WORKING PAPERS

N° 1545

June 2024

“Yes, in your backyard: Forced technological adoption and spatial externalities”

Anouch Missirian

Toulouse School of Economics

Yes, in your backyard: Forced technological adoption and spatial externalities*

Anouch Missirian†

Version: 5th June 2024

Abstract

I study a phenomenon of hastened technology adoption facilitated by a negative spatial externality. GMO seeds have been engineered to withstand the application of particular weedkillers: farmers can use them in-crop, killing the weeds, leaving the crop unscathed. I show that the adoption of such seeds generates negative externalities on downwind neighbors, increasing the probability of the adoption of the same seed by 29% as well as a conversion of cropland to different crops able to withstand the weedkiller. Overall yields remained unchanged as the benefits of the weedkiller on yields are offset by the negative effects of crop failures for neighbors. Consequences of such rapid adoption include possible monopolization on the seed market.

Keywords: technology adoption, spatial externalities, land use, pesticides.
JEL Classification: Q5, Q15, Q16, O33.

*I am much indebted to my advisors Wolfram Schlenker, Douglas Almond, Jeffrey Shrader, Shahid Naeem for their invaluable advice and support. I thank Geoffrey Heal, Rodrigo Soares, Suresh Naidu, Eyal Frank, Ignacia Mercadal for their precious guidance. I am also grateful to Anthony D'Agostino, Eugénie Dugoua, Florian Grosset, Kyle Meng, Marion Desquilbet; participants to the Sustainable Development seminar at Columbia, members of the Schlenker Lab, members of emLab, members of the UMR d'Economie Publique (now PSAE) and of the UMR Centre d'Economie de l'Environnement - Montpellier (CEE-M) at INRAe; participants at the LSE Workshop in Environmental Economics, and at the Causal Inference with Spatial Data workshop in Essen for their comments. Errors are mine.

†Toulouse School of Economics & INRAe. 1 esplanade de l'Université, 31000 Toulouse, France. Email: anouch.missirian@tse-fr.eu.

Introduction

The adoption of new technologies is often slow. Sometimes inefficiently so, because of frictions such as knowledge spillovers or aversion to change (Sunding and Zilberman, 2001; Jaffe et al., 2005; Cowan and Gunby, 1996). For instance, Griliches (1957) describes the adoption of the newly developed hybrid corn seeds in the 1930s-1950s. Full adoption of these higher-yielding seed varieties within a state took anywhere from six to more than twenty years, in part because of a slow-paced social learning process. More recently, the adoption of the glyphosate-tolerant varieties of soybean took over ten years (see Figure S1). Slow adoption of productivity-enhancing technologies is a problem for growth (Solow, 1957; Abramovitz, 1986; Arrow, 1962), and eliminating frictions to adoption is an important policy issue, in particular for development (Besley and Case, 1993; Jack, 2013), and more recently in light of the ongoing environmental transition. On the other hand, fast adoption can result in lock-in (David, 1985; Choi and Thum, 1998); market power (Reinganum, 1989); public health or environmental disasters (e.g., consider asbestos (Thives et al., 2022), or chlordecone (an insecticide) (Multigner et al., 2016)).

In this paper, I study a phenomenon of hastened technology adoption facilitated by a negative spatial externality imposed by adopters on non-adopters. Indeed in contrast to the agricultural technologies mentioned above, dicamba-tolerant (DT) seeds have been adopted extremely rapidly. Within four years of their release in 2015, dicamba-tolerant seeds made up 80% of all U.S. soybean acreage, and more than 70% of U.S. cotton acreage. What might have been different here is the process through which the technology penetrated U.S. fields. I propose that in the case of DT seeds, negative externalities imposed by adopters on non-adopters are the cause for such a rapid adoption.

Tolerance here refers to the capacity of a plant to survive a specific herbicide ("the complementary herbicide") that would normally kill it, conferred by genetic manipulation. So, specifically, the drift of the complementary herbicide to DT crops, dicamba, on nearby fields could have hastened adoption. DT soybean and cotton have been genetically modified to tolerate the weed-killer dicamba, and this enables farmers to continue using it in DT fields and get rid of weeds while the crops are growing. However other crops, including non-DT soybean and cotton, do not possess that trait and suffer damage if exposed to dicamba. Dicamba is also highly prone to drift. It can get carried over miles after having been sprayed, and re-volatilize even after it has first settled. Thus could dicamba drift, and the compulsion to avoid crop damage, have caused the unusually high speed of adoption of the DT technology?

In this paper, I demonstrate that spatial externalities were a driving force in the fast adoption of the new dicamba-tolerant varieties of soybean and cotton. In particular, I show that a determining factor involved in the adoption dynamics was wind patterns during the soybean growing season – the growing season being the time when soybeans are the most sensitive to damage, dicamba most useful to spray on DT crops, and when climatic conditions are most conducive to volatilization and drift of dicamba. I do so by leveraging spatial variation in wind patterns to identify their effect on the probability of adoption of DT crops at the county level. Said otherwise, does being in the same wind corridor as an adopter make a county more likely to adopt DT crops the following year? Given the potency of the herbicide dicamba, two other questions immediately follow. First, since dicamba damages many crops in addition to soybean and cotton,[1] is DT adoption accompanied by land-use change *away* from vulnerable crops, and *towards* dicamba-tolerant crops? And second, what is the effect of DT adoption on soybean and cotton yields?

I find evidence supporting the proposed adoption mechanism. Adoption was more likely in counties

[1]Dicamba kills all dicotyledons, i.e. crops like sunflowers, hemp, (non-DT) soybean, all specialty crops. Monocotyledons, however, are relatively unharmed – crops like maize and wheat, while not immune, are far less susceptible to dicamba.

situated within the same wind corridor as counties with high adoption of DT seeds in the previous year. On the other hand, having high adoption in cross-wind counties did not affect the likelihood of adoption. This asymmetry clearly rules out the competing interpretation of the results as a diffusion by word-of-mouth and observation of successful neighbors (which are isotropic, i.e. are the same in every direction of space).

Furthermore, examining the effect of DT adoption on other crops, I find that the adoption of DT seeds led to the conversion on average of over 1,800 ha (4,500 acres) per county to soybean or cotton. The decision to change crops altogether, beyond the scope of normal crop rotations, is complicated and costly. The data at hand only concerns the first three years with DT seeds (2015-2017) but the adoption trend since then has not abated, so crop switching has likely also continued. It is all the more likely that in 2017 harmed farmers might still have been in the process of updating their expectations that dicamba damage every year will be the new normal, or hoped for the intervention of their federal or state governments to limit dicamba damage. The continued trend in DT acreage suggests that damage and land-use changes might intensify after my sample ends.

Turning to soybean and cotton yields, a slightly higher crop failure associated with the arrival of the new technology confirms the harm to non-adopters, and suggests that it is indeed a tangible enough threat to motivate adoption. On the other hand, there is no overall effect on yield of cotton and soybeans at the county level. This null effect suggestions suggests that the damage endured by non-adopters was of about the same magnitude on average as the yield benefits enjoyed by adopters.

Finally, I calculate an average application rate for dicamba in-crop use on DT fields, and find it is but a fraction of the label-mandated rate, indicating that only a fraction of adopters use the seeds as prescribed. The fact that some farmers apparently choose to forego herbicide application made possible by DT seeds, even though they did switch to the new technology further goes to show that some of the adopters did not intend to adopt the DT cropping system and purchased the seeds to avoid losses. While in appearance contrary to their best self-interest, it is consistent with the existence of strong social norms to address negative externalities (Ostrom, 2000), or with limited yield gain earned by the new technology. I take that finding as additional evidence that part of the success of DT seeds in penetrating the soybean and cotton seed markets was earned by forced adoption operating through fear of negative externalities and losses incurred by non-adopters.

Put simply, this paper questions the popular notions that technology adoption always goes slower than socially optimal and that faster adoption is always better.

For indeed while the hypothesized adoption process can seem problematic in itself, its acceleration of the adoption of DT seeds raises further questions that a historical detour will help to highlight. The development of the first herbicide-tolerant (glyphosate-tolerant) crops via genetic engineering in the mid 90s magnified the potency, and the use, of the broad-spectrum herbicide glyphosate. The herbicide-GM combination was obviously perceived as a boon against yield-depressing weeds, as the herbicide could be used during the growing season, killing the weeds, leaving the crops unscathed. With it also came questions. Some were ethical, pertaining to the direct human editing of genomes. Others were ecological, concerning the evolutionary, population genetics, community dynamics consequences of the introduction of these new varieties of plants. Yet others concerned human health, whether by ingestion of GM-based food or by increased environmental exposure to the herbicide.

More than twenty years after the commercial release of the first glyphosate-tolerant crops, and about a tenfold increase in glyphosate use later,[2] substantial concerns over the innocuity of glyphosate have surfaced (e.g., see Dias et al., 2023). Given the experience of U.S. agriculture with glyphosate-tolerant crops, and the

[2] In the United States. In 1996, the estimated use in agriculture was 14,934 tons; in 2016, 131,673 tons (USGS).

biochemical properties of dicamba,[3] this rapid adoption calls for an early examination of the DT seed-dicamba cropping system for potential effects on health, or any other herbicide-tolerant seed in the future.

Moreover, the realization that the widespread use of glyphosate as part of a GM-glyphosate cropping system had led to the prompt and widespread emergence of glyphosate-resistant weeds following a typical Red Queen Race dynamics[4] (Van Valen, 1973; Powles, 2008) is disturbing in light of the speed at which DT seeds are being adopted and dicamba use is rising. Thus the very pattern of adoption, enhanced, in speed and possibly in extent, by the side-effects of the technology may be problematic: fast and widespread enough for resistance to evolve, fast and widespread enough for significant and irreversible damage to be incurred by farmers, by the neighboring populations, and by the surrounding ecosystems, and too fast for policymaking to take place (evaluation, regulation).

This paper adds to the literature on technological change, by proposing a new mechanism for technology adoption, and one that, contrary to most of the literature so far, explains why adoption of a new technology can be remarkably fast, rather than slow. In their study on the adoption of tractors in U.S. agriculture, Manuelli and Seshadri (2014) show that the neoclassical model (without frictions), adequately specified, accounts for the relatively slow adoption of tractors. The 10-90 lag[5] for tractors was about 29 years, compared to 4 to 12 years for hybrid corn (Griliches, 1957; Manuelli and Seshadri, 2014), ten years for glyphosate-tolerant soybeans and 18 years for glyphosate-tolerant cotton (Figure S1). In their case, adequate specification means accounting for the continual quality improvement of the new technology, and the cost of operating the old (draft horses). While their research cautions against the overuse of frictions to explain slow adoption, frictions do matter in other contexts, as exemplified in Griliches (1957) where "passive social learning"[6] explains the non-immediate diffusion of hybrid seeds, or more recently in BenYishay and Mobarak (2019) who show the existence of learning frictions by incentivizing them away in an RCT, leading to faster adoption of the technology. Guiteras et al. (2019), on the other hand, show in another experimental setting that strategic interactions between adopters and non-adopters can play an important role in fostering technology adoption. In a similar vein, I show that protection against the negative spatial externalities generated by a new technology *by in turn adopting the new technology* can drastically increase the speed of adoption of the said technology.

This paper further relates to Heal et al. (2004) in that it exemplifies the authors' claim that crop choices are interdependent *via* spatial externalities imposed by farmers on one another. Wechsler et al. (2018) offer a dynamic perspective in interdependent production choices in agriculture, which may with time become even more relevant to the DT seed case: they show that a farmer's adoption of glyphosate-tolerant crops *ultimately* affects her neighbors' weed-control efficiency by accelerating the emergence of glyphosate-resistant weeds, whereas in the present case a farmer's adoption of DT seeds *contemporaneously* affects her neighbors' ability to grow anything else profitably. In the future, with the emergence of dicamba-resistant weeds,[7] the same dynamic case of spatial externalities could apply. The present inquiry therefore lies at the intersection of the study of the mechanisms of technology adoption and of strategic complementarity (*sensu* Bulow et al., 1985).

[3] Suspected teratogenic (induces malformations in test rodents) and known irritant. See Bunch et al. (2012) for a summary.

[4] The Red Queen hypothesis in Ecology states that "a set of interacting species reaches an evolutionary equilibrium at which all their rates of coevolution exactly balance each other" (Rosenzweig et al., 1987); said otherwise, species (e.g. a predator and its prey) keep developing mutually-counteracting strategies (via evolution and natural selection), e.g. for attack and escape, such that the relationship between the species remains constant in the long run despite an ever-changing set of traits.

[5] Time elapsed between the moments when the penetration rate of the technology 10% and 90%.

[6] BenYishay and Mobarak (2019).

[7] Already reported in 2019: NPR, "As weeds outsmart the latest weedkillers, farmers run out of easy options," 11/04/2019.

This investigation of spatial environmental externalities is akin in spirit to prior work on mobile natural resources. While the questions asked and methods used differ, the underlying phenomena at play are similar: the profit-maximizing activity of one individual or firm deteriorates the revenues of others by reducing or destroying their output. Costello and Polasky (2008) for instance considered the consequences of fish stock mobility on optimal harvesting rules and concluded that sustainable harvest could only be obtained under drastically more stringent policies than if the fish did not move. Similarly, seed dispersal across a landscape of private landowners complicates the eradication of an invasive weed (Costello et al., 2017). Closer to the topic of this paper, but still applying a theoretical approach, Munro (2008) wonders at the possible coexistence of GM and non-GM crops, when cross-pollination of GM onto non-GM (genetic contamination, not examined here) generates a negative externality and existential risk for non-GM growers. He concludes that absent legislation imposing draconian rules for the spatial arrangement of GM and non-GM crops, the non-GM crops are bound to disappear because of the spatial externality imposed by the dispersal of, and contamination with, GM material. Here, I show empirically that such patterns of spatial externalities can hasten technology adoption and displace activities across sectors (namely towards soybean and cotton), and do so by exploiting the chemical properties of the complementary input to the technology (the volatility of dicamba) and wind patterns.[8]

The rest of the paper is organized as follows: Section 1 provides a brief description of the dicamba-tolerant technology and to what extent it differs from, or is similar to, other GM crops, Section 2 describes the data sources, Section 3 details the empirical strategy, the results are presented and analyzed in Section 4, and finally, Section 5 outlines areas for future research and Section 6 concludes.

[8] In that respect, I follow Schlenker and Walker (2016) and Deryugina et al. (2019) in using wind speed and direction for my identification strategy. The specifics, and the implications for identification, however, differ (see section 3).

1 Background: Dicamba-tolerant seeds in the landscape of U.S. genetically modified crops

Dicamba-tolerant (DT) seeds are the continuation of the technical and agronomic paradigm of the Green Revolution and of its later avatar, genetically modified crops, that gradually conquered the U.S. agricultural landscape, in both the figurative and the literal sense (Figure S1), since 1996. 1996 was the year that saw the first commercial release of genetically modified (GM) seeds including glyphosate-tolerant soybean, corn, and cotton. Few other herbicide tolerances have since then been engineered in field crops[9] and in that sense the release of DT seeds in 2015 was a landmark in the history of GM crops. Tolerance to glyphosate was always the most salient trait until 2015. The 20-year experience of glyphosate-tolerant crops has produced a set of difficult ethical, legal, ecological, and epidemiological questions that can be directly transposed to dicamba-tolerant crops. But in addition to these, the very physicochemical properties of dicamba, and in particular its propensity to drift, pose other.

Dicamba-tolerant cotton and soybean seeds had been in development for about ten years when the USDA approved their commercial release in January of 2015. Farmers started buying and planting them during the 2015 growing season. Quickly they were used over the majority of the U.S. soybean and cotton acreage: DT soybean represented only 2.4% of all soybean planted (82.7 million acres) in 2016, but 79.1% in 2019 (totalling 60 million acres), whereas DT cotton covered 0.5 million acres in 2015 (6.3% of U.S. upland cotton area) and about 7 million acres (73%) in 2018.

Problems were quick to emerge. As early as 2015, complaints about damage caused by off-target movement of dicamba applied on dicamba-tolerant crops surfaced. Tensions between neighbors mounted season after season, and things came to a head in October of 2017 when a dispute between Arkansan cotton farmers over DT seeds and the use of dicamba led to the murder of one of them.[10]

Yet GM crops had been part and parcel of the U.S. agricultural toolset for more than twenty years when DT seeds came about. In 2015 they had conquered an overwhelming majority of the acreage for soybean (herbicide-tolerant, HT), corn (HT, Bt[11]), and cotton (HT, Bt). Leaving aside insecticide-producing GM crops for now, the revolution operated by herbicide-tolerant varieties was that the chemical battle against weeds did not have to give way to other means of weed management (e.g. mechanical weeding) once the seeds were planted: herbicides (specifically, glyphosate) could, and were meant to, be sprayed over-the-top in HT crops *during the growing season*. All plants without a tolerance trait to the herbicide would die, and HT plants would be the only ones left standing; the benefit was such that as of 2015, 94% of all soybean cultivated in the US is HT (hence glyphosate-tolerant). DT seeds function just the same: DT cotton and soybean have been genetically modified to tolerate the broad-spectrum herbicide dicamba. Dicamba kills most weeds. All plants are somewhat sensitive, but broadleaf weeds (dicotyledons) are the main target, grasses (monocotyledons) being less sensitive to dicamba. Therefore farmers planting DT crops can continue using dicamba into the growing season to eliminate weeds while their soybean or cotton plants keep thriving.

What makes DT seeds stand out though, is that their companion herbicide, dicamba, is highly prone to drifting. This is due to the physicochemical properties of the dicamba compound itself, and of the herbicide products containing it. Drift is problematic given how deadly to broadleaf plants dicamba is. Drift comes from two separate phenomena: spray drift (during herbicide application) and post-application volatilization.

[9] Exactly two: tolerance to glufosinate and to 2,4-D.

[10] *Arkansas Times*, "Farmer vs. farmer. The fight over the herbicide dicamba has cost one man his life and turned neighbor against neighbor in East Arkansas," 10/08/2017.

[11] Engineered to produce an insecticide protein. It is metonymically called Bt, for *Bacillus thuringiensis*, the bacterium in which the protein was first isolated.

With dicamba, both are important risks. Dicamba has repeatedly been identified as one of the leading causes of spray drift incidents. But perhaps most significantly, it is known to re-suspend (volatilize) up to several hours after the spray first settled because of its fairly high vapor pressure,[12] and subsequently get transported over long distances. Vapor pressure is an intrinsic property of a chemical compound or mixture that indicates its propension to evaporate (volatilize) at a given temperature. This was not only a known characteristic of dicamba, but a concern explicitly expressed in 2013 during the public comment phase of the preparation of the Environmental Impact Statement that eventually led to the approval by USDA APHIS of the two varieties of dicamba-tolerant seeds:

> "Non-target plant damage associated with herbicide spray drift and volatilization is a major concern for specialty crop growers and processors. [...] Dicamba, because of its potential to drift and volatilize, has proven to be one of America's most dangerous herbicides for non-target plant damage." (online comment APHIS-2013-0043-0030 by Kimberly Iott, Iott Ranch & Orchard)

Worries about maintaining non-GMO (genetic contamination) or organic (pesticide contamination) certifications were also expressed, but concerns about herbicide volatilization and ensuing damage were by far the most numerous and pressing.

[12] 3.38×10^{-5} mm Hg at 25°C. Higher vapor pressure at a given temperature corresponds to more volatile compounds, e.g. compare with the vapor pressure of notoriously volatile ether, 538 mm Hg, and also contrast with that of glyphosate, 2.89×10^{-10} mm Hg.

2 Data

This section describes the data sources used: the land use data with which I monitor the extent and location of soybean and cotton fields, the pesticide (dicamba) use data that serves to track adoption of the new soybean and cotton seed, the wind patterns that enable the mapping of counties according to their wind-relatedness, and the agricultural and weather data that are used to assess agricultural outcomes.

