. Soybean growers in several states, including Kentucky, are grappling with herbicide drift between neighbors growing Dicamba-resistant and non-resistant soybeans. Our framework and parameterization methods are appropriate to study these problems, provided the researchers changed the parameter values. Crop choice, number of agents within a network, technology,[13] and prices can all vary dramatically across time and space. This suggests that modeling choices and policies for dealing with SANEPs should evolve also.

Another extension of work includes adding in farmer risk aversion. We assumed risk neutrality to focus on the interactions among networks, externalities and pollination damage. This abstraction discounts the fact that feminized hemp is riskier to produce than non-feminized (Mark et al. 2020). Incorporating growers' risk preferences could be accomplished by modifying the distribution of $\frac{v_i}{c_i}$ to make payoffs a function of utility rather than just a function of expected payouts. Additionally, all forms of hemp carry a risk source that commodity crops do not: legal risk. Any hemp crop that tests above the legal threshold for THC content is lost and not covered by federal crop insurance. This legal risk amplifies all other forms of risk hemp growers face

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[13] Supply chains for floral hemp are different in Europe's older hemp industry. One difference is European processors' ability to refine floral material with lower CBD concentrations and higher seed content. Floral growers can sell pollinated floral material. If the U.S. floral market develops in that fashion, tipping will become even more likely, but pollination damage would be lower.

(Raszap Skoriabsky, Thornsbury, and Camp 2021). This would have implications for what the two most attractive crop choices would be for any grower who is not risk neutral.

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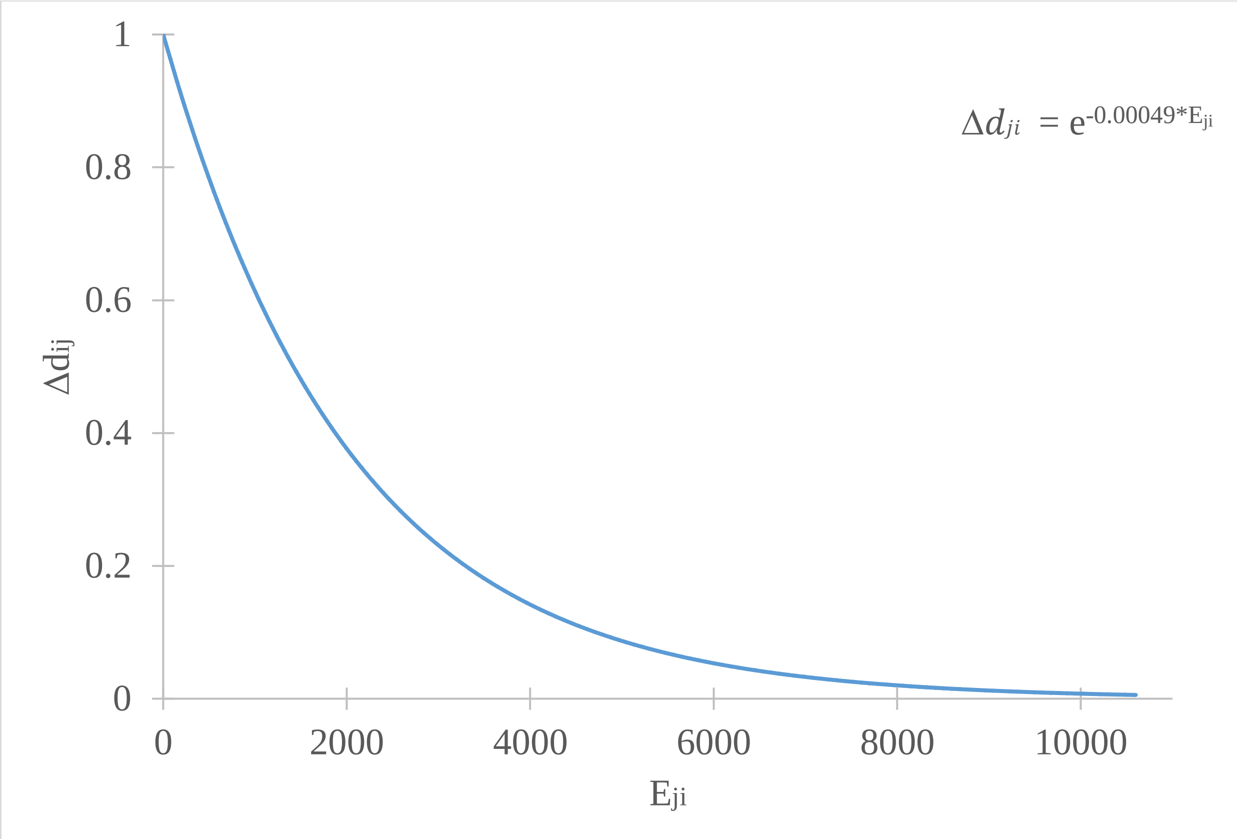