2.1 Spatial distribution of land cover

Spatially-explicit land cover at a 30-m resolution, the Cropland Data Layer (CDL), is available for the conterminous United States for the years 2008 through 2018 (Boryan et al., 2011; Han et al., 2012) and is provided by the National Agricultural Statistics Service (NASS) at the U.S. Department of Agriculture (USDA). I use the CDL to compute annual cropland area at the county level, and its crop-specificity enables me to track land cover change at the ($900\,\mathrm{m}^2$) pixel level, in particular conversions to and away from soybean and cotton land covers.

I further exploit the spatially-explicit nature of the CDL for the computation of indices capturing the spatial aggregation or dispersion of soybean fields within a county. These are the Patch Cohesion Index and the Aggregation Index; they are borrowed from landscape ecology, and described in McGarigal et al. (2002).

The CDL is derived from remotely sensed data through a classification process, and words of caution as to their usage apply (Lark et al., 2017). As far as this study is concerned, the thematic classes for which spatially-explicit data is leveraged correspond to common, widespread crops, and are exceedingly well identified by the classification algorithms (user accuracy above 90%[13]). Remaining classification error in producing the CDL is plausibly independent from the phenomena studied here, and can therefore be considered as white noise in the statistical analyses below. Finally, county-level estimates of crop-specific acreage obtained with the CDL track closely those obtained independently by the USDA using surveys. See for instance Figure S11 in appendix. While that does not guarantee the quality at the pixel level, it supports the relevancy of these data on at least as fine a scale as that of the county.

2.2 Pesticide use

Dicamba use is obtained from the US Geological Survey (USGS). As part of the USGS's National Water-Quality Assessment (NAWQA), the Pesticide National Synthesis Project collects estimates of pesticide use in agriculture for the conterminous United States by compound (i.e. chemical species, for instance dicamba, atrazine, 2,4-D, etc.), in kilograms, at the county level and on a yearly basis since 1992. These are produced by combining proprietary pesticide-by-crop use data collected every year throughout the country with crop acreage (Baker and Stone, 2015; Thelin and Stone, 2013). 525 compounds are assessed. Pesticide use data for compounds other than dicamba, e.g. glyphosate, come from the same database.

2.3 Wind speed and direction

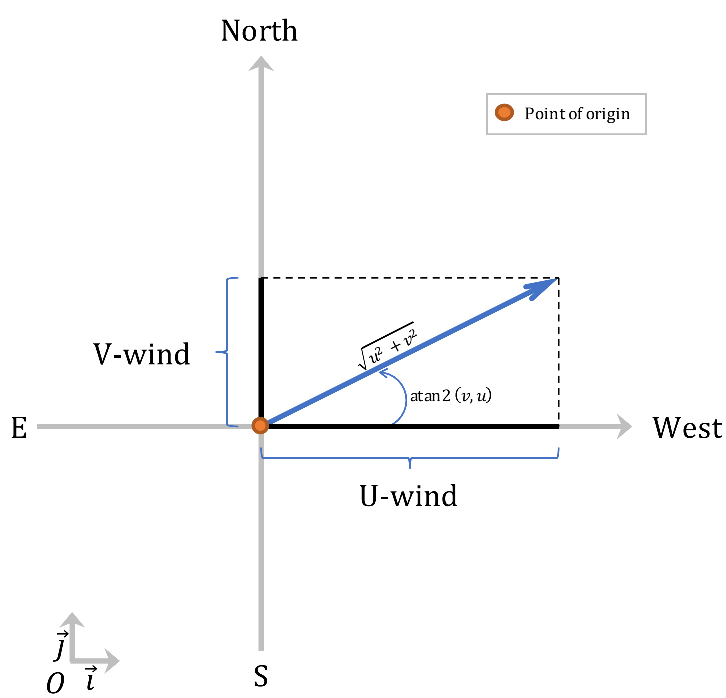
Exposure to the externality, dicamba drift, is shaped by wind patterns. It does not suffice to be neighbors with an adopter to be considered "treated": the two counties also have to be connected by winds, which is a unique feature of this technology diffusion process.

[13] Accuracy matrices by year and state can be found here: www.nass.usda.gov.

County connectivity by wind is determined using wind speed and direction data produced by the Earth System Research Laboratory at the National Oceanic and Atmospheric Administration (NOAA). The NCEP NARR data set provides gridded weather,[14] and in particular, U-wind and V-wind data in meters per second, for 1979 through 2019 (Mesinger et al., 2006). The grid is Northern Lambert Conformal Conic which in practice means that the spatial resolution varies: the mesh size is finer towards the Equator, specifically about 33 km at the southern tip of Texas, 50 km at the 49th parallel north border with Canada. The values for U-wind and V-wind in that data set are used to produce a mapping of counties, i.e. associate every county with all of its up-, down-, and cross-wind neighbors.

As illustrated in Figure 1 U-wind and V-wind are the components in cartesian space of a wind vector, that is to say, U-wind is the projection of the wind vector on a parallel (a positive U-wind is from the West), and V-wind that on a meridian (a positive V-wind is from the South). Denoting $\vec{W}$ the wind vector, it suffices to sum its $\vec{U} = U\vec{i}$ and $\vec{V} = V\vec{j}$ components to obtain it (U, V in meters per second, $\vec{i}$, $\vec{j}$ unity vectors pointing East and North, respectively), $\sqrt{U^2 + V^2}$ will give the wind speed, and atan2 (V, U) the direction.[15] Summing $\pm\vec{U}$ and $\pm\vec{V}$ enables one to find points up-, down-, and cross-wind from the initial location. It then suffices to associate these locations (identified by their latitude and longitude) to obtain the set of counties located up-, down-, and cross-wind from a focal county; an illustration of the procedure is shown in Figure 2 (more detail in C.4).

Figure 1: Wind data



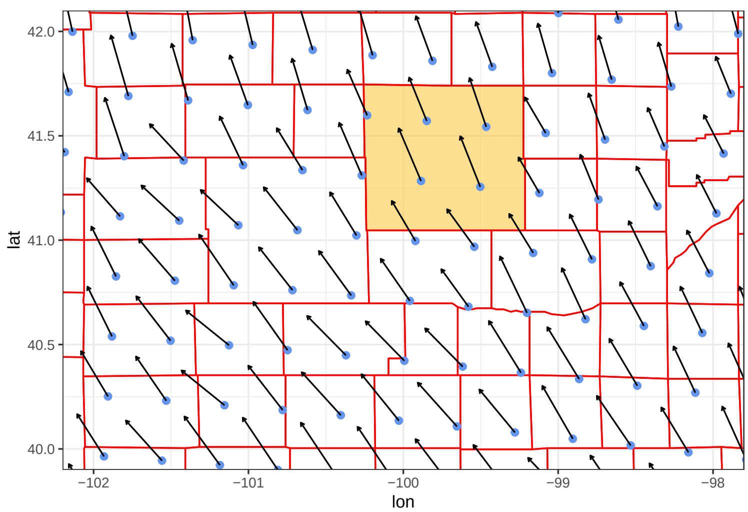
Notes: Schematic presents the NOAA wind data (U-wind, V-wind) and how to derive wind speed and direction.

Given that the initial grid is somewhat coarse, this operation potentially misses some up-, down-, and cross-wind neighbors with the original wind data. For robustness checks, I therefore interpolate (linearly)

[14]From their website at www.esrl.noaa.gov/psd. The NCEP are the National Centers for Environmental Prediction, NARR stands for North American Regional Reanalysis.

[15]The result is an oriented angle from the Equator. atan2 is the two-argument arctangent function.

Figure 2: Illustration of neighbor assignment method: downwind



Notes: Figure displays U.S. county boundaries (red) in Nebraska overlaid with transformed wind data (June 2016) in the native resolution. The blue dots correspond to the points of origin (i.e. where U-wind and V-wind are measured); black segments are the vector sum of U- and V-winds; the tips of the black arrows highlight the destination. Thus a given county is assigned as downwind neighbors all the counties other than itself in which land the arrow tips terminating segments emerging from it. For instance, Custer county, NE (yellow), is assigned three downwind counties (North from it; from West to East, Thomas, Blaine, Loup counties) and is downwind county to three other counties (South from it; from West to East, Dawson, Buffalo, Sherman counties). Upwind counties are obviously obtained taking $-\left(\vec{U}+\vec{V}\right)$, crosswind $-\vec{U}+\vec{V}$ and $\vec{U}-\vec{V}$.

the U- and V-wind components to roughly double the resolution (about 16 km, on a rectangular grid) and thus obtain a richer and more exhaustive set of neighbors for each county of the conterminous United States (compare top bottom panels of Figure S2).

Wind data provided by NOAA are provided at the monthly and daily frequencies. For the purpose of assigning wind-neighbor relationships between counties, I use the monthly resolution, and specifically the value reported for the month of June. Windborne dicamba particles are not acutely problematic throughout the year, and therefore, wind patterns matter for drift only part of the year. Prior to the introduction of DT seeds, dicamba was sprayed before planting. This "burndown application," was meant to clean the field. The novelty with DT seeds is that they tolerate dicamba use during the growing season, while the crop is growing. June is the month when all soybean is planted (in normal years), plants are vulnerable and damage is likely to cause not only visible signs but yield losses (McCown et al., 2018), and application of dicamba is still recommended by manufacturers on DT soybeans.[16] Monthly data are therefore well-suited for the neighbor assignment procedure described above, but one may wonder monthly values adequately identify the places where herbicide could drift and settle. I explore the heterogeneity of wind direction at the daily level in the appendix (see C.1). I conclude that daily variations are not a threat to the identification strategy adopted in this paper, but that being "within a same wind corridor" might turn out to be more important than being down- as opposed to up-wind from an adopter county.

[16]The R1 stage of soybean growth (i.e. beginning of bloom) occurs late June; another key period for soybeans is the R3 stage (formation of pods) which tends to happen late July, but the "application window" on DT soybeans as recommended by the seed manufacturers closes at the beginning of R1. This is also corroborated by the dates picked for most recent (2018, 2019) local (state) bans on in-crop dicamba use, meant to protect sensitive crops: most of these bans start mid- to late-June, though these are co-determined by political drivers in addition to agronomic considerations. See nonetheless robustness checks for results using July and May instead of June in appendix, tables S5 and S6.

2.4 Agricultural outcomes

I use production and acreage data at the county level compiled by the USDA's National Agricultural Statistics Service (NASS), on the basis of surveys conducted monthly every year from May (small grains such as wheat) or August (row crops such as soybeans, cotton) through November by NASS on representative samples of farms, and extrapolated at the county level for each crop. Production and areas planted and harvested at the county level by crop (soybean, cotton, wheat, corn) are obtained for 2008-2017. These measures are used to construct the following agricultural outcomes at the county level: harvested-to-planted area ratio, yield by area planted, and yield by area harvested.

Since the geographical coverage is not as extensive as that of the CDL, the latter is my preferred source of acreage data in all other cases. While independently produced, the agreement between the two sources at the county-year level is excellent (see for instance the case of soybeans, Figure S11).

2.5 Weather controls

Temperature and precipitation variables at the county level are used as controls in the yield regressions. They are derived from PRISM data (PRISM Climate Group at Oregon State University, 2019) and processed as done in Schlenker and Roberts (2009).[17] These include, at the county and year level: the minimum temperature, the maximum temperature, degree days above 10°C, degree days above 29°C, and total precipitation in millimeters from 1950 to 2017.

[17] http://prism.oregonstate.edu. I am grateful to Prof. Schlenker for providing the county-level data.

3 Empirical strategy

I estimate the role of chemical drift in the adoption of dicamba-tolerant seeds by exploiting wind patterns occurring during the growing season preceding adoption, thus abstracting from other modes of technology diffusion. I then estimate the effects of dicamba-tolerant (DT) seed adoption on land use, and specifically quantify what I call protective land-use change, in other words, land-use change away from vulnerable crops into potentially dicamba-tolerant crops (cotton or soybean). Similarly, one could expect consequences of DT seed adoption on crop yields, and I assess that claim. Finally, I turn to consequences at the national scale for the diffusion speed of the technology.

This section details the procedure by which counties are assigned the adopter/non-adopter status in a given year. I later describe the empirical strategy leveraging wind patterns used to identify the effect of windborne externalities and in particular attribute adoption decisions to the exposure to other adopters (via the wind), and likewise attribute land conversions. Finally I turn to the identification of effects on agricultural outcomes and describe how the strategy can be modified to uncover them.

3.1 Adopters

Where dicamba-tolerant seeds were sown in a given year is unknown. I therefore need to infer where adoption took place. I do so by observing the use of the complementary input to DT seeds: the herbicide dicamba itself.

Before the release of DT seeds, dicamba was used routinely to "clean" fields before planting any kind of crop. Use is constrained by label prescriptions that bound per-hectare use, from above and from below.[18] It is a broad spectrum herbicide, so any crop would suffer from contact with dicamba after the seeds have germinated and broken ground, *apart* from monocotyledons (e.g. wheat), less sensitive than dicotyledons (i.e. all trees, vegetables, beans, root crops, and some grains like buckwheat and sorghum).[19]

I therefore model annual dicamba use by county (DicambaUse_{it}, in kg) *prior to the introduction of DT seeds* (2008-2014) as proportional to cropland area (Cropland_{it}, in ha) in that county:

$$\text{DicambaUse}_{it} = \beta_0 + \beta_1 \cdot \text{Cropland}_{it} + \varepsilon_{it} \tag{1}$$

and thus β_1 is the average dicamba use intensity in kilograms per hectare of cropland. I find $\beta_1 \simeq 0.0132\,\text{kg/ha}$, and with this model can explain about 17% of the variance in dicamba use (see column (1) in Table 1).

Given that (a) some crops (monocots) can tolerate more dicamba than most in a given growing season, and (b) some of them are important users of dicamba (as shown in appendix, Figure S3), I further refine the model on the margins to allow for an increased use in some crops and land uses, namely wheat and pasture/hay.[20] The coefficients associated to those variables can be interpreted as the additional dicamba

[18] E.g. the label for dicamba sold as XTENDIMAX®. The minimum application rate is 11 fl. oz/acre, and the label further reads: "DO NOT broadcast apply *more than 44 ounces per acre for a single application* and DO NOT exceed broadcast applications of *more than 88 ounces per acre within the growing season* when a sequential application is needed for control. Use the higher rate when treating dense vegetation or perennial weeds with established root growth." (emphasis added) The label further specifies the maximum rates for each crop (Table 2, p.4) and commands to "not cultivate within 7 days after applying this product." The label is legally binding for "[i]t is a violation of Federal law to use this product in any manner inconsistent with its labeling. This product can only be used in accordance with the Directions for Use on this label."

[19] Note however that monocots are not *immune* to dicamba; for instance, Bayer is currently working on developing a dicamba-tolerant variety of corn (a monocot).

[20] Including corn area would be suggested by that logic, but it doesn't add much explanatory power (see column (4) of Table 1), maybe because corn area is highly correlated with cropland area (corr. = 0.71).

per hectare expended on those crops. My preferred model is that shown in column (3) of Table 1, with an improved explanatory power reflecting the specificities of dicamba use in wheat fields and in pasture.

	(1)	(2)	(3)	(4)
Cropland (ha)	**0.013*****	**0.009*****	**0.009*****	**0.010*****
	(0.000)	(0.000)	(0.000)	(0.001)
Wheat (ha)		**0.018*****	**0.013*****	**0.012*****
		(0.001)	(0.001)	(0.001)
Pasture/hay (ha)			**0.003*****	**0.003*****
			(0.000)	(0.000)
Corn (ha)				-0.001
				(0.001)
(Intercept)	**248.804*****	**300.809*****	**185.130*****	**183.550*****
	(13.806)	(13.648)	(14.336)	(14.398)
R^2	0.16	0.20	0.22	0.22
Dep. var. mean	788.82	788.82	788.82	788.82
Num. obs.	18983	18983	18983	18983
RMSE	1463.09	1433.17	1413.00	1412.98

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Table shows results for regression of dicamba use (in kg) at the county level against agricultural land uses to obtain in years 2008-2014 to obtain typical per-hectare dicamba use (kg/ha). The models in columns (2)–(4) further add crop acreage for two land uses that are major receivers of dicamba according to USDA statistics, namely wheat (column 2), hay/pasture (column 3), and corn (column 4). Excludes Kansas.

Table 1: Dicamba use models

The coefficients obtained from this regression define an average dicamba use per hectare, and I use them to extrapolate out-of-sample "typical" or expected dicamba use in the years 2015-2017 given land use figures obtained from the CDL. This extrapolation serves as a baseline, against which I compare actual dicamba use. The difference between extrapolated and actual values enables me to assign adopter status. Large positive values reveal adoption.

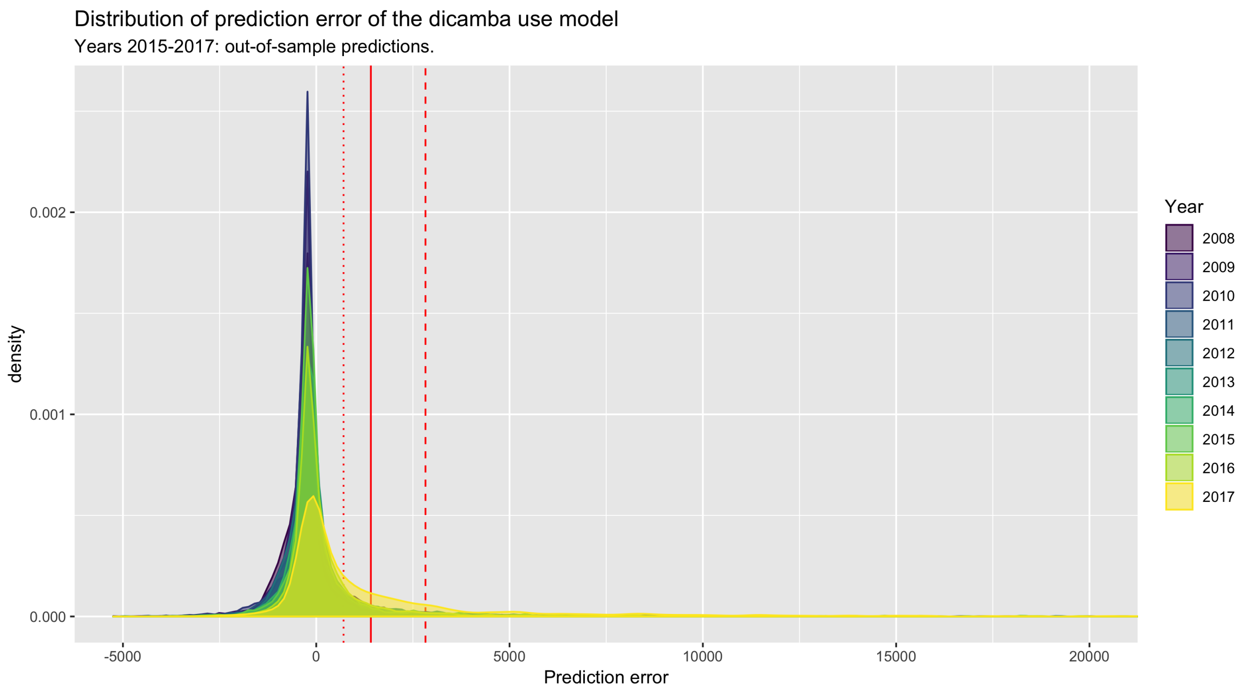
I use $\sigma(\hat{\varepsilon}_{it})$ as my primary threshold ("1sd"), the rationale being that anomalies larger than one standard deviation of the error term of that regression are, given the high excess kurtosis of their distribution,[21] outside the range of typical use and measurement error. Note indeed on Figure 3 that most of the mass sits below the continuous red line denoting $\sigma(\hat{\varepsilon}_{it})$ ($\simeq 1412$). Despite its groundedness in the statistical features of the pesticide data and the agronomic characteristics of its use, this threshold may seem somewhat arbitrary still. While the dicamba tolerance trait in DT seeds clearly confers the possibility to double (soybeans) or octuple (cotton) the quantity of dicamba used on these crops in a given growing season (see again crop-specific restrictions on dicamba labels), there is no obvious *a priori* cut-off value for the dicamba anomaly above which a county i can clearly be labelled as adopter in year t. I therefore check the robustness of my results to the use of other values (namely half ("0.5sd") and one-and-a-half ("1.5sd") $\sigma(\hat{\varepsilon}_{it})$) and report them in the corresponding appendix sections. It is just equally natural to consider the anomaly-per-hectare a measure of adoption intensity in a given county, but defining thresholds is more problematic. I therefore keep that alternative definition for the appendix, and provide results for two empirically-defined thresholds based on Figure S4.

Dicamba use anomaly (in kilograms), and intensity of dicamba use anomaly (in kg/ha[22]) are used as al-

[21] Kurt$[\hat{\varepsilon}] \simeq 67$, and their distributions pictured year by year in Figure 3 are obviously leptokurtic.
[22] Here, county area is used for surface normalization. Indeed, for county-wide consequences what matters is the pseudo-concentration of the substance, not how much more per hectare of *cropland* there is.

ternative (continuous) measures of adoption in sections B.4.2 and B.4.2. However the main analyses presented in the paper, namely the contagion analysis in section 3.2 and the examination of land use changes and yields in sections 3.3-3.4, all rely on the binary variable defined above tracking adopter/non-adopter counties.

Figure 3: Distribution of dicamba anomaly



Notes: Figure displays the distribution of dicamba anomaly at the county level (homogeneous to kilograms) for every year in the data *without* surface normalization; years 2008-2014 correspond to in-sample error ($\hat{\varepsilon}_{it}$), errors for years 2015-2017 are out-of-sample errors. Note the symmetry around zero and small standard deviation of the distributions for years 2008-2014 ($\sigma < 1700$) and the positive skew, larger standard deviation of later years ($\sigma_{2016} = 2540$, $\sigma_{2017} = 5762$). The red solid line marks an arbitrary threshold at one standard deviation of the regression residuals ($\hat{\varepsilon}_{it}$ from Equation (1) and Table 1 column (3)), the red dotted line at half a standard deviation, and the red dashed line two times a standard deviation. The plot was truncated at $x = 20,000$ to facilitate reading (the full support is $[-5,253.1; 72,588.9]$).

3.2 Estimation of contagion

Having assigned adopter status for each county and each year (section 3.1) and mapped each county to its up-, down-, cross-wind neighbors (section 2.3), I can now estimate a wind-biased adoption model, formulated in its most general form as follows:

$$Pr\left(\text{SelfAdopt}_{it}\right) = f\left(\text{UpwindAdopt}_{i,t-1}, \text{DownwindAdopt}_{i,t-1}, \text{CrosswindAdopt}_{i,t-1}\right) + \varepsilon_{it} \tag{2}$$

where $Pr\left(\text{SelfAdopt}_{it}\right)$ is the probability that county i is an adopter in year t (2017). It is modelled as a function of whether any county upwind ($\text{UpwindAdopt}_{i,t-1}$), downwind ($\text{DownwindAdopt}_{i,t-1}$), crosswind ($\text{CrosswindAdopt}_{i,t-1}$) from i was an adopter in year $t-1$ (2016).

As for $f(.)$, I estimate Equation (2) fitting a probit, and also provide results for a logit and a linear probability model in the appendix.

The fact that wind patterns are assigned exogenously to any confounding agricultural and socioeconomic features of the counties and their neighbors enables me to clearly identify the endogenous from the exogenous effects (*sensu* Manski (1993)) leading to adoption, and the role of the wind itself in the adoption process.

My hypothesis is that being related by way of wind matters for DT seed adoption; therefore positive coefficients for UpwindAdopt and DownwindAdopt,[23] a non-significant coefficient on CrosswindAdopt, would be in accordance with that hypothesis.

3.3 Protective land-use change

What do farmers do when they incur losses (or the possibility thereof)? If they expect the cause to persist, they have two choices: persist (at the risk of taking losses) or adapt. For those farmers that were not soybean or cotton growers, one way to adapt is to become one, and specifically one that uses DT seeds. Switching from a vulnerable crop to a crop where the DT trait is available guarantees that no harm from dicamba drift will be suffered. While harm to specialty crop has been widely reported,[24] some crop changes are more unlikely than others, due to the important fixed costs and changes in farm management practices required by, for instance, converting an orchard into a soybean field (compared to converting a tomato field into a soybean field). The changes are therefore expected to be small especially in the years just following the introduction of DT seeds, for which I have data.

To measure land use changes, I track pixel values from one year to the next in the Cropland Data Layer (see the Data section) to get actual conversion from vulnerable crops to soybean and cotton – rather than picking up, for instance, the expansion of soybean into new (marginal) cropland. In years preceding the release of DT seeds, net conversions to soybean and cotton (i.e. the surface switching to soybean and cotton, minus that switching away from soybean and cotton) should be close to zero, lest there be a gradual disappearance or conversely hegemony of those crops in the county.

The hypothesized sequence, if such protective land-use changes exist, unfolds as follows: soybean and cotton growers within the (wind) neighborhood of non-DT seed users increase their use of dicamba in a given year, and neighboring non-DT crop farmers incur losses; the following year, the latter switch to a DT crop. Given the county-level resolution of the data at hand, this sequence becomes: large positive dicamba use anomaly in the county increases in a given year, and the following year more conversion to DT crops is observed in that county – this corresponds to Equation (3).

$$Y_{i,t\to t+1} = \alpha_1 \cdot Treated_{it} \times Post_{it} + \lambda_i + \lambda_t + \varepsilon_{it} \tag{3}$$

with $Y_{i,t\to t+1}$ the net conversion between years t and $t+1$ to soybean and cotton from some other land use, $Treated_{it}$ a binary variable taking the value of one if county i in year t is treated, i.e. has an adopter in its wind corridor (based on dicamba use anomaly (kg, kg/ha) compared to model predictions, see 3.1). λ_i, λ_t are county and year fixed effects, respectively. Errors ε_{it} are clustered at the state level. Alternative formulations also consider $Treated_{it}$ to correspond directly to the focal county being itself considered an adopter (again, based on deviation from baseline dicamba use, cf. 3.1), or as a placebo, $Treated_{it}$ is assigned a value of one if county i has adopters cross-wind but not up- or down-wind.

[23] See section C.1 for a detailed discussion of why that is. In a nutshell, wind tends to blow along a certain cardinal direction (e.g. NS), but the way it blows varies (North to South, and vice versa). Therefore calling a county *downwind* (upwind) from another is probably a misnomer, as the wind will blow from (toward) it a large fraction of the time.

[24] E.g. *The Fern* reports on tomato, pecan farmers incurring seizable losses for three years in a row (*The Fern*, 11/13/2018: "Scientists warned this weedkiller would destroy crops. EPA approved it anyway").

3.4 Yields

The effect on yields of DT seed adoption is *a priori* ambiguous for cotton and soybean. On the one hand, it could lead to improved yields if the new seeds were performing better than the old, whether because they are intrinsically higher-yielding, or because they enable the farmer to destroy their weed competitors in the field. On the other hand, DT seed adoption could also depress yields if there is a trade-off between traits (i.e. the seeds tolerate the herbicide but are of a lesser yielding variant) offsetting yield gains; if the coexistence of DT and non-DT crops means significant dicamba drift and damage on non-DT plots, possibly up to crop failure; if the protective land-use change described in the previous section means that plots less suitable for soybean and cotton are sown with DT seeds, therefore adding low-yielding acres. It could also be null if the damage doesn't translate into yield losses.[25]

The effect on non-DT crops is expected to be near zero for monocots (wheat, corn), and negative for dicots (beetroots, potatoes, etc.). I only consider the former because of data limitations.

To unpack the effect of DT seeds on yields, I consider two outcome variables: yield (in physical quantity per *planted*[26] acre), and the planted-to-harvested ratio, to account for the fact that farmers observing damage beyond repair do not harvest those fields.

$$Y_{it} = \alpha_1.Treated_{it} \times Post_{it} + \mathbf{X_{it}}\theta + \lambda_i + \lambda_t + \varepsilon_{it} \tag{4}$$

with Y_{it} the yield (bushel/acre for soybeans, lb/acre for cotton) or planted-to-harvested ratio for the focal crop (soybean, cotton, and two non-target crops, wheat and corn), $Treated_{it}$ is a binary variable taking the value of one if county i in year t has an adopter in its wind corridor (see 3.1 and above), $Post_{it}$ is a dummy signifying post-2015 (after the commercialization of DT seeds). $\mathbf{X_{it}}$ are weather controls (growing degree-days, killing degree-days, minimum and maximum temperatures, precipitations). λ_i, λ_t are county and year fixed effects, respectively. Errors ε_{it} are clustered at the state level.

[25] Indeed, visible damage (leaf cupping, stunting) can occur without consequences on yield, depending on the stage at which the damage occurs, and its extent (McCown et al., 2018).

[26] USDA NASS reports yield per harvested acre.

4 Results

4.1 Verifying dicamba use anomaly as an adequate proxy for DT seed adoption

The lack of data on where and when dicamba-tolerant seeds were actually planted made the use of proxies for DT seed adoption necessary. And while their construction relies on a straightforward logic, it is important to verify that those proxies are reasonable representations of the phenomenon.

At the county level, a good proxy for DT seed adoption should correspond to counties where soybean and/or cotton are grown (refer to map in Figure S6), and preferably where they are the dominant crop (it is indeed unlikely that a small soybean/cotton area adopting DT seeds would produce a change large enough in dicamba use to pass the threshold I defined). A good proxy for DT adoption should also colocate with places reporting dicamba injury.[27] Finally, a good proxy should correspond to places where, DT seeds having become a divisive and fractious subject, social media activity around dicamba and DT seeds is high.

Data for the last two points are only available at the state level. Dicamba injury and complaints were compiled in 2017 and 2018 by the agricultural extension at University of Missouri; these data can only be taken as a lower bound estimate of actual damage, and the difficulty in obtaining them means that the sample is potentially selected.[28] Location data for tweets could only be obtained from user profiles (i.e. tweets couldn't be geolocated themselves) with substantial heterogeneity in precision and formatting, hence only the stated state could be identified without losing most of the database. As visible on Figure S13, the affected region corresponds roughly, but the limitations of the corroborating data sets are such that they can only be considered as reassuring evidence rather than definitive validation.

Although soybean and cotton acreage did not enter into the determination of the adoption metric, adopter counties fall overwhelmingly in the counties with the largest soybean acreage in the United States – 47% of the 769 adopter counties (in 2017) are in the top quintile[29] and 71% in the top two quintiles for soybean acreage, and the majority of the rest falls in the top tercile (see Figure S6) or even top quintile for cotton. Only 8 counties fail that test in that the CDL acreage in cotton and soybean at baseline (2008-2014) is zero and remains minimal in 2017.

4.2 Forced adoption: Evidence of wind-biased adoption

The wind-biased model of DT seed adoption is estimated using a probit; the coefficients are reported in Table 2 and the marginal effects of the preferred specification (column (3) of Table 2) are plotted on Figure 4. The figure also reports for comparison purposes the coefficients on a linear probability model using the same predictors (top, red),[30] a logit (beneath it, grey), and the marginal effects of the same probit model but with different definitions of adoption (specifically, different threshold-based rules).

Having an adopter county upwind or downwind increases likelihood of adoption, by about 28% and 15%, respectively, and these coefficients (Table 2) and marginal effects are statistically significant at the 5% level, and robust to the addition of the crosswind variable. Having an adopter county crosswind, however, doesn't

[27] Note however that the relationship between adoption and soybean injury is complex (not even mentioning reporting and other data issues): when adoption is low, damage is low, and increases as adoption increases, until it reaches a point where there are enough adopters for very few non-DT fields to remain, and for damage on soybean to start decreasing for want of vulnerable soybean plots until full adoption.

[28] There is no centralized reporting system, not all state plant boards, not all agricultural extensions record nor report those estimates. Being based in Missouri, the team was able to conduct field visits and obtain damage data through more channels than for other states. Therefore all things otherwise equal, soybean injury in Missouri should be reported as larger just because of the bias in reporting.

[29] A quintile has 522 counties for soybean, 228 for cotton.

[30] Fitted values lie between 0.28 and 0.57, hence are all in $[0, 1]$.

	(1)	(2)	(3)
Upwind, but not downwind 2016 adopter	$\mathbf{0.73}^{**}$		$\mathbf{0.73}^{**}$
	(0.23)		(0.23)
Downwind, but not upwind 2016 adopter	$\mathbf{0.40}^{*}$		$\mathbf{0.40}^{*}$
	(0.18)		(0.18)
Crosswind 2016 adopter		0.12	0.13
		(0.34)	(0.34)
(Intercept)	$\mathbf{-0.56}^{***}$	$\mathbf{-0.55}^{***}$	$\mathbf{-0.56}^{***}$
	(0.03)	(0.03)	(0.03)
AIC	3134.69	3147.52	3136.53
BIC	3152.28	3159.24	3159.98
Log Likelihood	-1564.34	-1571.76	-1564.26
Deviance	3128.69	3143.52	3128.53
Num. obs.	2600	2600	2600

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Table shows regression results (coefficients and standard errors) for probit models regressing adopter status in 2017 on adopter status in 2016 of up-, down-, cross-wind neighbors. Adoption is defined using the preferred dicamba use model and an absolute threshold on out-of-sample prediction error. All regressions exclude Kansas.

Table 2: Probability of adoption

affect the probability of adoption, and this is consistently observed across all models and specifications. While the point estimates are different for the up- and downwind coefficients, their confidence intervals overlap, and the estimates are not statistically significantly different from one another (Wald chi-squared test: $\chi^2 = 1.3$, df=1, $p = 0.25$). The results are unchanged (significance, sign, magnitude) if one uses a logit or a linear probability model instead of a probit (see Figure 4 with the preferred threshold and Figure S5 for the full set of thresholds using a logit model).

Overall, this means that being connected by winds to a DT seed-adopter neighbor increases by 15 to 28%[31] the likelihood that DT seeds will be adopted the following year. The fact that crosswind neighborhood relationships should not matter when up- and down-wind do suggests that this is not merely a matter of diffusion by word-of-mouth and observation among neighbors, but that there is *something* in the wind – and in the present case, the something is herbicide particles.

Finally, while the comparable effects of adopters up- and down-wind could intuitively be surprising (the county should receive pesticide particles from its upwind neighbors, not from its downwind neighbors), it is easily explained. As discussed in depth in the appendix (C.1), daily wind patterns tend to alternate between one direction and its cardinal opposite. Therefore, the "downwind" direction given by the monthly data is actually, in the overwhelming majority of cases, the minor upwind direction experienced at the daily level at that location – in other words, the distribution of wind direction in a given location can be approximated with a bimodal distribution, the monthly data gives the major mode, and I find the minor mode to be about 180° from it (see C.1).

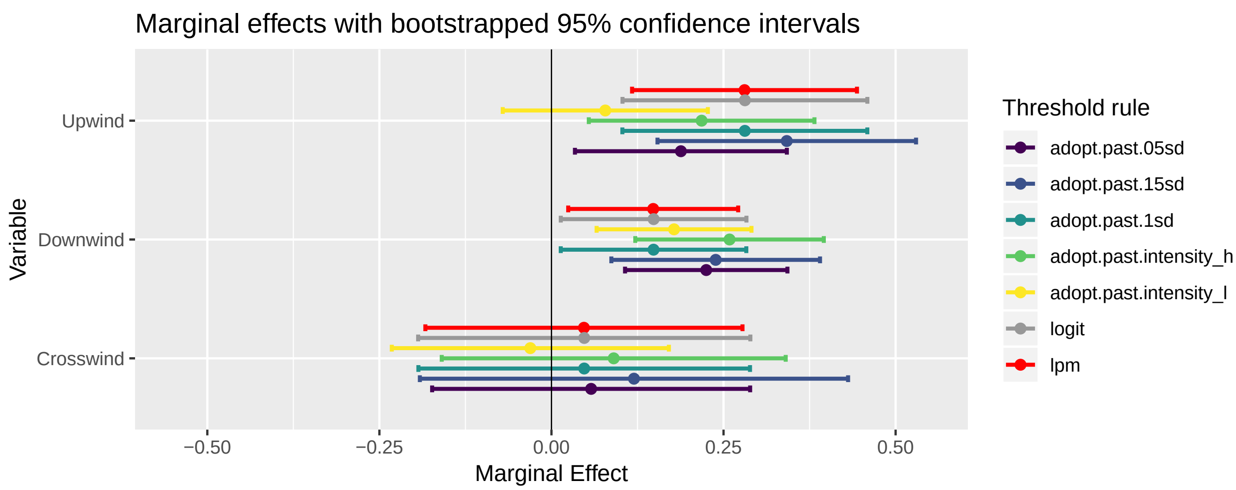
4.3 Cross-sectoral spillovers: Protective land-use change

The coefficients obtained by the estimation of Equation (3) are reported in Table 3.

Both treatment variables (lines 1 and 3 in Table 3) show a large and positive effect of DT seed adoption on land conversion expressed in hectares of vulnerable uses to soybean and cotton, while the placebo (line 2)

[31] Taken together, by 29%.

Figure 4: Preferred specification: marginal effects



Notes: Graph displays marginal effects corresponding to the probit coefficients in column (3) of Table 2, i.e. the preferred specification of the adoption model. In red and in grey, the marginal effects obtained with a linear probability model ("lpm") and a logit model ("logit"), respectively, using the preferred threshold rule. The 95% confidence intervals for the logit and probit coefficients are calculated using bootstrapped standard errors.

	Hectares	% Cropl.	Hectares	% Cropl.	Hectares	% Cropl.
Treated (Upwind adopt.) x Post	**1852.15*****	**2.00e-04****				
	(274.18)	(0.00)				
Placebo (Crosswind adopt.) x Post			1139.32	−4.44e-05		
			(751.28)	(0.00)		
Treated (Self adopt.) x Post					**529.78****	2.99e-06
					(196.68)	(0.00)
R^2	0.00	0.00	0.00	0.00	0.00	0.00
Dep. var. mean	462.17	1.03e-04	462.17	1.03e-04	462.17	1.03e-04
Num. obs.	23473	23465	23473	23465	23473	23465

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Table shows regression results for net land-use change soybean and cotton area (in hectares and as a percentage of baseline (2008-2014) cropland area).

Table 3: Protective land-use change

does not. The magnitude of the effect corresponds to the size of a few fields (per county): 1,852 ha (4,576 A) is approximately 116 (small) fields,[32] while 529 ha (1,307 A) corresponds to about 33 such fields.

The fact that on the other hand, the specifications using area converted as a proportion of total cropland as their dependent variable (columns 2, 4, 6) show positive coefficients that are less robust (significant on line 1 with treatment defined by presence of adopter in the wind, non-significant on line 3 with treatment defined by being an adopter county oneself) says probably more about the distribution and availability of vulnerable crops as a function of county size.

[32]Quarter-quarter section (16 ha). The quarter-quarter section is the smallest subdivision of the U.S. rectangular survey system (White, 1983, p. 90), and a typical field delineated according to the rectangular system covers either a quarter-quarter section or a quarter section (64 ha).