Figure 1. Marginal contribution of neighbor $j$ to grower $i's$ degree, as a function of field distance

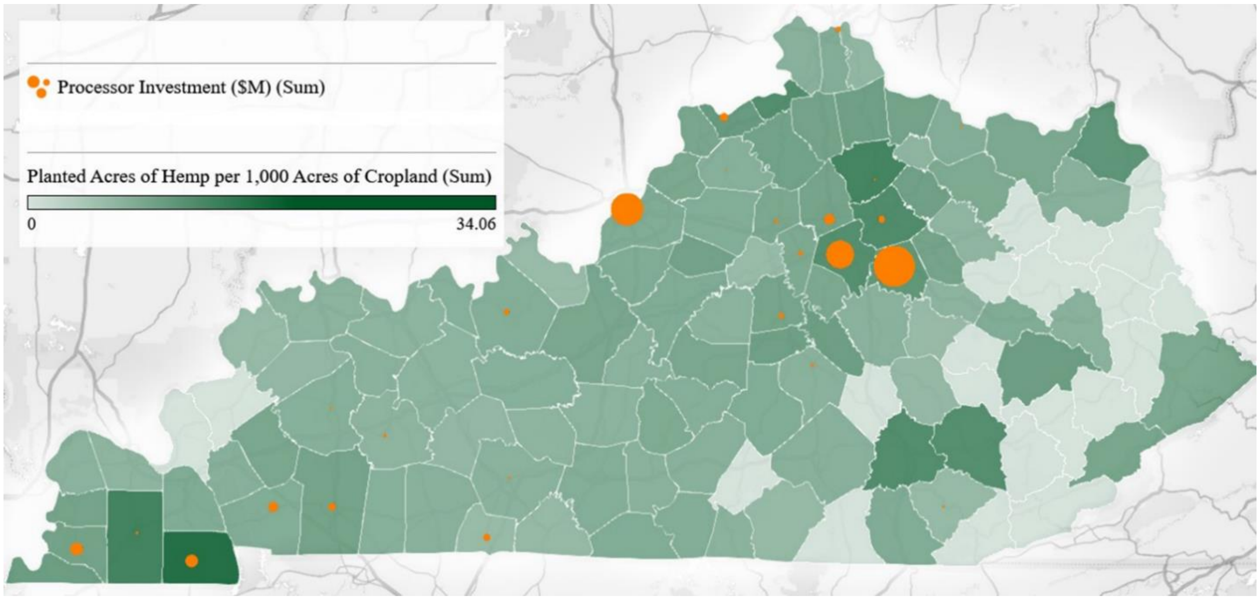


Figure 2. Relationship between capital investment by hemp processors and relative acres of hemp in Kentucky (2019 crop year)

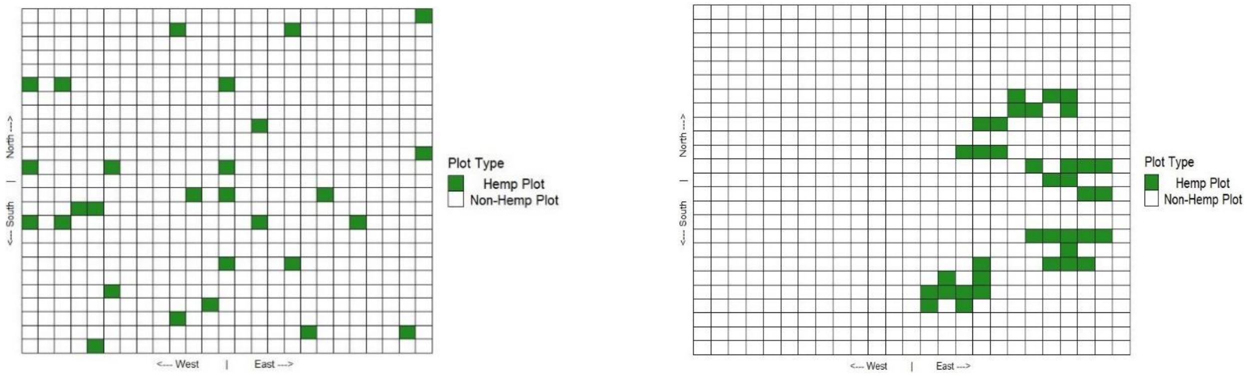


Figure 3. An example 25x25 grid, with (left) spatially random hemp plots, $\rho = 0$; (right) spatially clustered hemp plots, $\rho = 0.95$.