4.4 In-sector agricultural outcomes are mixed, consistent with damage for non-adopters and benefits for adopters

4.4.1 Harvested-to-planted area

The results of the estimation of Equation (4) with the harvested-to-planted ratio as the dependent variable are reported in Table 4. Focusing on the Cotton and Soybean columns, the effects on the harvested-to-planted area ratios for the crops where DT seeds are available seem overall negative (i.e., more crop failure), but are imprecise; in addition, situations in which the adoption of dicamba-tolerant seeds should not have affected crop failure (wheat; cross-wind placebo) produce relationships that are statistically significant but not meaningful.

	Soybean			Cotton			Wheat			Corn		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treated x Post	−0.08			−1.71			**3.38***			−0.15		
	(0.51)			(1.91)			(1.71)			(0.90)		
Placebo x Post		−1.70			**−9.17***			−4.85			1.94	
		(1.39)			(4.23)			(4.53)			(2.54)	
Adopted x Post			**−0.94*****			−1.44			0.75			−0.07
			(0.25)			(1.46)			(1.00)			(0.48)
R^2	0.15	0.15	0.15	0.30	0.31	0.30	0.07	0.07	0.07	0.10	0.10	0.10
Dep. var. mean	97.98	97.98	97.98	92.58	92.58	92.58	81.17	81.17	81.17	86.63	86.63	86.63
Num. obs.	11903	11903	11903	2771	2771	2771	9380	9380	9380	13478	13478	13478

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Table shows regression results for fixed-effect models regressing production outcomes on dicamba use anomaly at the county level, for four major crops, for two of which DT technology is available (cotton, soybean), the other two (wheat, corn) are relatively tolerant to dicamba, owing to their being monocotyledones. Areas are expressed in acres, production in bushels (soybean, wheat, corn) or pounds (cotton), and yields are accordingly in bushels or pounds per acre. Includes weather controls.

Table 4: Harvested-to-planted models

4.4.2 Soybean and cotton yields

Observing the results of the estimation of Equation (4) with yields (here, production per acre *planted*) as the dependent variable in Table 5, there seems to be no net effect of adoption, and the additional amount of dicamba used, whether in-county or in-corridor, on crop yields.[33]

[33] Except maybe on corn; an interpretation could be that counties with higher-than-normal dicamba use pre-DT seeds fare better because there are fewer weeds, or because it indicates that famers use more inputs in general, and the negative coefficient could be driven by the larger support (with more extreme positive values).

	Soybean			Cotton			Wheat			Corn		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treated x Post	−0.18			0.09			−0.05			−4.04		
	(0.79)			(0.06)			(1.41)			(2.47)		
Placebo x Post		−1.36			−0.03			**−7.57***			6.82	
		(2.15)			(0.13)			(3.74)			(6.98)	
Adopted x Post			0.73			−0.09			0.27			**−2.57***
			(0.38)			(0.05)			(0.83)			(1.31)
R^2	0.30	0.30	0.30	0.16	0.16	0.16	0.11	0.11	0.11	0.32	0.32	0.33
Dep. var. mean	42.09	42.09	42.09	1.70	1.70	1.70	46.38	46.38	46.38	124.39	124.39	124.39
Num. obs.	11903	11903	11903	2771	2771	2771	9380	9380	9380	13478	13478	13478

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Table shows regression results for fixed-effect models regressing production outcomes on dicamba use anomaly at the county level, for four major crops, for two of which DT technology is available (cotton, soybean), the other two (wheat, corn) are relatively tolerant to dicamba, owing to their being monocotyledones. Areas are expressed in acres, production in bushels (soybean, wheat, corn) or pounds (cotton), and yields are accordingly in bushels or pounds per acre. Includes weather controls.

Table 5: Yield models

Put together with the faint negative effect on cotton and soybean harvested-to-planted ratios, this suggests that while some soybean and cotton farmers suffer from the introduction of DT seeds in their neighborhood (4.4.1) and may in addition see effects on their yield, overall thanks to the increased weed control permitted by DT seeds in DT fields, yields were stable at the county level.

Agronomic studies have investigated the action of dicamba on soybean plant development and yield, and in light of that, the results found here on yields are not surprising: the amount of damage to the plant and of yield loss depends on the growth stage at the time of exposure, the number of exposures and the quantity of dicamba. The most sensitive stages are R1 (beginning of bloom) and R3 (beginning of pod formation) as far as effects on yields are concerned; yield losses therefore range from moderate to severe for single exposure events at sublethal doses such as those typically experienced from drift (e.g. 1% to 19%, respectively, as found in McCown et al. (2018) for doses ranging from 1/256th to 1/64th the labeled rate), and have been reported to amount to as much as 50% in case of exposure in both R1 and R3 stages.[34]

4.5 Robustness checks

I list and address below possible threats to identification, and provide corroborating evidence of the proposed mechanism.

Sensitivity to sample and treatment definition

Three educated choices have been made in defining the sample and the treatment that could affect the results obtained. Although these choices are based on agronomic and contextual knowledge and are in my view improving the quality of the signal while not adulterating it, it is important to check that they do not bear an undue responsibility in the results.

The first choice concerns sample definition, and specifically the decision to exclude Kansas from the analysis. The reason for that exclusion is detailed in appendix (C.3) but in short, has to do with very strong pre-trends in dicamba use at the state level: dicamba use quintupled in the five years preceding the commercial release of DT seeds, for reasons unrelated to the adoption of dicamba-tolerant seeds (since they

[34] This latter figure is cited by a crop specialist in DTN, July 12th 2019, "Dicamba Injury Study: Reproductive Stage Soybeans More Sensitive to Dicamba".

did not exist then), as illustrated on Figure S19. No other state displays such a behavior. This was concerning for two reasons. First, the detection of DT seed adopters relies on how closely counties follow a dicamba use model established during the "pre" DT seed period (2008-2014). The elevated use of dicamba and its ramp-up (starting 2010) are likely to compromise the precision and accuracy of the model, and therefore threaten the rest of the analyses of the paper. Second, given its elevated use of dicamba in 2014 and, again, the reliance on positive dicamba anomaly to detect adopters, it is likely that all of Kansas would have been considered adopter *even before 2015*, which is obviously incorrect. As anticipated, including Kansas in the model of dicamba use reduces its explanatory power and changes the point estimates,[35] albeit slightly (Table S17). Accordingly, the point estimates of the probit adoption model are modified slightly, and the goodness-of-fit is reduced (compare tables S4 and 2); the magnitude, significance, and direction of the effects, however, remain the same. Excluding Kansas was therefore justified, but the results do not hinge upon that decision.

The second choice affects the definition of treatment: the assignment of up-, down-, and cross-wind neighbors based on the NOAA data described in the Data section. A concern here might be that some matches are missed in a systematic way under the native resolution. Indeed while the distance between two points in the data set is typically smaller than the width of a county, not all counties are assigned a wind direction and speed, and therefore are not assigned up-, down-, and cross-wind counties (they could however be up-, down-, or cross-wind from another focal county). The reason why this could be problematic is that this omission is not entirely random: smaller counties are more likely to be missed, and so are counties in the North. The latter is caused by the reliance on a conical projection for the NOAA wind data, such that wind data points are slightly denser in the South than in the North.[36] To address this concern, I interpolate the wind data to obtain a coverage that is uniform in space, and twice as dense as the original (Figure S2 helps visualize the change); this procedure is liable to introducing measurement error and therefore attenuation bias. Nevertheless, the results of the adoption models are stable, as reported in appendix, Table S7, which alleviates the concern over spurious relationships found because of potentially poor county matching.

The third choice more directly affects the definition of treatment: the determination of the threshold in dicamba anomaly over which counties are considered as adopters of DT seeds. As explained in section 3.1, there is no obvious way to define it. I picked one that was both intuitive and relevant, such that a county is "adopter" if its dicamba use anomaly is above one standard deviation, but verifying that the dynamic is not sensitive to variations around that definition is important to ascertain the validity of the findings. I therefore contemplate a variety of other definitions based on dicamba use anomaly (visualized on figures 3 and S4); as shown already in Figure 4 (plotting the marginal effects for various threshold values including the preferred one), it is indeed stable; the full set of corresponding regression tables is reported in the appendix, tables S8 to S11.

Does landscape configuration play a role in adoption?

Since the proposed mechanism for the pattern of adoption identified in section 4.2 is through the resuspension and drift of dicamba particles from one soybean (or cotton) field to the next (the former DT, the latter not) the arrangement in space of the fields should matter for adoption at the county level. Indeed if the soybean fields of a given county are all perfectly interspersed with other crops where the DT trait is not available,

[35]For instance, Kansas being the first wheat producer of the U.S., its high dicamba use is passed along to a larger coefficient on wheat, but smaller on pasture.

[36]See section 2.3 of the Data section; refer to NOAA's page for more information on the Lambert Conformal Format (that in which the wind data is made available) at www.esrl.noaa.gov and to visualize the grid and the distorsions in coverage it engenders across a latitudinal gradient.

then the likelihood for damage by drifting dicamba will be minimal; conversely, if they are aggregated, dicamba drift from those among them that are DT can engender more damage among the non-DT. To evaluate this hypothesis, I leverage methods of landscape ecology: McGarigal et al. (2002) and Cushman et al. (2008) describe landscape metrics that characterise the composition (land covers) and structure (how they are arranged in space) of a landscape. I apply them on the CDL at the county level, and extract two metrics describing the dispersion of patches (here, soybean plots) in space: the Patch Cohesion Index and the Aggregation Index. While this approach is typically used to characterize suitable habitat patches for animal or plant species in a landscape, it is are relevant here as those metrics inform the propension of dicamba sprayed on a DT seed-sown field to drift to other soybean (possibly non-DT) fields.

The Patch Cohesion Index and the Aggregation Index increase as soybean plots are clustered together in space;[37] I hypothesize that including them in the adoption model should improve model fit and that their effect on probability of adoption should be positive. The results are presented in Table 6.

	(1)	(2)	(3)	(4)	(5)	(6)
Patch Cohesion Index	**0.24*****					
	(0.03)					
Aggregation Index		**0.02*****	**0.02*****	**0.02*****	**0.02*****	**0.02*****
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Upwind, but not downwind 2016 adopter			**0.75****		**0.75****	
			(0.25)		(0.25)	
Downwind, but not upwind 2016 adopter			0.33		0.33	
			(0.20)		(0.20)	
Crosswind 2016 adopter				0.24	0.26	
				(0.35)	(0.35)	
Up- or downwind 2016 adopter						**0.82*****
						(0.13)
(Intercept)	**−2.67*****	**−2.02*****	**−2.04*****	**−2.02*****	**−2.05*****	**−2.09*****
	(0.24)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)
AIC	2781.86	2671.42	2663.19	2672.96	2664.66	2634.53
BIC	2793.39	2682.99	2686.33	2690.31	2693.59	2651.88
Log Likelihood	-1388.93	-1333.71	-1327.59	-1333.48	-1327.33	-1314.26
Deviance	2777.86	2667.42	2655.19	2666.96	2654.66	2628.53
Num. obs.	2356	2405	2405	2405	2405	2405

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Table shows regression results (coefficients and standard errors) for probit models regressing adopter status in 2017 on adopter status in 2016 of up-, down-, cross-wind neighbors. Adoption is defined using the preferred dicamba use model and an absolute threshold on out-of-sample prediction error. All regressions exclude Kansas.

Table 6: Probability of adoption – Influence of landscape structure

Both dispersion indices are associated with a higher adoption probability, and improve model fit. In addition, the results obtained previously remain overall stable: having an adopter county crosswind the previous year does not hasten adoption, while having an adopter county upwind does; having an adopter county downwind is less precisely estimated (the coefficient becomes non significant) but the point-estimate remains fairly stable.

These results further illustrate the importance of spatial processes in the adoption of the DT technology,

[37] Specifically, the Aggregation Index (AI $\in [0, 100]$) is "the ratio of the observed number of like adjacencies to the maximum possible number of like adjacencies given the proportion of the landscape comprised of each patch type", and attains 100 if soybean fields are a single compact patch. The Patch Cohesion Index (PCI $\in [0, 1]$) is "proportional to the area-weighted mean perimeter-area ratio divided by the area-weighted mean patch shape index", and the closer to 1, the higher the physical connectedness of soybean fields. The metrics are strongly correlated, and are therefore not used together.

and corroborate the mechanism proposed here of negative spatial externalities imposed by adopters on non-adopters, that are all the more damaging that DT-eligible fields are aggregated in space.

4.6 Alternative hypotheses

This section briefly overviews alternative hypotheses to the negative spatial externality-mediated forced adoption process presented here.

Land-use change: Commodity prices

The land use changes observed in section 4.3 could alternatively be happening because of changes in commodity prices such that after 2015, soybean and cotton would be more profitable to grow. First, for that phenomenon to explain the findings detailed in Table 3, they would have to differentially affect counties positioned downwind from adopter counties, which while not impossible, seems peculiar. Second, commodity prices should indeed evolve according to the hypothesis, which they do not (refer to the price time series plotted in the appendix, Figure S7). Cotton and soybean were certainly not becoming more attractive in 2016-17.

Technical and economic superiority of the new technology

Another explanation for the rapid adoption of dicamba-tolerant seeds could be that they were technically superior to the available technologies, and satisfied a demand or need of the farmers.

DT seeds are at face value similar to the GM seeds that preexisted in soybean and cotton, only with an *additional* feature. In practice, that may not be so straightforward; for instance, new genetic traits may come at a cost for yields (fitness tradeoff or less adapted variety). And indeed, reports on the yields of DT soybeans and cotton are contrasted, with some agricultural extensions reporting no better production per hectare and even slight decreases, and some individual farmers reporting better harvests. The average effects on yields that I find are consistent with that, and see also the discussion on labor, seeds, and chemicals expenses in section 4.7.

This hypothesis cannot in any case explain the findings: adoption patterns on the grounds of superiority of the new technology should be isotropic (the same in all directions of space), hence are incompatible with the wind-biased adoption uncovered here.

4.7 On forced adoption

4.7.1 "Listen, I did not want to do this but I am going to be forced to go dicamba"[38]

If the adoption of DT seeds is indeed forced for some farmers, rather than a deliberate choice of a superior technology, it should be then possible that some of them adopt the seed to protect their yields but refrain from using the herbicide as specified so as not to cause harm to their neighbors. That would translate into a lower-than-expected increase in dicamba use.

The standard application rate of dicamba as a post-emergence treatment (that available only for DT seeds) is 0.56 kg/ha (as specified on the label and cited in Sciumbato et al. (2004)), and farmers can make two applications during the growing season, hence an additional 1.2 kg/ha sprayed per season on DT soybean and cotton *only*.

[38] Neighbor to soybean grower Randy Brazel. Reported by NPR (Feb 7th, 2019).

	Add. dicamba used (kg)	Area under DT crops (ha)	Avg. application rate (kg/ha)
Method 1	5,596,694	10,521,827	0.53
Method 2	5,163,434		0.49

Notes: Methods 1 and 2 correspond to different ways of calculating the additional dicamba use attributable to DT crops; both amount to attributing dicamba use that deviates from the expected quantities to usage on DT crops. Method 1 takes the sum of all non-negative anomalies (as defined in 3.1), and Method 2 sums only the anomalies that are larger than one standard deviation (i.e. those that translate in the assignment of a "adopter" status to the county), both for 2017. The area under DT crops is obtained from figures cited in the press as communicated by Monsanto (specifically, 20 million acres of soybean, 6 million acres of cotton, in 2017).

Table 7: In-crop application rate estimates

Table 7 shows application rates that are of the right order of magnitude, but still well below the label specification; said otherwise, the increase in dicamba use because of DT seeds is lower than an engineering estimate based on (legally binding) pesticide use restrictions would suggest. Using DT seeds without spraying dicamba over-the-top in the fields in which they are planted defeats the purpose of the technology, and amounts to purposefully and knowingly taking losses (rather, not reaping benefits). While Table 7 does not rely on micro data of application rates during the soybean and cotton growing seasons, these highly stylized facts suggest that some of the growers adopted the technology intending *not* to use it, i.e. only to protect themselves from dicamba drift.

4.7.2 Farmers' expenses

Despite the absence of clear effect on yields, the technology could have benefited adopters in reducing expenses; indeed, by simplifying substantially the management of weeds during the growing season, the technology is *a priori* labor-saving. It might also have saved expenses on alternative herbicides, possibly enough to compensate the increased use of dicamba; the *a priori* effect on seed expenses is unclear, but discounts were offered on seed-dicamba bundles in the first years after the technology became available.

However, comparing adopters and non-adopters before and after the introduction of the new technology in two consecutive agricultural census year (2012, 2017) in Table 8, the counties with high adoption were at no advantage: their labor expenses (column 3) remained unchanged, and their expenditures for seeds and chemicals (columns 4 and 1, respectively) increased.

Note nonetheless that an important limitation of the data used here is its lack of specificity to soybean and cotton growers, and the findings are therefore to be interpreted with caution.

4.8 Limitations and caveats

As far as the costs are concerned, the monetary costs associated with yield losses and crop failures for non-DT plots are not measured; while it seems an important component in the assessment of DT seeds as a whole, this endeavor is rendered difficult by the dearth of data. Indeed, there is no systematic accounting and monitoring of damages and losses. Efforts have been made, in particular by the agricultural extension at University of Missouri to collect and gather such data across the United States, but in addition to showing the alarming extent of the damage, they have also shown the scantness and partial nature of the data.[39] Attempts at identifying a signal of dicamba damage via remote sensing (not shown) proved fruitless: while

[39] For further information, the reader is referred to Dr. Kevin Bradley's articles on the newsletter of the Integrated Pest & Crop Management department at University of Missouri. See for instance "July 15 Dicamba injury update. Different Year, same questions" (19/07/2018).

	Chemicals	Fertilizers	Labor	Seeds	Land
	(1)	(2)	(3)	(4)	(5)
Adopter X post	**407905***	**−1879248*****	33520	**591425****	1251
	(203235)	(295327)	(368364)	(189621)	(1306)
tMin	1613506	2374571	1840022	1293750	−9238
	(926356)	(1340664)	(1699966)	(861813)	(5909)
tMin2	**−97706***	−74370	−122460	−67986	268
	(40427)	(58532)	(74029)	(37660)	(258)
tMax	−3411177	**15471139*****	−5036363	2195726	−6122
	(1874193)	(2719112)	(3439735)	(1736024)	(11911)
tMax2	22407	**−276035*****	44618	**−59287***	113
	(32607)	(47350)	(59828)	(30229)	(207)
prec	−796	**2105***	−351	**−1288***	−7
	(701)	(1004)	(1280)	(652)	(4)
prec2	−1	−1	−1	0	0
	(1)	(2)	(2)	(1)	(0)
dday10C	**31745****	−24651	33944	2121	21
	(9646)	(13948)	(17687)	(8979)	(61)
dday10C2	−3	6	−0	2	−0
	(2)	(4)	(5)	(2)	(0)
dday29C	−2889	**38532*****	−7174	3202	−4
	(6738)	(9743)	(12278)	(6281)	(43)
dday29C2	**48*****	**−53****	5	**30***	−0
	(13)	(19)	(23)	(12)	(0)
R^2	0	0	0	0	0
Dep. var. mean	5,666,969	8,590,222	2,383,954	6,714,904	128,608.5
Num. obs.	5296	5335	5164	5296	5369

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Table shows regression results for fixed-effect models regressing costs for chemicals, fertilizers, labor, seeds (USD), land extent (acres), on adopter status before (2012 census) and after (2017) the commercialization of the dicamba technology. All regressions include weather controls.