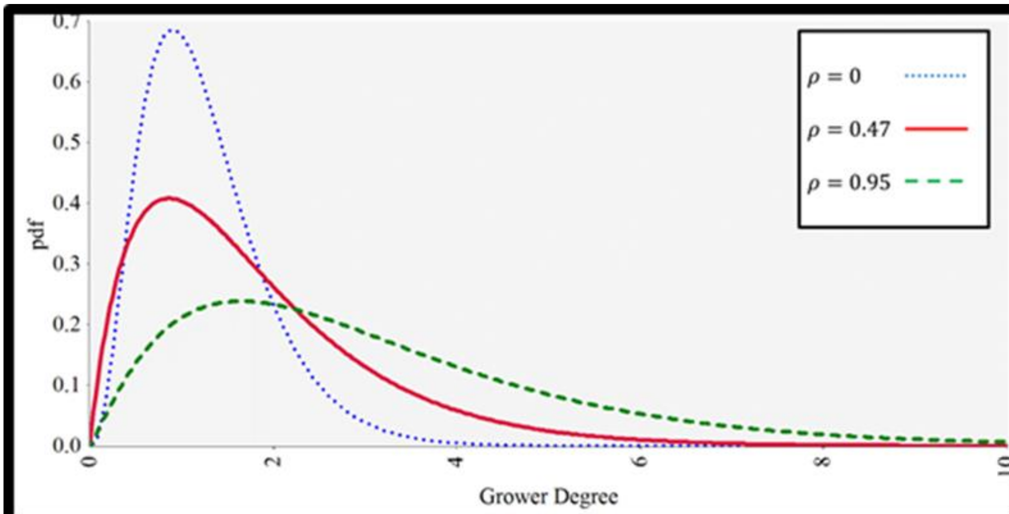


**Figure 4A:** The effect of $\rho$ on hemp network structure

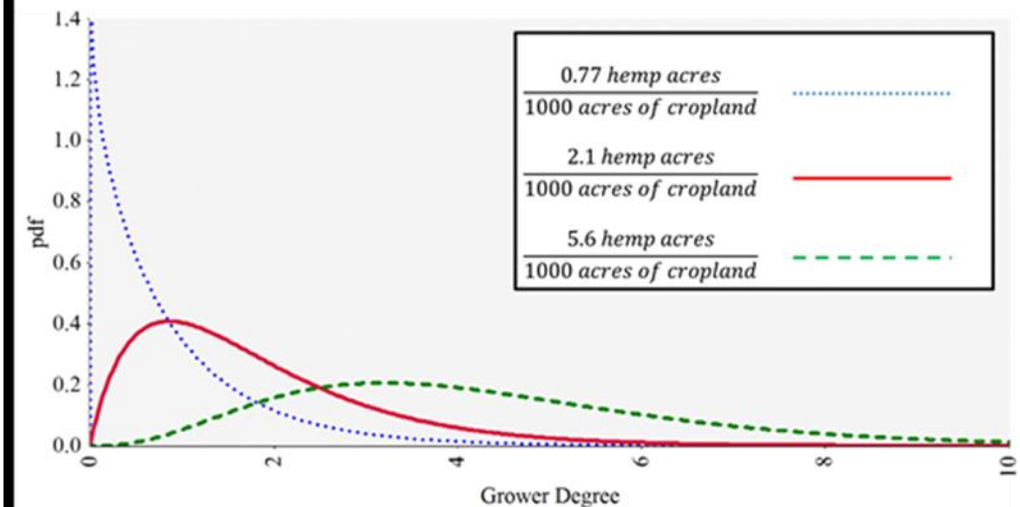


**Figure 4B:** The effect of hemp grower density on hemp network structure

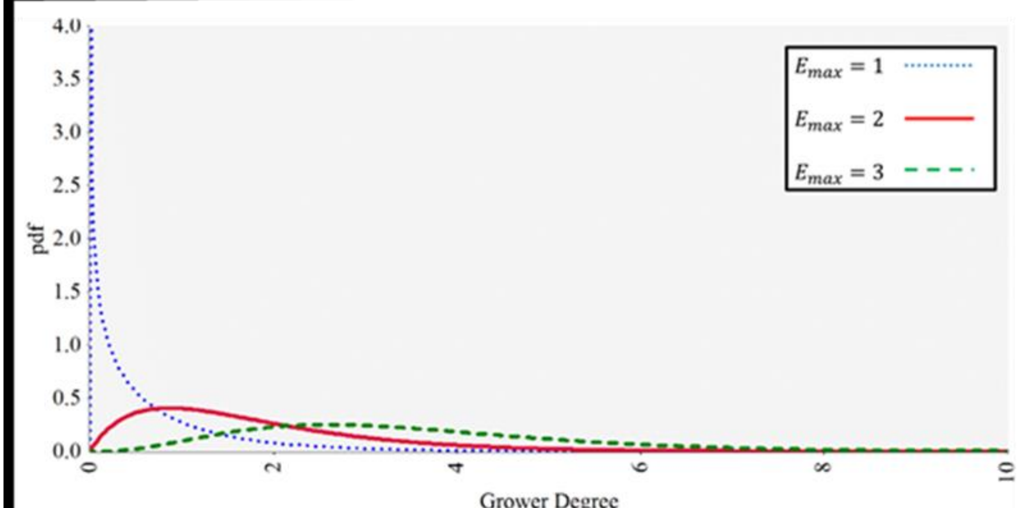


**Figure 4C:** The effect of $E_{max}$ on hemp network structure

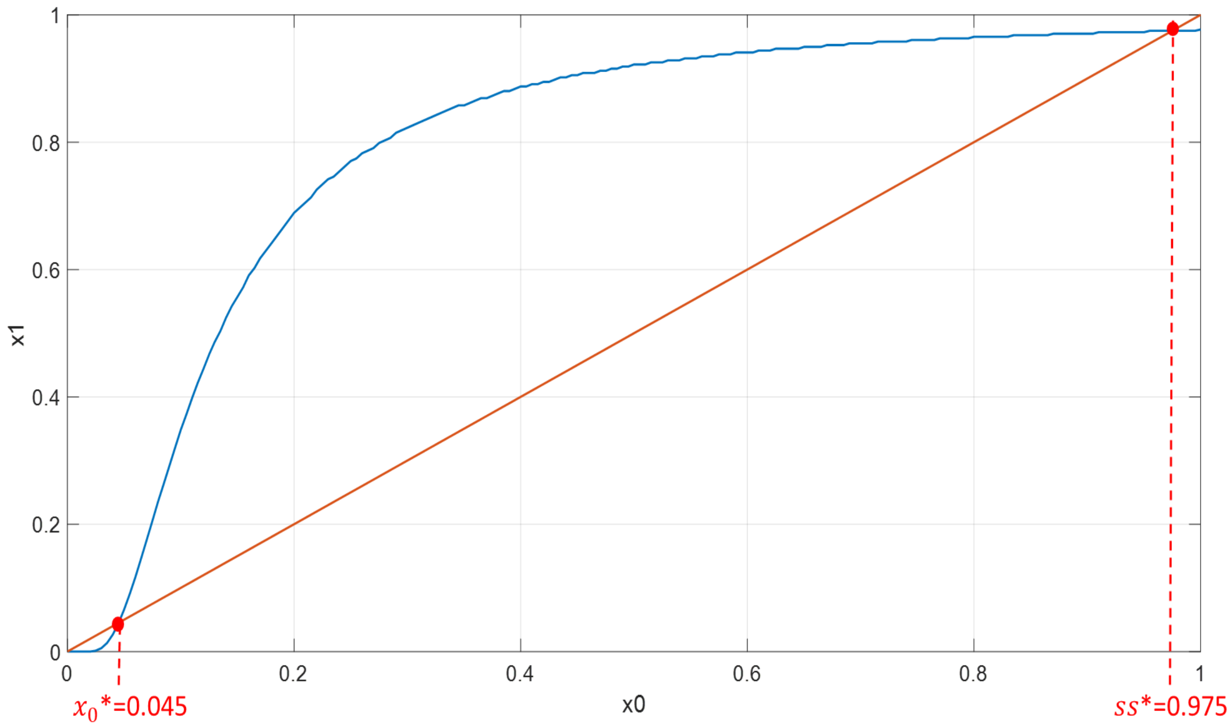


Figure 5. Tipping point and steady state analysis of baseline network structure

Table 1a. Spatial Autoregressive Lag MLE Results

| Parameter | Estimate | Std. Error | z-value |
|---|---|---|---|
| Intercept ($\beta_0$) | 1.45 | 0.58 | 2.82*** |
| Capital Investment ($\beta_1$) | 0.34 | 0.15 | 2.29** |
| Spatial Lag ($\rho$) | 0.47 | 0.11 | 4.92*** |

Note. Single, double, and triple asterisks (*, **, ***) denote statistical significance at the 10%, 5%, and 1% levels, respectively. The pseudo-$R^2$ is 0.22, the log likelihood is -364.06, the AIC is 736.11, and the likelihood ratio statistic is 14.03 with $p$-value 0.00.

Table 1b. Spatial Autoregressive Lag Decomposed Effects

| Effect: Capital Investment | Magnitude | Std. Error | z-value |
|---|---|---|---|
| Average Direct Effect | 0.37 | 0.01 | 71.75*** |
| Average Indirect Effect | 0.31 | 0.01 | 48.02*** |