Table 8: Cost models

the signs of damage such as leaf cupping (soybean plants) are unmistakable and visible from the ground, the remote sensing technology I used (Landsat, 30 m ground resolution) might be too coarse in time and space to capture them (I took GPP, gross primary productivity, as an indicator of good plant health, and computed it at the county and monthly level); and while drones have been able to detect dicamba damage over some fields,[40] it is unclear for now that dicamba damage, even when it impacts yields, translates *necessarily* into a markedly different and characteristic spectral signal (e.g. depending on concentrations, growth stage, crop, etc.). It has been shown that dicamba's effect on soybean yields depends on the growth stage at which the soybean plant is exposed to dicamba (McCown et al., 2018), but plant scientists are just beginning to uncover the range of outcomes following an encounter with dicamba.

Further words of caution concern the procedure employed to quantify adoption at the county level. The fact that some farmers can buy DT seeds just to be protected from the drift from their neighbors' fields, without using dicamba in-crop themselves, is a known limitation of the method. Another known limitation is that the relationship between crop acreage and herbicide use is not deterministic, and while the fit obtained here for dicamba is reasonable, the construction the proxy for DT seed adoption relies on it and

[40]E.g. see false color image tweeted by a farmer, showing extensive dicamba damage in his field, reproduced in Appendix Figure S12.

that necessarily introduces noise.[41]

[41] The case of Kansas provides an extreme illustration of the noise to which those estimations are subject.

5 Further implications, future research

This paper but scratches the surface of the transformations brought about by DT seeds. I touch here on a few foreseeable consequences to which historical analogues or anecdotal evidence point, and that in light of this study deserve further research. Only after considering these, in combination with the adoption mechanism highlighted here, will the welfare analysis of DT seeds be possible. But all have a broader relevance beyond the case of DT seeds: market structure consequences are to be anticipated in any case of forced technological adoption, while genetically modified crops in general, and in particular those tolerant to herbicide, bring about questions regarding health and ecological processes that can be addressed thanks to the DT seed adoption setting.

There are mainly four types of consequences one should be concerned with: first, consequences on the Farm structure in the U.S. because of the possible supplement of bankruptcies, second, consequences on the Structure of the soybean and cotton seed sector because of the emergence of a dominant firm, third, consequences on the Health of surrounding populations following the increased release of a volatile known irritant and suspected teratogenic substance, fourth, consequences on the Ecology and evolution of the agroecosystems where DT seeds arrive because of the heightened potential for the evolution of resistant weeds, and of the rippling effects through the ecosystem of off-target movement of dicamba on the vegetation.

Farm structure

First, dicamba damage means financial distress for specialty crop growers, it has been reported, and likely for non-DT soybean and cotton growers as well. And while farmers can for the most part withstand a year with inferior yields, several in a row may prove fatal and lead to bankruptcy, but quantifying the effect of DT seed penetration on farm bankruptcy will require longer hindsight. In the specialty crop sector, bankruptcies and decreased production are expected in the DT seed-exposed counties; bankruptcies are to be expected as well in soybean and cotton, but also farm sales, and consolidation. These hypotheses stem directly from the mechanism uncovered in this paper, and are easily testable (and quantifiable) once the data becomes available.

Structure of the soybean and cotton seed sector

> "I have a neighbor, a friend. He calls me and says, 'I am going to have to go dicamba.' [...] Then I have to get on the phone and call every other neighbor and say, 'Listen, I did not want to do this. But I am going to be forced to go dicamba.' Well, then that forces all those neighbors to call all their neighbors. And eventually what you have is a monopoly."
>
> Randy Brazel, soybean grower at the MO/TN border, to NPR (Feb 7th, 2019)

A second line of inquiry will require a longer view still: what are the consequences of the sudden dominance of a single product made by a single firm in terms of competition on the seed market? While the seed producer has reportedly offered discounts to early adopters, it could very well turn to extracting substantial rents should the dominance situation persist and intensify. The notorious opacity of the seed market[42] (at both the manufacturer and retailer levels) certainly should be no hindrance to that.

To get at the welfare consequences of the emergence of a dominant situation on the seed market, it is useful to think in terms of the model of the dominant firm with competitive fringe laid out in Carlton and

[42] E.g. see "Silicon Valley Company Aims To Help Farmers Compare Seed Prices," NPR, 23/04/2019.

Perloff (1994). Since only one firm possesses the DT technology, and that, by 2019, DT seeds made well over 70% of both the soybean seed and the cotton seed markets, that firm detains a dominant position ensured by monopoly over the DT technology and secured by the negative externalities it generates on non-adopters; therefore the model of the dominant firm is appropriate.

The paper highlights two phenomena: the within-sector spillovers that force soybean and cotton growers to adopt DT seeds, and the cross-sectoral spillovers, that force the conversion of land into soybean and cotton. There is therefore on the one hand the constitution of a less competitive sector (considering that the seed market for soybean and cotton was either perfectly competitive or an oligopoly with $n > 2$ firms), and on the other hand the transfer of land from a competitive sector (other seeds) to the newly reshaped sector with a dominant firm, soybean and cotton seeds. The total welfare loss associated with the decreased competition in the soybean and cotton seed sector will therefore be the sum of these two effects.

Health

Studies such as Dias et al. (2023); Jones (2020); Frank (2021) have demonstrated the effect of pesticides applied in the environment on infant health – namely, of one herbicide (glyphosate); of fungicides and insecticides as a "cocktail"; or just insecticides, again as a "cocktail", respectively. Given those precedents, and the known high volatility of dicamba, and epidemiological evidence of its carcinogenicity (McDuffie et al., 2001; Lerro et al., 2020), effects on health are possible; they are expected in particular on birth outcomes (malformations, death) and respiratory health.

The sudden increase in dicamba use, along with its wind-biasedness would enable the causal identification of the effects of the substance on health, which is in itself of interest for policymaking purposes in general, and in the assessment of DT seeds in particular. Direct evidence the existence, nature, and magnitude of health effects of pesticides on the health of surrounding populations is lacking, were it not for the two studies cited above. Given that those studies have indeed found deleterious effects on birth outcomes (developmental issues and deaths), and given the disproportionate effects of the fetal environment on later life outcomes (Almond and Currie, 2011), it is important to produce such evidence.

Ecology and evolution of the agroecosystems

The sudden and widespread dominance of a single variety of seeds could have agro-ecological consequences too, with the onset of a Red Queen race (Van Valen, 1973; Rosenzweig et al., 1987) (roughly speaking, an evolutionary arms race) between weeds and farmers. The risk was clearly anticipated in the Environmental Impact Statement prepared to inform the decision to deregulate DT seeds:

> "Increased selection pressure caused by wide-spread adoption of HR [herbicide resistant] crops and reduction in the use of other herbicides and weed management practices, resulted in both weed population shifts and growing numbers of HR individuals among some weed populations" (*Monsanto Petitions (10-188-01p and 12-185-01p) for Determinations of Nonregulated Status for Dicamba-Resistant Soybean and Cotton Varieties*, Final Environmental Impact Statement, December 2014, p. 81)

Said otherwise, the massive use of a single pesticide could lead to the selection of resistance traits in the pest, and the constitution of resistant populations, similar to what happened with glyphosate and glyphosate-resistant weeds (Powles, 2008). The more widespread the use, the sooner the resistance. And while resistance to dicamba has just been discovered in Palmer amaranth,[43] the extent of dicamba resistance, the role of DT seeds in fostering it, and its cost to farmers, remain open questions for future research.

Finally, unintended consequences on wildlife have been reported that are poised to be of both economic and ecological importance. Dicamba mimics a plant growth hormone (auxin), and its mode of action is to grow the plants to exhaustion. This is true not only for non-DT soybean, cotton, and specialty crops, but also for wild vegetation. Its off-target moves have reportedly caused damage on trees[44] and wild flowering plants. While in themselves preoccupying, they could translate into farther-reaching consequences for the species that depend on them (for instance for food), e.g. insect pollinators and birds. This dearth of flower resources has already been blamed for the decline (and subsequent displacement by their beekeepers) of some bee colonies, and could alter the ecosystem services provided by birds (e.g. pest suppression) should their populations decline for want of food. Both bearing on the rural economies of places where DT seeds are widely adopted. Assessing any of these ecosystem-mediated consequences will again require a longer record of the post-DT crop world.

[43] "Palmer amaranth resistance to 2,4-D and dicamba confirmed in Kansas", Kansas State University Agronomy eUpdate, Issue 734, March 1st, 2019, webapp.agron.ksu.edu.

[44] See for instance "A Drifting Weedkiller Puts Prized Trees At Risk" (NPR, 27/09/2018) on damage to protected cypress trees in Tennessee.

6 Conclusions

Can technology diffusion go "too fast"?

Taken in positive terms, I show that negative externalities imposed by adopters on non-adopters can indeed hasten technology diffusion, a mechanism similar to that described in Guiteras et al. (2019). And while in their case the negative externality consisted of shame, was purely a social construct, and led to the adoption of health-improving latrines, in the case I present here, the negative externality consists of windborne particles of herbicide drifting from adopters' fields and damaging non-adopters' crops, leads to financial losses for non-adopters, and spills over to other sectors apparently unrelated to those for which the technology was developed.

The implications of this paper are twofold. The first set of consequences concerns the possibility of "forced technological adoption" because of the existence of negative externalities, the second pertains to broader implications for policy regarding herbicide tolerant GMOs of which DT crops are but an avatar. While other drivers of adoption are not ruled out (and should not be), windborne negative externalities paved the way for the new DT seed technology by deteriorating the bottom line of recalcitrant soybean and cotton growers *to the extent that they had adopters in their wind-vicinity* while leaving the adopters' unscathed. In that way, and because otherwise irrelevant wind patterns are shown here to matter for adoption, the extra help provided by windborne dicamba particles to the diffusion of the DT technology amounts to forced technological adoption. Examples of such strategic interactions leading to technological change (rather, switch) need not be restricted to agriculture: one naturally thinks about the possibility of coexistence of organic and non-organic fields, GM and non-GM crops (Munro, 2008), but a similar pattern of adoption in individual cars in the United States provides the starting point in White (2004), where drivers switch to SUVs and light trucks to be better protected in the event of a crash, especially one with a SUV or a light truck, four times deadlier than with a smaller car, thereby giving way to an "arms race" for larger, safer, yet deadlier cars (see also Anderson and Auffhammer, 2013). This phenomenon, whether leading to desirable (latrine adoption), undesirable (traffic fatalities), or questionable (dicamba-tolerant seeds) outcomes, seems understudied compared to other phenomena of technology adoption, despite its vast potential for policy intervention, obvious from the three examples cited here.

The second set of implications concerns the regulation of GMOs and in particular of those of the herbicide-tolerant (HT) type. What this study has shown is that DT seeds led to the increased use of a potent broad-spectrum herbicide that (a) *happens* to be very volatile, and (b) *by design* was to be sprayed during the growing season (i.e., in-crop), which led to a variety of problematic outcomes for farmers. While (a) seems to be an unfortunate chemical property of the complementary herbicide, all herbicides have some propensity to drift[45] and (b) is not an accident but a *feature* of HT crops in general. Therefore what has been happening with DT seeds since 2015 is only a mildly more vivid example of the typical consequences to be expected from herbicide-tolerant GMOs. Said otherwise, negative production externalities among farmers are a necessary consequence of HT GMO varieties. Externalities are famously inefficient, and therefore warrant policy intervention to restore efficiency. And that the damage should not be caused by the seed itself but by the herbicide is both factually correct (the herbicide is the proximal cause) and a gross fallacy (the HT seed commands the use of the herbicide during the growing season). Policy tools exist, from taxes

[45] Despite not being just as salient, glyphosate drift was also an issue when the first HT crops were introduced in the late 90s: "In the first years after the introduction of Roundup Ready soybean it was not unusual to see 10 to 20 rows of corn damaged, even killed, by glyphosate drift," writes professor of agronomy Bob Hartzler of the Agricultural Extension at Iowa State University. He adds: "However, it was rare to see glyphosate injury across entire fields." ("Thoughts on the Dicamba Dilemma," 13/07/2017)

to quotas and bans, that could prevent further inefficiencies from occurring, such as the constitution of a monopoly situation in the soybean or cotton seed market, and alleviate the public health burden borne by rural populations in the vicinity of fields planted with herbicide-tolerant crops. For instance, Ambec and Desquilbet (2012) theoretically showed the conditions under which optimality was restored by a tax in the face of yet another spatial externality generated by genetically modified crops (emergence of pest resistance).

To conclude on the adoption mechanism unpacked here, forced or faster adoption raises the following concerns in general, that I will illustrate with the dicamba-tolerant seeds case. First, the rapid adoption of this patented technology has had market structure consequences. Its owner acquired a dominant position within a few years on the seed market, and was able to exercise more market power (though the extent to which it actually did would be difficult to quantify given the opacity of the seed sector); seed retailers have been pressured to offer the new technology at the expense of the other varieties and manufacturers, inducing a loss of product diversity at both levels, the farmer's and the retailer's. This was not so much the case for dicamba itself, as the herbicide was already produced by several companies, even though the seed manufacturer encouraged (incentivized) using their brand of the herbicide. The mechanism of adoption mediated by negative externalities on non-adopters results in a situation of multiple equilibria and, unless the regulator intervenes, a likely case of lock-in into that particular technology (as opposed to intermediate levels of adoption). Second, the massive use of the DT seeds–dicamba pair following fast and widespread adoption has meant the release into the environment of a biocide (dicamba, a herbicide) on an unprecedented scale. This is a natural experiment on a very large scale with poorly known consequences as yet. As case-studies have shown (Gillespie et al., 1979; Portier, 2020), the human health hazard of pesticides is known but imprecisely at best at the time of their authorization. Releasing such substances in the environment on that scale might cause a public health problem, as did the massive use of asbestos (later found carcinogenic and toxic for the lung) or PCBs (later found toxic -including carcinogenic-, reprotoxic, ecotoxic). It can likewise have rippling effects through ecosystems, as have many other technologies fast-adopted and hard to eliminate *a-posteriori* (plastic fishing nets, lead ammunition). Third, in the case of a biocide, its widespread use drives the evolution of resistance – it makes the technology fast obsolete, and is yet another externality imposed on non-users of the DT seeds (their herbicide becomes useless as well). The pervasiveness and the speed of diffusion are key in all these three aspects, as they prevent the entry of competitors to challenge the monopoly; they lead to a possible technology lock-in; they leave little time for an evaluation of unforeseen and undesired consequences while fueling the evolution of resistance. Except this last point,[46] these are general features of fast technology adoption in the presence of uncertainty. This raises the question, in particular in light of the need for innovation and technology diffusion for the green transition, what is the optimal speed of adoption?

[46]Specific to technologies involving biological control, e.g., antibiotics, pesticides.

References

Abramovitz, M. (1986). Catching Up, Forging Ahead, and Falling Behind. *The Journal of Economic History 46*(2), 385–406.

Almond, D. and J. Currie (2011). Killing Me Softly: The Fetal Origins Hypothesis. *Journal of Economic Perspectives 25*(3), 153–172.

Ambec, S. and M. Desquilbet (2012). Regulation of a Spatial Externality: Refuges versus Tax for Managing Pest Resistance. *Environmental and Resource Economics 51*(1), 79–104.

Anderson, M. L. and M. Auffhammer (2013). Pounds That Kill: The External Costs of Vehicle Weight. *Review of Economic Studies 81*(2), 535–571.

Arrow, K. J. (1962). The Economic Implications of Learning by Doing. *The Review of Economic Studies 29*(3), 155–173.

Baker, N. T. and W. W. Stone (2015). Estimated Annual Agricultural Pesticide Use for Counties of the Conterminous United States, 1992–2009. *Geological Survey Data Series 907*, 1–9.

BenYishay, A. and A. M. Mobarak (2019). Social Learning and Incentives for Experimentation and Communication. *The Review of Economic Studies 86*(3), 976–1009.

Besley, T. and A. Case (1993). Modeling Technology Adoption in Developing Countries. *The American Economic Review 83*(2), 396–402.

Boryan, C., Z. Yang, R. M. Mueller, and M. Craig (2011). Monitoring US agriculture: the US Department of Agriculture, National Agricultural Statistics Service, Cropland Data Layer Program. *Geocarto International 26*(5), 341–358.

Bulow, J. I., J. D. Geanakoplos, and P. D. Klemperer (1985). Multimarket Oligopoly: Strategic Substitutes and Complements. *Journal of Political Economy 93*(3), 488–511.

Bunch, T. R., J. A. Gervais, K. Buhl, and D. Stone (2012). Dicamba Technical Fact Sheet. *National Pesticide Information Center, Oregon State University Extension Services*.

Burton, N., S. W. Shirriff, and H. J. Beckie (2014). Response of glyphosate-resistant kochia (Kochia scoparia L. Schrad.) to alternative herbicides. *Canadian Journal of Plant Science 94*(8), 1407–1411.

Carlton, D. W. and J. M. Perloff (1994). Monopolies, Monopsonies, and Dominant Firms. In *Modern Industrial Organization* (2nd ed.)., pp. 132–174. Harper Collins.

Choi, J. P. and M. Thum (1998). Market structure and the timing of technology adoption with network externalities. *European Economic Review 42*(2), 225–244.

Costello, C. and S. Polasky (2008). Optimal harvesting of stochastic spatial resources. *Journal of Environmental Economics and Management 56*(1), 1–18.

Costello, C., N. Quérou, and A. Tomini (2017). Private eradication of mobile public bads. *European Economic Review 94*, 23–44.

Cowan, R. and P. Gunby (1996). Sprayed to Death: Path Dependence, Lock-in and Pest Control Strategies. *The Economic Journal 106*(436), 521.

Cushman, S. A., K. McGarigal, and M. C. Neel (2008). Parsimony in landscape metrics: Strength, universality, and consistency. *Ecological Indicators 8*(5), 691–703.

David, P. A. (1985). Clio and the Economics of QWERTY. *American Economic Review 75*(2), 332–337.

Deryugina, T., G. Heutel, N. H. Miller, D. Molitor, and J. Reif (2019). The Mortality and Medical Costs of Air Pollution: Evidence from Changes in Wind Direction. *NBER Working Paper* (22796).

Dias, M., R. Rocha, and R. R. Soares (2023). Down the River: Glyphosate Use in Agriculture and Birth Outcomes of Surrounding Populations. *The Review of Economic Studies* (February), 1–39.

Frank, E. G. (2021). The Economic Impacts of Ecosystem Disruptions: Private and Social Costs From Substituting Biological Pest Control. pp. 104.

Gillespie, B., D. Eva, and R. Johnston (1979). Carcinogenic Risk Assessment in the United States and Great Britain: The Case of Aldrin/Dieldrin. *Social Studies of Science 9*(3), 265–301.

Griliches, Z. (1957). Hybrid Corn: An Exploration in the Economics of Technological Change. *Econometrica 25*(4), 501–522.

Guiteras, R., J. Levinsohn, and A. M. Mobarak (2019). Demand Estimation with Strategic Complementarities: Sanitation in Bangladesh.

Han, W., Z. Yang, L. Di, and R. M. Mueller (2012). CropScape: A Web service based application for exploring and disseminating US conterminous geospatial cropland data products for decision support. *Computers and Electronics in Agriculture 84*, 111–123.

Heal, G., B. H. Walker, S. A. Levin, K. J. Arrow, P. Dasgupta, G. C. Daily, P. R. Ehrlich, K.-G. Maler, N. Kautsky, J. Lubchenco, S. H. Schneider, and D. Starrett (2004). Genetic diversity and interdependent crop choices in agriculture. *Resource and Energy Economics 26*(2), 175–184.

Jack, K. (2013). Constraints on the adoption of agricultural technologies in developing countries. Technical report.

Jaffe, A. B., R. G. Newell, and R. N. Stavins (2005). A tale of two market failures: Technology and environmental policy. *Ecological Economics 54*(2-3), 164–174.

Jones, B. A. (2020). Invasive species control, agricultural pesticide use, and infant health outcomes. *Land Economics 96*(2), 149–170.