| Average Total Effect | 0.68 | 0.01 | 63.32*** |

Note: The standard errors of all average effects are bootstrapped with B = 1,000 iterations. Single, double, and triple asterisks (*, **, ***) denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2. Summary Statistics by Hemp Type (matched sample)

| Primary Harvest | Min. | Max. | Mean | Std. Dev. | Median |
|---|---|---|---|---|---|
| Feminized Hemp (n=58) | | | | | |
| Gross Revenue | $642 | $49,119 | $10,572 | $9,335 | $6,521 |
| Operating Costs | $99 | $37,818 | $5,613 | $6,641 | $2,400 |
| Profit | $542 | $13,200 | $4,959 | $3,190 | $4,959 |
| Non-Feminized Hemp (n=11) | | | | | |
| Gross Revenue | $421 | $767 | $619 | $89 | $642 |
| Operating Costs | $66 | $467 | $148 | $123 | $99 |
| Profit | $200 | $550 | $471 | $125 | $538 |

Note: Figures derived from authors' calculations on matched sample from KDA 2019 Grower and Processor reports. Units are in dollars per acre. Any hemp that was planted but not sold was omitted from the matching pool. This allowed us to avoid double counting the effect of cross-pollination within our modeling. Both types of hemp can be considered the range of outcomes if everything goes well. The negative externality is included as a separate parameter.