Kumar, V., R. P. Engel, R. Currie, P. Jha, P. W. Stahlman, and C. Thompson (2019). Dicamba-resistant kochia (Bassia scoparia) in Kansas: Characterization and management with fall- or spring-applied PRE herbicides. *Weed Technology 33*(2), 342–348.

Lark, T. J., R. M. Mueller, D. M. Johnson, and H. K. Gibbs (2017). Measuring land-use and land-cover change using the U.S. department of agriculture's cropland data layer: Cautions and recommendations. *International Journal of Applied Earth Observation and Geoinformation 62*(June), 224–235.

Lerro, C. C., J. N. Hofmann, G. Andreotti, S. Koutros, C. G. Parks, A. Blair, P. S. Albert, J. H. Lubin, D. P. Sandler, and L. E. B. Freeman (2020). Dicamba use and cancer incidence in the agricultural health study: an updated analysis. *International Journal of Epidemiology 49*(4), 1326–1337.

Manski, C. F. (1993). Identification of Endogenous Social Effects: The Reflection Problem. *The Review of Economic Studies 60*(3), 531–542.

Manuelli, R. E. and A. Seshadri (2014). Frictionless Technology Diffusion: The Case of Tractors. *American Economic Review 104*(4), 1368–1391.

McCown, S., T. Barber, and J. K. Norsworthy (2018). Response of Non-Dicamba-Resistant Soybean to Dicamba As Influenced by Growth Stage and Herbicide Rate. *Weed Technology 32*(5), 513–519.

McDuffie, H. H., P. Pahwa, J. R. McLaughlin, J. J. Spinelli, S. Fincham, J. A. Dosman, D. Robson, L. F. Skinnider, and N. W. Choi (2001). Non-Hodgkin's lymphoma and specific pesticide exposures inmen: Cross-Canada study of pesticides and health. *Cancer Epidemiology Biomarkers and Prevention 10*(11), 1155–1163.

McGarigal, K., S. A. Cushman, M. C. Neel, and E. Ene (2002). FRAGSTATS: Spatial Pattern Analysis Program for Categorical Maps.

Mesinger, F., G. DiMego, E. Kalnay, K. Mitchell, P. C. Shafran, W. Ebisuzaki, D. Jovic, J. Woollen, E. Rogers, E. H. Berbery, M. B. Ek, Y. Fan, R. Grumbine, W. Higgins, H. Li, Y. Lin, G. Manikin, D. Parrish, and W. Shi (2006). North American Regional Reanalysis. *Bulletin of the American Meteorological Society 87*, 343–360.

Multigner, L., P. Kadhel, F. Rouget, P. Blanchet, and S. Cordier (2016). Chlordecone exposure and adverse effects in French West Indies populations. *Environmental Science and Pollution Research 23*(1), 3–8.

Munro, A. (2008). The spatial impact of genetically modified crops. *Ecological Economics 67*(4), 658–666.

Ostrom, E. (2000). Collective action and the evolution of social norms. *Journal of Economic Perspectives 14*(3), 137–158.

Portier, C. J. (2020). A comprehensive analysis of the animal carcinogenicity data for glyphosate from chronic exposure rodent carcinogenicity studies. *Environmental Health: A Global Access Science Source 19*(1), 1–18.

Powles, S. B. (2008). Evolved glyphosate-resistant weeds around the world: lessons to be learnt. *Pest Management Science 64*(4), 360–365.

PRISM Climate Group at Oregon State University (2019). Gridded Climate Data.

Reinganum, J. F. (1989). The timing of innovation: Research, development, and diffusion. In *Handbook of Industrial Organization*, Volume 1, Chapter 14, pp. 849–908.

Rosenzweig, M. L., J. S. Brown, and T. L. Vincent (1987). Red Queens and ESS: the coevolution of evolutionary rates. *Evolutionary Ecology 1*(1), 59–94.

Schlenker, W. and M. J. Roberts (2009). Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. *Proceedings of the National Academy of Sciences of the United States of America 106*(37), 15594–15598.

Schlenker, W. and W. R. Walker (2016). Airports, air pollution, and contemporaneous health. *Review of Economic Studies 83*(2), 768–809.

Sciumbato, A. S., J. M. Chandler, S. A. Senseman, R. W. Bovey, and K. L. Smith (2004). Determining Exposure to Auxin-Like Herbicides. II. Practical Application to Quantify Volatility. *Weed Technology 18*(4), 1135–1142.

Solow, R. M. (1957). Technical Change And The Aggregate Production Function. *The Review of Economics and Statistics 39*(9), 312–320.

Sunding, D. L. and D. D. Zilberman (2001). The Agricultural innovation process: Research and technology adoption in a changing agricultural sector. In B. L. Gardner and G. C. Rausser (Eds.), *Handbook of Agricultural Economics, Volume 1A*, Chapter 4, pp. 207–261. Elsevier B.V.

Thelin, G. P. and W. W. Stone (2013). Estimation of annual agricultural pesticide use for counties of the conterminous United States, 1992–2009. *U.S. Geological Survey Scientific Investigations Report 2013-5009*, 1–54.

Thives, L. P., E. Ghisi, J. J. Thives Júnior, and A. S. Vieira (2022). Is asbestos still a problem in the world? A current review. *Journal of Environmental Management 319*(July), 115716.

USDA National Agricultural Statistics Service (2018). Cropland Data Layer 2008-2018.

Van Valen, L. (1973). A New Evolutionary Law. *Evolutionary Theory 1*, 1–30.

Wechsler, S. J., J. R. McFadden, and D. J. Smith (2018). What do farmers' weed control decisions imply about glyphosate resistance? Evidence from surveys of US corn fields. *Pest Management Science 74*, 1143–1154.

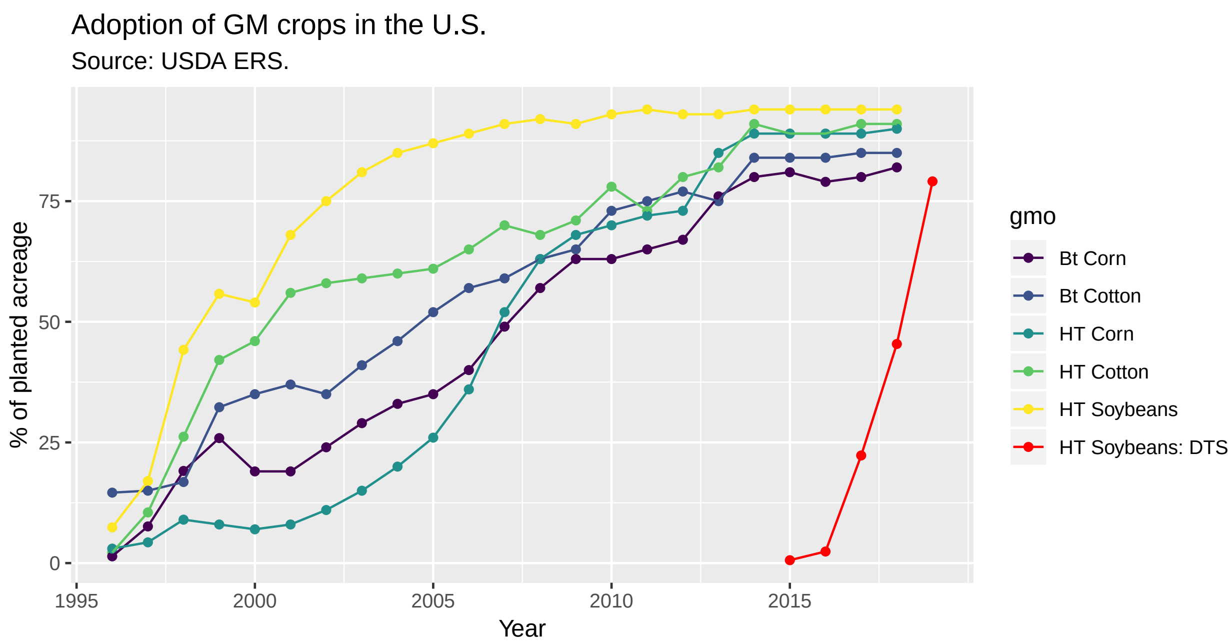
White, C. A. (1983). *A History of the Rectangular Survey System.* Washington, D.C.

White, M. J. (2004). The "Arms Race" on American Roads: The Effect of Sport Utility Vehicles and Pickup Trucks on Traffic Safety. *The Journal of Law and Economics 47*(2), 333–355.

Appendix

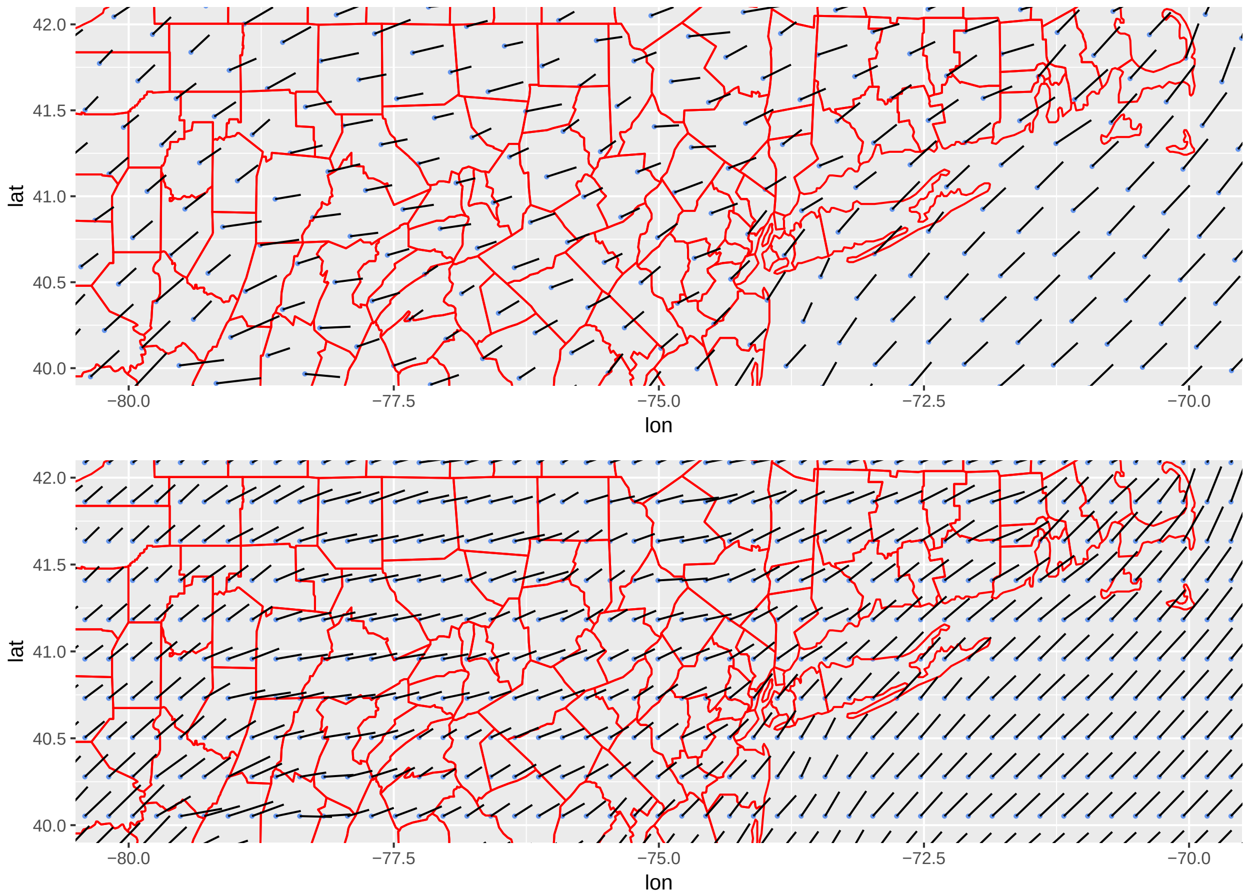
A Additional figures

Figure S1: GM variety uptake in soybean, cotton, corn



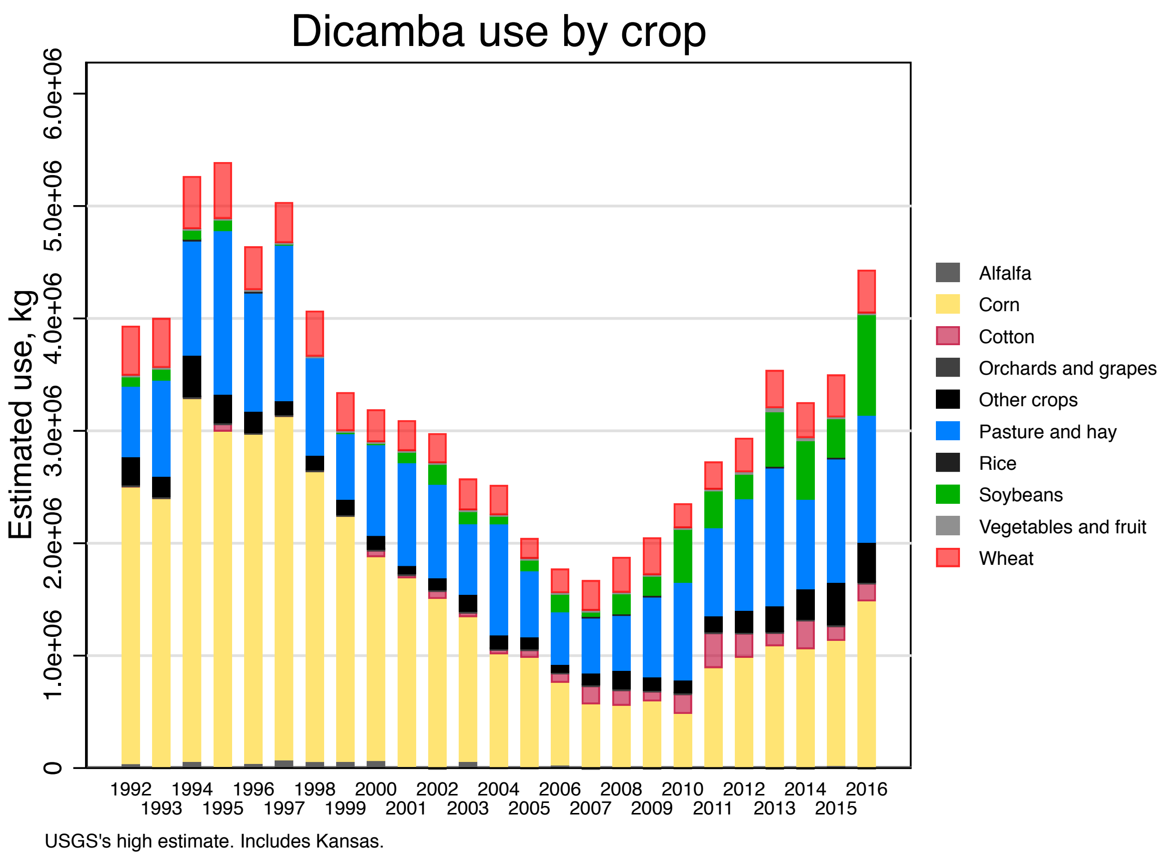
Notes: HT stands for "herbicide tolerant" (and until 2015, it meant glyphosate tolerant), Bt denotes insecticide-producing varieties (Bt stands for *Bacillus thuringiensis*, the bacterium from which the δ-endotoxin genes conferred to Bt crops are taken). Some varieties of corn and cotton are both Bt and HT (data: USDA). In red, HT soybeans that are dicamba-tolerant as a percentage of total U.S. soybean acreage (data: Monsanto/Bayer, USDA).

Figure S2: Interpolation of the wind speed and direction data: illustration



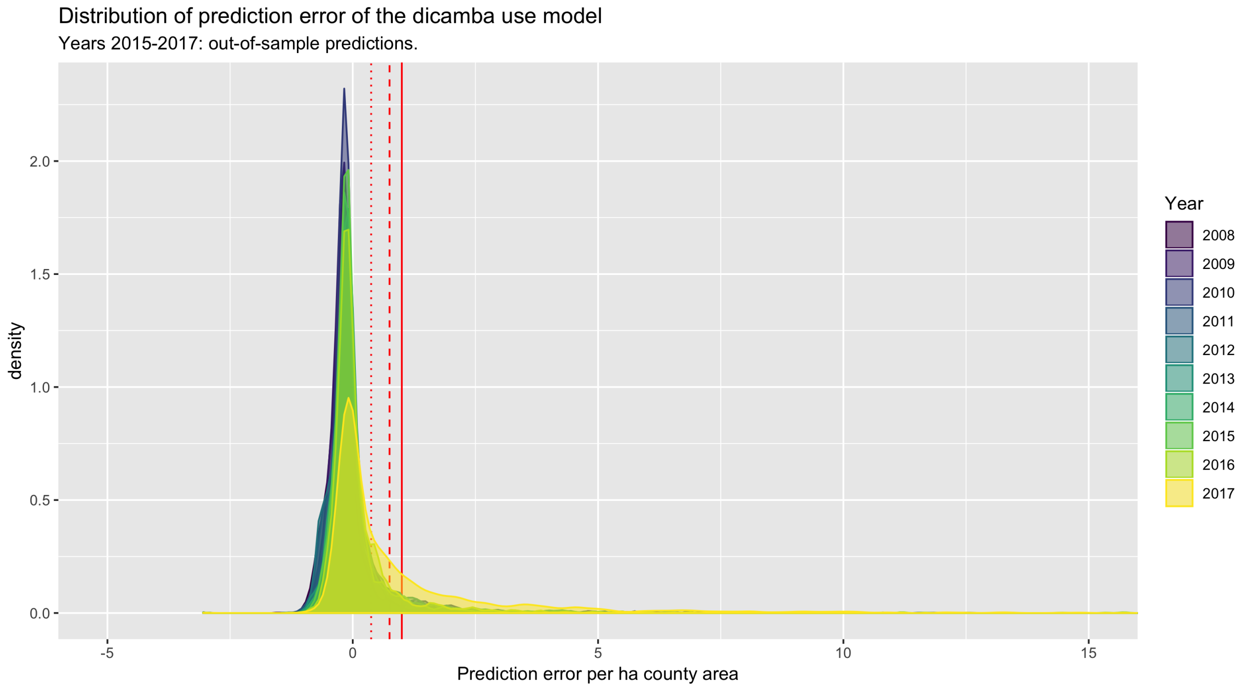
Notes: The top panel shows the original resolution of the NOAA wind data (June 2016), the bottom panel shows the interpolated data (June 2016), with points about two times denser (the distance between two points is divided by $\sim \sqrt{2}$: 32 km in the top panel, 23 km in the bottom panel). The blue tips mark the coordinates of the location to which the u-wind and v-wind values are associated, and the black segments are their projection, therefore the end of the segment would be considered "downwind". Note that the overall pattern is conserved, and that the interpolation enables more matches, but consistently misses some.

Figure S3: Breakdown of usage by crop



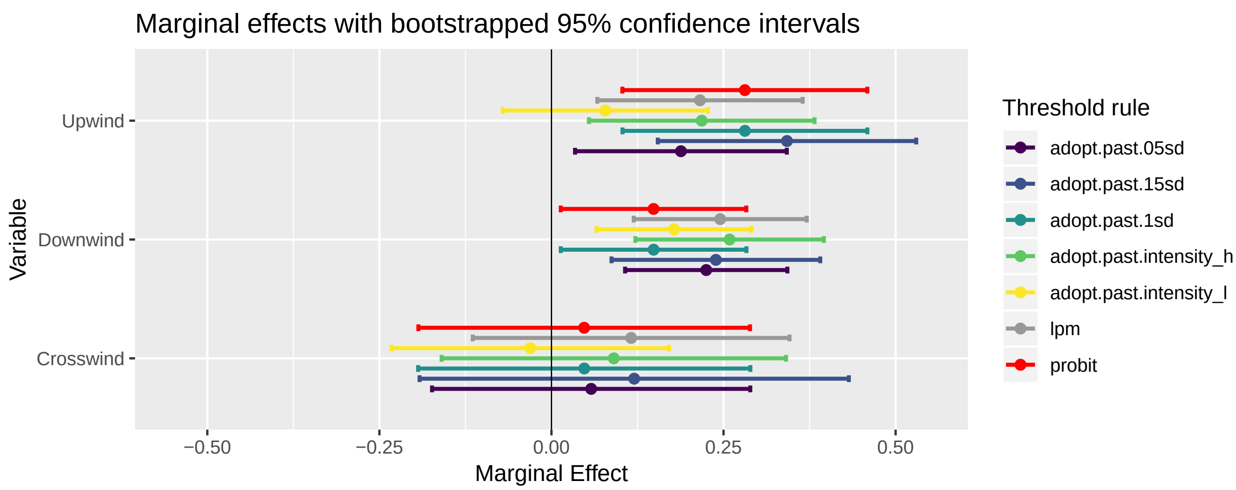
Notes: graph shows dicamba use by year for the conterminous United States, broken down by crop (data: see section 2.2). In our sample period (2008-2017), corn and wheat (monocots, but also two of the most important U.S. crops by acreage) are major receivers, as are pasture and hay land uses. The data by crop only goes as far as 2016 as of the writing of this version; 2017 totals for dicamba use are 9.05×10^6 kg.

Figure S4: Distribution of dicamba anomaly, normalized per ha county area



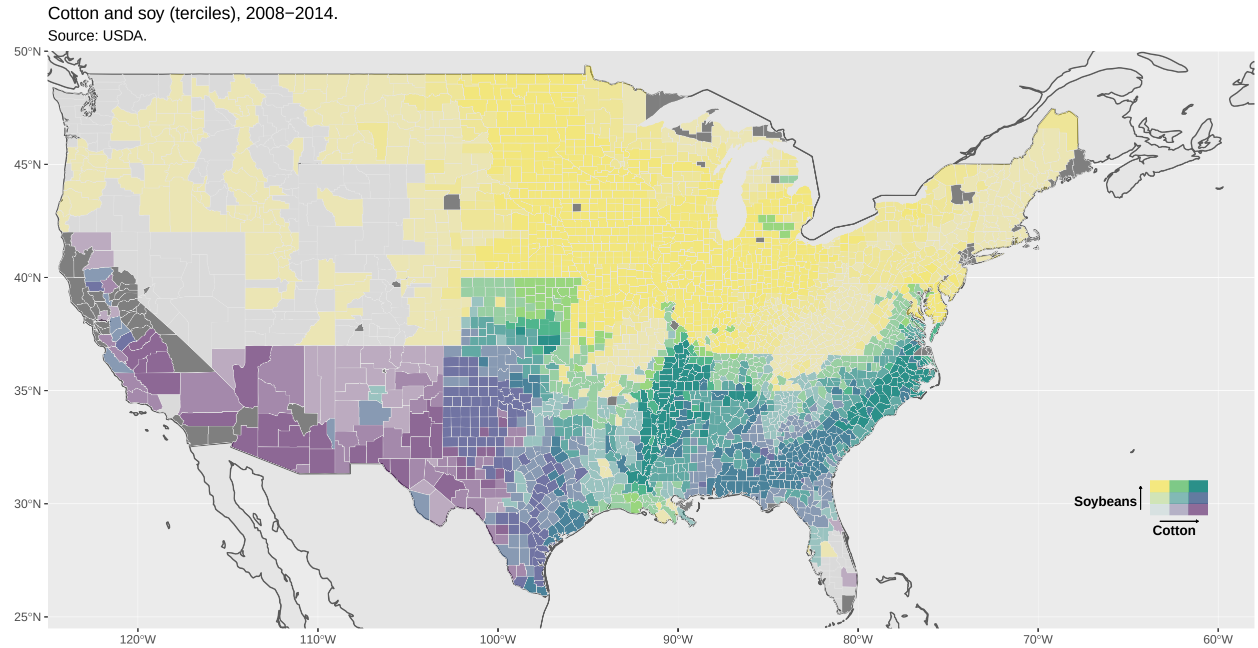
Notes: Figure displays the distribution of dicamba anomaly (homogeneous to kilograms) normalized by the surface of the county (in hectares) for every year in the data; years 2008-2014 correspond to in-sample error ($\hat{\varepsilon}_{it}$), errors for years 2015-2017 are out-of-sample errors. Note the symmetry around zero and small standard deviation of the distributions for years 2008-2014 ($\sigma < 0.9$) and the positive skew, larger standard deviation of later years ($\sigma_{2016} = 1.36$, $\sigma_{2017} = 2.82$). The red dotted line marks an arbitrary threshold at 0.375, the red dashed line at 0.75, the red solid line at 1.00. The plot was truncated at $x = 15$ to facilitate reading (the full support is $[-3.05; 41.47]$ with values beyond 14 kg/ha attained only in 2016 and 2017).

Figure S5: Adoption models: marginal effects – Logit



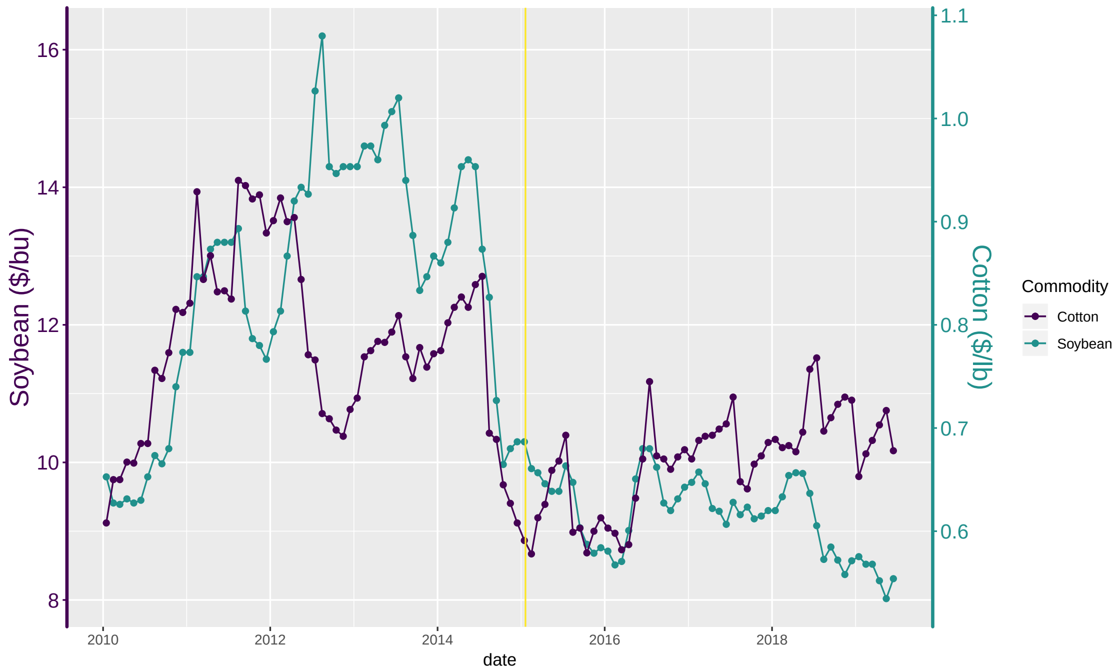
Notes: Plot shows the marginal effects for the logit approach to estimating the adoption model (probability of adoption in 2017 as a function of neighbors' adoption in 2016), with added for reference, the marginal effects associated with the probit model (in red) and the coefficients of the linear probability model (in grey) with the preferred threshold (moderate) already presented in the main text (Figure 4).

Figure S6: Spatial distribution of soybean and cotton growing areas



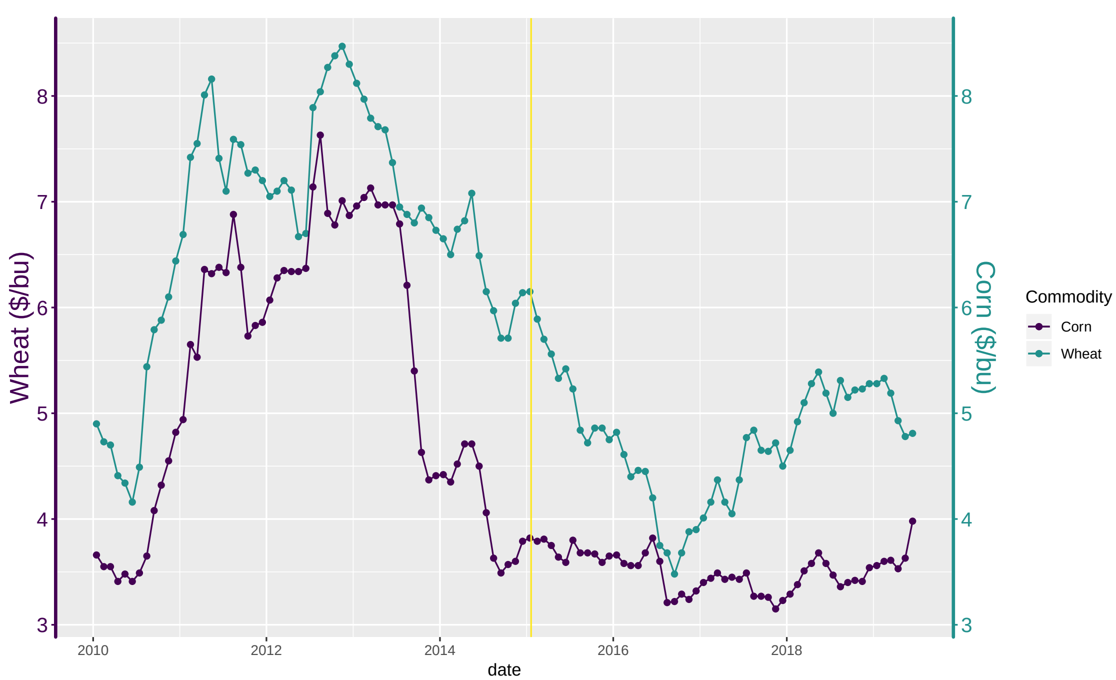
Notes: Maps shows arrangement in space of cotton and soybean growing areas in the pre-DT period (2008-2014) by tercile, based on yearly CDL estimates. Darker shades of purple indicate counties with larger cotton growing areas, more intense shades of yellow counties with larger soybean growing areas, darker blue-green hues counties with jointly larger soybean and cotton growing areas. Note that the total surface under soybeans is about 7.5 times larger than that under cotton in the United States (in 2017 figure), and that there are more counties with any soybean than counties with any cotton; tercile values and sizes differ therefore vastly for the two crops.

Figure S7: Soybean and cotton prices



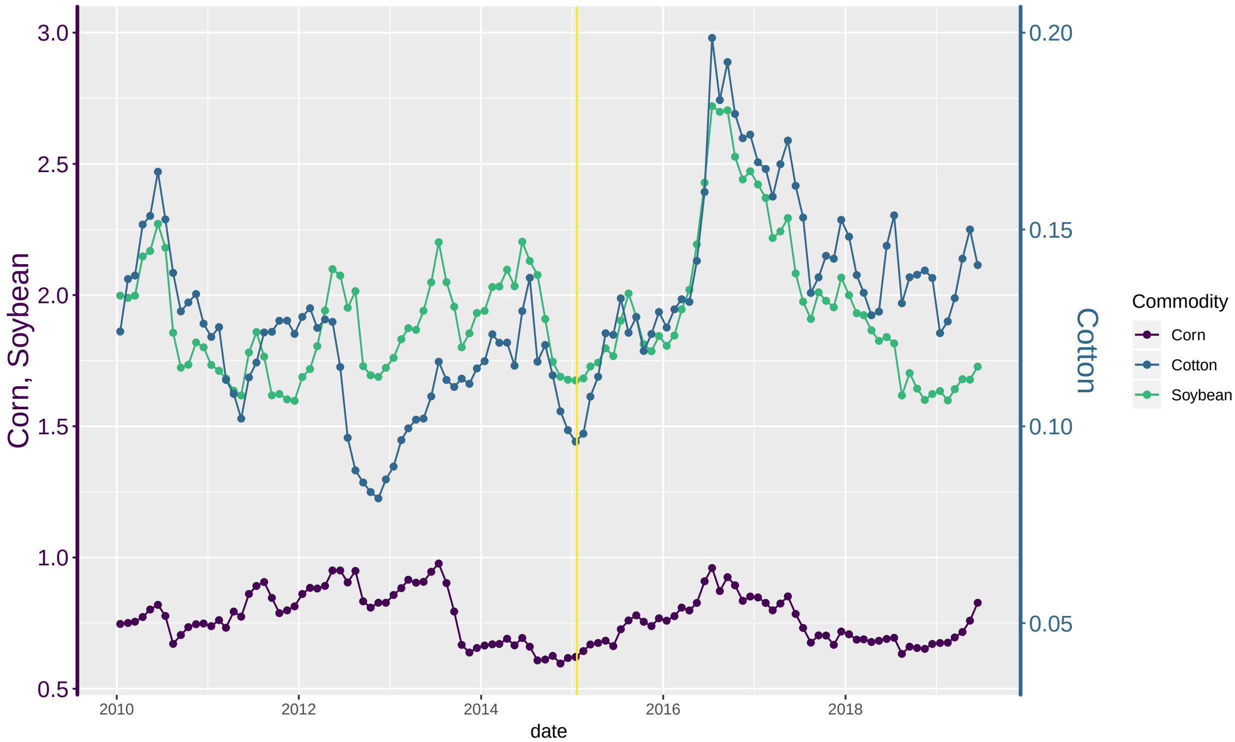
Notes: Graph plots monthly prices received for U.S. soybean (purple, left y-axis) and cotton (teal, right y-axis). Source: USDA. The yellow line corresponds to January 20th, 2017, and the deregulation by the USDA-APHIS of dicamba-tolerant seeds, marking the onset of their commercialization.

Figure S8: Wheat and corn prices



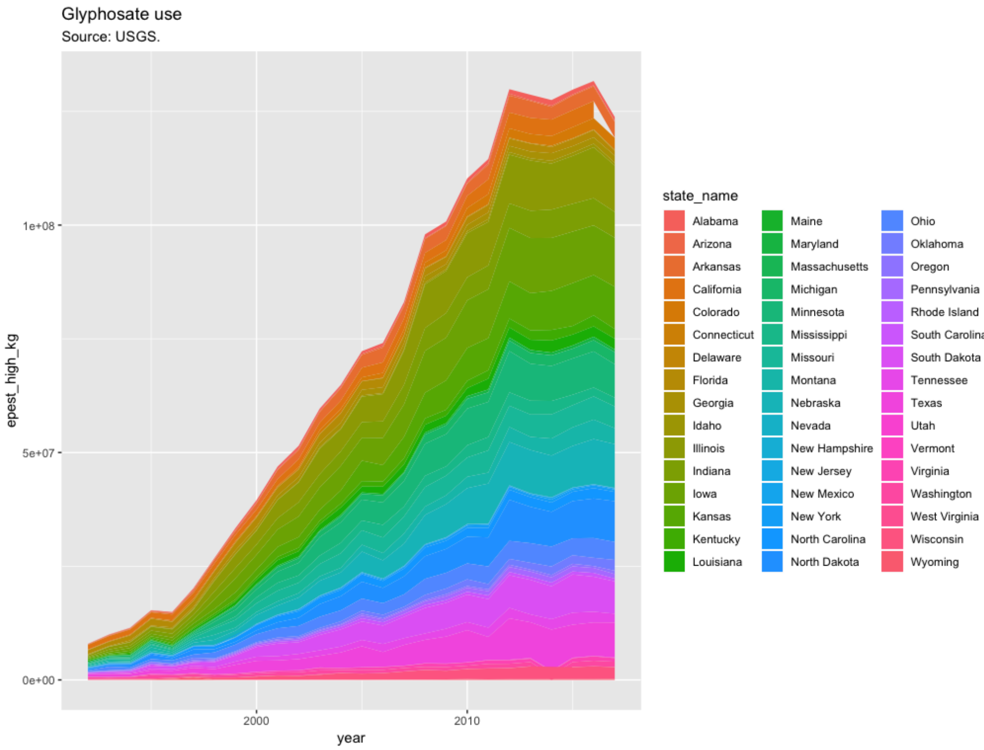
Notes: Graph plots monthly prices received for U.S. wheat (purple, left y-axis) and corn (teal, right y-axis). Source: USDA. The yellow line corresponds to January 20th, 2017.

Figure S9: Cotton, soybeans, corn, wheat: Relative prices



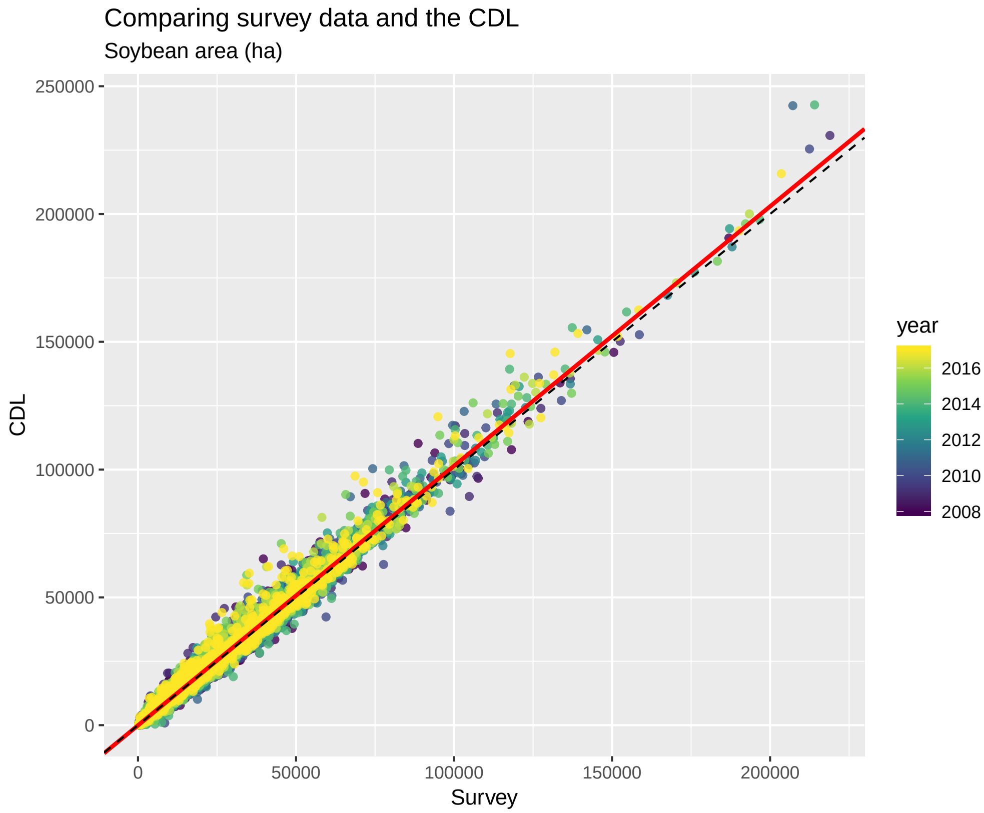
Notes: Graph plots monthly prices received for U.S. corn (purple, left y-axis), soybeans (green, left right y-axis) and cotton (teal, right y-axis) relative to that of wheat in the same month. Source: USDA. The prices of wheat, corn, soybeans are in dollars per bushel, that of cotton is in dollars per pounds.The yellow line corresponds to January 20th, 2017.