Table 3. Tipping, Steady State and Single Season Response to Spatial Correlation "$\rho$"

| | $\rho$ = 0.00 | $\rho$ = 0.47 | $\rho$ = 0.95 |
|---|---|---|---|
| Tipping point | 9.1% | 4.6% | 2.6% |
| Steady state | 99.3% | 97.5% | 99.4% |
| Total damage at steady state | $2,012,795 | $1,976,708 | $2,014,620 |
| $T\|(x_0 = 0.07)$ | 2 | 4 | 3 |
| $x_1\|(x_0 = 0.07)$ | 2.5% | 17.6% | 45.2% |
| $FSD\|(x_0 = 0.07)$ | $0 | $214,498 | $774,869 |

Note: This damage constitutes a lower bound for pollination losses in 2019. There is a direct loss from the pollination (reported) and a loss in profitability from switching to a less lucrative crop. Prices of various hemp cultivars will change over time. Rather than making price projections based on only three years of data we decided to estimate a lower bound for damage. Including the present value of loss associated with a less valuable crop would increase this estimate. Additionally, feral hemp can pollinate feminized fields. Due to lack of data, we could not include it in our modeling but inclusion of feral hemp would further lower tipping points, increase steady states, and increase pollination damage.

Table 4. Tipping, Steady State and Single Season Response to Grower Density

| | Low density: 77 acres/region | Medium density: 210 acres/region | High density: 560 acres/region |
|---|---|---|---|
| Tipping point | 9.4% | 4.6% | 2.3% |
| Steady state | 70.8% | 97.5% | 100.0% |
| Total damage at steady state | $526,460 | $1,976,708 | $5,406,380 |
| $T\|(x_0 = 0.07)$ | 3 | 4 | 2 |
| $x_1\|(x_0 = 0.07)$ | 4.3% | 17.6% | 71.5% |
| $FSD\|(x_0 = 0.07)$ | $0 | $264,169 | $3,486,574 |

Table 5. Tipping, Steady State and Single Season Response to Pollen Travel Distance

| | $E_{max} = 1\ mile$ | $E_{max} = 2\ miles$ | $E_{max} = 3\ miles$ |
|---|---|---|---|
| Tipping point | 13.4% | 4.6% | 2.7% |
| Steady state | 50.8% | 97.5% | 100.0% |
| Total damage at steady state | $1,028,902 | $1,976,708 | $2,027,393 |
| $T\|(x_0 = 0.07)$ | 2 | 4 | 2 |
| $x_1\|(x_0 = 0.07)$ | 3.0% | 17.6% | 58.3% |
| $FSD\|(x_0 = 0.07)$ | $0 | $264,169 | $1,040,052 |

Table 6. Kentucky Counties Most Vulnerable to Tipping Post-2019 Crop Year

| County Name | Hemp Acres per 1,000 total acres | $x_0$ |
|---|---|---|
| Hickman | 6.09 | 100.00% |
| Whitley | 2.52 | 98.35% |
| Oldham | 3.91 | 88.79% |
| Greenup | 13.16 | 85.10% |
| Trimble | 4.84 | 68.76% |
| Lewis | 3.94 | 63.83% |
| Caldwell | 4.11 | 52.32% |
| Spencer | 6.60 | 52.20% |
| Metcalfe | 0.77 | 48.51% |
| Carter | 1.15 | 48.51% |
| Casey | 2.32 | 44.82% |
| Fulton | 8.47 | 39.59% |
| Franklin | 3.98 | 29.97% |
| Shelby | 2.13 | 29.06% |
| Carlisle | 5.73 | 12.17% |
| Jefferson | 2.44 | 10.84% |
| Christian | 5.60 | 8.08% |
| Kenton | 1.95 | 6.46% |
| Jessamine | 4.02 | 3.84% |
| Bourbon | 17.98 | 2.60% |

Note: Observations are from 2019.