Figure S10: Glyphosate use by state



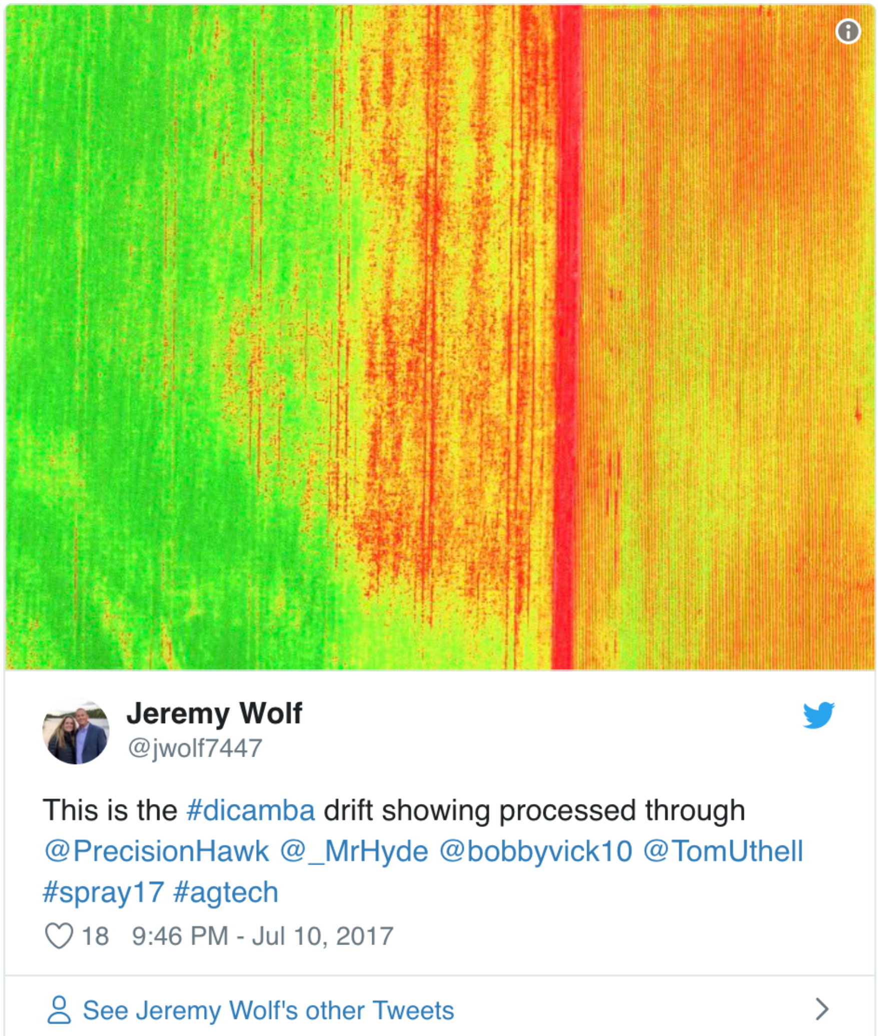
Notes: Graph plots stacked time series of glyphosate use (kg) by U.S. state (one state, one color) using USGS (NAWQA, see Section 2 data (high estimate). At the time of writing, the estimates for pesticide use in 2017 in California have not been released.

Figure S11



Notes: Graph plots county area planted in soybean (in hectares, i.e.10^4m) as calculated by NASS (USDA) from surveys, against area calculated from the CDL, 2008-2017. Color denotes survey/layer year. Slope (red sold line): 1.02 (p-value < 0.01), R^2: 0.98. The black dashed line corresponds to the 45° line where the CDL and survey areas coincide perfectly.

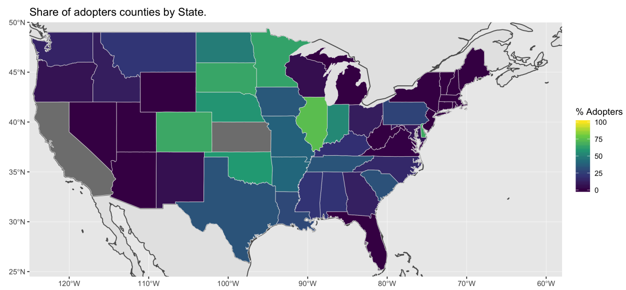
Figure S12: Evidence of dicamba drift and damage by RGB drone imaging



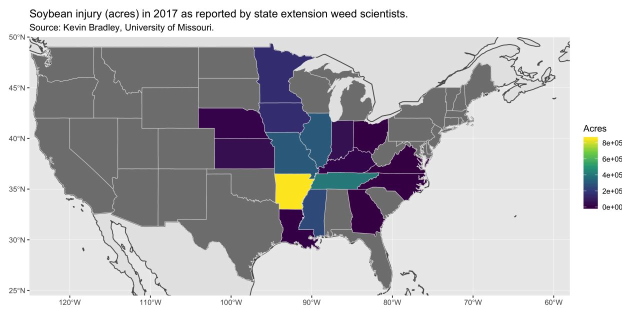
Notes: Tweet by farmer Jeremy Wolf (@jwolf7447) of Homer, Illinois (10/07/2017). Green corresponds to photosynthetic material (healthy plants), red to non-photosynthetic surfaces (road, dead plants). Reproduced with permission.

Figure S13: State maps

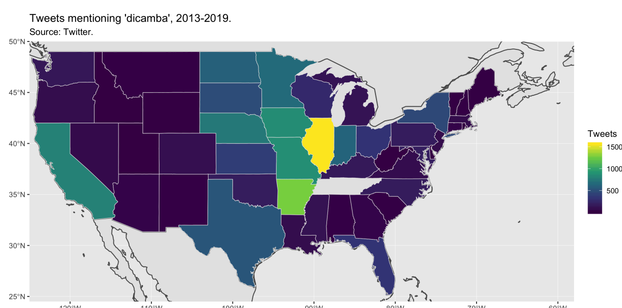
(a) Adoption (% of counties)



(b) Soybean injury



(c) Tweet volume



Notes: Maps show various proxies for adoption at the state level. In (a) the share of counties found as "adopters" by the method described in 3.1. (b) plots the injured soybean areas found by Dr. Kevin Bradley from University of Missouri for 2017; note that the brightest state is Missouri. (c) shows tweet volume for tweets that containted "dicamba".

B Additional tables

B.1 Dicamba use models: alternative samples

	(1)	(2)	(3)	(4)
Cropland (ha)	**0.016*****	**0.009*****	**0.009*****	**0.004*****
	(0.000)	(0.000)	(0.000)	(0.001)
Wheat (ha)		**0.029*****	**0.024*****	**0.031*****
		(0.001)	(0.001)	(0.001)
Pasture/hay (ha)			**0.002*****	**0.002*****
			(0.000)	(0.000)
Corn (ha)				**0.011*****
				(0.001)
(Intercept)	**252.906*****	**337.354*****	**230.416*****	**244.805*****
	(18.377)	(17.971)	(19.054)	(19.092)
R^2	0.140	0.192	0.202	0.205
Dep. var. mean	928.7	928.7	928.7	928.7
Num. obs.	19718	19718	19718	19718
RMSE	1960.445	1900.347	1888.061	1884.575

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Table shows results for regression of dicamba use (in kg) at the county level against agricultural land uses to obtain in years 2008-2014 to obtain typical per-hectare dicamba use (kg/ha). The models in columns (2)–(4) further add crop acreage for two land uses that are major receivers of dicamba according to USDA statistics, namely wheat (column 2), hay/pasture (column 3), and corn (column 4). Includes Kansas.

Table S1: Dicamba use models – Including Kansas

B.2 Adoption models: alternative specifications and samples

B.2.1 Logit models

	(1)	(2)	(3)	(4)	(5)
Upwind, but not downwind 2016 adopter	**1.18****		**1.18****		
	(0.37)		(0.37)		
Downwind, but not upwind 2016 adopter	**0.65***		**0.65***		
	(0.28)		(0.28)		
Crosswind 2016 adopter		0.19	0.22		0.26
		(0.55)	(0.55)		(0.55)
Up- or downwind 2016 adopter				**1.24*****	**1.24*****
				(0.19)	(0.19)
(Intercept)	$-$**0.91*****	$-$**0.88*****	$-$**0.91*****	$-$**0.95*****	$-$**0.95*****
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
AIC	3134.69	3147.52	3136.53	3105.98	3107.77
BIC	3152.28	3159.24	3159.98	3117.70	3125.36
Log Likelihood	-1564.34	-1571.76	-1564.26	-1550.99	-1550.88
Deviance	3128.69	3143.52	3128.53	3101.98	3101.77
Num. obs.	2600	2600	2600	2600	2600

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Table shows regression results (coefficients and standard errors) for logit models regressing adopter status in 2017 on adopter status in 2016 of up-, down-, cross-wind neighbors. Adoption is defined using the preferred dicamba use model and an absolute threshold on out-of-sample prediction error. All regressions exclude Kansas.

Table S2: Probability of adoption: logit models

B.2.2 Linear probability models

	(1)	(2)	(3)	(4)	(5)
Upwind, but not downwind 2016 adopter	$\mathbf{0.28}^{***}$		$\mathbf{0.28}^{***}$		
	(0.08)		(0.08)		
Downwind, but not upwind 2016 adopter	$\mathbf{0.15}^{*}$		$\mathbf{0.15}^{*}$		
	(0.06)		(0.06)		
Crosswind 2016 adopter		0.04	0.05		0.05
		(0.12)	(0.12)		(0.12)
Up- or downwind 2016 adopter				$\mathbf{0.29}^{***}$	$\mathbf{0.29}^{***}$
				(0.04)	(0.04)
(Intercept)	$\mathbf{0.29}^{***}$	$\mathbf{0.29}^{***}$	$\mathbf{0.29}^{***}$	$\mathbf{0.28}^{***}$	$\mathbf{0.28}^{***}$
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
R^2	0.01	0.00	0.01	0.02	0.02
Adj. R^2	0.01	-0.00	0.01	0.02	0.02
Num. obs.	2600	2600	2600	2600	2600
RMSE	0.45	0.46	0.45	0.45	0.45

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Table shows regression results (coefficients and standard errors) for linear probability models regressing adopter status in 2017 on adopter status in 2016 of up-, down-, cross-wind neighbors. Adoption is defined using the preferred dicamba use model and an absolute threshold on out-of-sample prediction error. All regressions exclude Kansas.

Table S3: Probability of adoption: linear probability models

B.2.3 Main specification, including Kansas

	(1)	(2)	(3)	(4)	(5)
Upwind, but not downwind 2016 adopter	$\mathbf{0.70}^{**}$		$\mathbf{0.71}^{**}$		
	(0.23)		(0.23)		
Downwind, but not upwind 2016 adopter	$\mathbf{0.62}^{***}$		$\mathbf{0.62}^{***}$		
	(0.18)		(0.18)		
Crosswind 2016 adopter		0.29	0.32		0.29
		(0.39)	(0.39)		(0.39)
Up- or downwind 2016 adopter				0.13	0.13
				(0.31)	(0.31)
(Intercept)	$\mathbf{-0.66}^{***}$	$\mathbf{-0.64}^{***}$	$\mathbf{-0.67}^{***}$	$\mathbf{-0.64}^{***}$	$\mathbf{-0.64}^{***}$
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
AIC	3088.37	3107.22	3089.71	3107.60	3109.03
BIC	3106.08	3119.03	3113.32	3119.41	3126.74
Log Likelihood	-1541.18	-1551.61	-1540.86	-1551.80	-1551.52
Deviance	3082.37	3103.22	3081.71	3103.60	3103.03
Num. obs.	2705	2705	2705	2705	2705

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Table shows regression results for probit models regressing adopter status in 2017 on adopter status in 2016 of up-, down-, cross-wind neighbors. Includes Kansas.

Table S4: Probability of adoption – Including Kansas

B.2.4 Main specification, alternative wind months

	(1)	(2)	(3)	(4)	(5)
Upwind, but not downwind 2016 adopter	$\mathbf{0.63}^{*}$		$\mathbf{0.63}^{*}$		
	(0.31)		(0.31)		
Downwind, but not upwind 2016 adopter	$\mathbf{0.51}^{*}$		$\mathbf{0.50}^{*}$		
	(0.25)		(0.25)		
Crosswind 2016 adopter		-0.30	-0.29		-0.27
		(0.64)	(0.64)		(0.64)
Up- or downwind 2016 adopter				$\mathbf{0.84}^{***}$	$\mathbf{0.84}^{***}$
				(0.16)	(0.16)
(Intercept)	$\mathbf{-0.56}^{***}$	$\mathbf{-0.55}^{***}$	$\mathbf{-0.55}^{***}$	$\mathbf{-0.57}^{***}$	$\mathbf{-0.57}^{***}$
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
AIC	3141.47	3147.41	3143.26	3119.02	3120.83
BIC	3159.06	3159.14	3166.71	3130.74	3138.42
Log Likelihood	-1567.73	-1571.70	-1567.63	-1557.51	-1557.41
Deviance	3135.47	3143.41	3135.26	3115.02	3114.83
Num. obs.	2600	2600	2600	2600	2600

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Table shows regression results (coefficients and standard errors) for probit models regressing adopter status in 2017 on adopter status in 2016 of up-, down-, cross-wind neighbors. *County relationships with respect to the wind are determined based on May 2016 data.* Adoption is defined using the preferred dicamba use model and an absolute threshold on out-of-sample prediction error. May 2016 winds determine up-, down-, and cross-wind relationships. All regressions exclude Kansas.

Table S5: Probability of adoption – May 2016 wind

	(1)	(2)	(3)	(4)	(5)
Upwind, but not downwind 2016 adopter	0.28		0.28		
	(0.27)		(0.27)		
Downwind, but not upwind 2016 adopter	$\mathbf{0.49}^{*}$		$\mathbf{0.49}^{*}$		
	(0.21)		(0.21)		
Crosswind 2016 adopter		-0.30	-0.29		-0.27
		(0.64)	(0.64)		(0.64)
Up- or downwind 2016 adopter				$\mathbf{0.77}^{***}$	$\mathbf{0.77}^{***}$
				(0.14)	(0.14)
(Intercept)	$\mathbf{-0.56}^{***}$	$\mathbf{-0.55}^{***}$	$\mathbf{-0.56}^{***}$	$\mathbf{-0.58}^{***}$	$\mathbf{-0.58}^{***}$
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
AIC	3142.94	3147.41	3144.73	3114.84	3116.66
BIC	3160.53	3159.14	3168.19	3126.57	3134.25
Log Likelihood	-1568.47	-1571.70	-1568.37	-1555.42	-1555.33
Deviance	3136.94	3143.41	3136.73	3110.84	3110.66
Num. obs.	2600	2600	2600	2600	2600

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Table shows regression results (coefficients and standard errors) for probit models regressing adopter status in 2017 on adopter status in 2016 of up-, down-, cross-wind neighbors. *County relationships with respect to the wind are determined based on July 2016 data.* Adoption is defined using the preferred dicamba use model and an absolute threshold on out-of-sample prediction error. All regressions exclude Kansas.

Table S6: Probability of adoption – July 2016 wind

B.2.5 Main specification, interpolated wind data

	(1)	(2)	(3)	(4)	(5)
Upwind, but not downwind 2016 adopter	**0.60****		**0.60****		
	(0.20)		(0.20)		
Downwind, but not upwind 2016 adopter	**0.48****		**0.48****		
	(0.16)		(0.16)		
Crosswind 2016 adopter		−0.22	−0.20		−0.17
		(0.33)	(0.33)		(0.33)
Up- or downwind 2016 adopter				**0.82*****	**0.82*****
				(0.11)	(0.11)
(Intercept)	**−0.57*****	**−0.54*****	**−0.57*****	**−0.60*****	**−0.60*****
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
AIC	3132.20	3147.17	3133.84	3087.99	3089.72
BIC	3149.79	3158.90	3157.29	3099.71	3107.31
Log Likelihood	-1563.10	-1571.59	-1562.92	-1541.99	-1541.86
Deviance	3126.20	3143.17	3125.84	3083.99	3083.72
Num. obs.	2600	2600	2600	2600	2600

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Table shows regression results (coefficients and standard errors) for probit models regressing adopter status in 2017 on adopter status in 2016 of up-, down-, cross-wind neighbors. Adoption is defined using the preferred dicamba use model and an absolute threshold on out-of-sample prediction error. Interpolated wind data. All regressions exclude Kansas.

Table S7: Probability of adoption

B.2.6 Alternative definitions of adoption based on "level" (anomaly)

	(1)	(2)	(3)	(4)	(5)
Upwind, but not downwind 2016 adopter	**0.47***		**0.48***		
	(0.20)		(0.20)		
Downwind, but not upwind 2016 adopter	**0.57*****		**0.57*****		
	(0.16)		(0.16)		
Crosswind 2016 adopter		0.12	0.15		0.18
		(0.30)	(0.30)		(0.30)
Up- or downwind 2016 adopter				**0.82*****	**0.83*****
				(0.10)	(0.10)
(Intercept)	**−0.29*****	**−0.26*****	**−0.29*****	**−0.32*****	**−0.32*****
	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)
AIC	3478.75	3495.22	3480.50	3428.29	3429.92
BIC	3496.34	3506.94	3503.95	3440.02	3447.51
Log Likelihood	-1736.37	-1745.61	-1736.25	-1712.15	-1711.96
Deviance	3472.75	3491.22	3472.50	3424.29	3423.92
Num. obs.	2600	2600	2600	2600	2600

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Table shows regression results (coefficients and standard errors) for probit models regressing adopter status in 2017 on adopter status in 2016 of up-, down-, cross-wind neighbors. Adoption is defined using the preferred dicamba use model and an absolute threshold on out-of-sample prediction error. All regressions exclude Kansas.

Table S8: Probability of adoption – Adoption based on level (low threshold)

	(1)	(2)	(3)	(4)	(5)
Upwind, but not downwind 2016 adopter	**0.93*****		**0.93*****		
	(0.24)		(0.24)		
Downwind, but not upwind 2016 adopter	**0.67*****		**0.67*****		
	(0.20)		(0.20)		
Crosswind 2016 adopter		0.33	0.36		0.38
		(0.43)	(0.43)		(0.43)
Up- or downwind 2016 adopter				**0.98*****	**0.98*****
				(0.14)	(0.14)
(Intercept)	**−0.79*****	**−0.76*****	**−0.79*****	**−0.80*****	**−0.81*****
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
AIC	2737.90	2760.95	2739.23	2710.39	2711.66
BIC	2755.49	2772.68	2762.69	2722.11	2729.25
Log Likelihood	-1365.95	-1378.48	-1365.62	-1353.19	-1352.83
Deviance	2731.90	2756.95	2731.23	2706.39	2705.66
Num. obs.	2600	2600	2600	2600	2600

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Table shows regression results (coefficients and standard errors) for probit models regressing adopter status in 2017 on adopter status in 2016 of up-, down-, cross-wind neighbors. Adoption is defined using the preferred dicamba use model and an absolute threshold on out-of-sample prediction error. All regressions exclude Kansas.

Table S9: Probability of adoption – Adoption based on level (high threshold)

B.2.7 Alternative definition of adoption based on "intensity" (anomaly per hectare)

	(1)	(2)	(3)	(4)	(5)
Upwind, but not downwind 2016 adopter	0.20		0.20		
	(0.19)		(0.19)		
Downwind, but not upwind 2016 adopter	**0.45****		**0.45****		
	(0.15)		(0.15)		
Crosswind 2016 adopter		−0.10	−0.08		−0.05
		(0.27)	(0.27)		(0.27)
Up- or downwind 2016 adopter				**0.66*****	**0.65*****
				(0.10)	(0.10)
(Intercept)	**−0.20*****	**−0.18*****	**−0.20*****	**−0.23*****	**−0.23*****
	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)
AIC	3546.10	3554.25	3548.01	3507.48	3509.45
BIC	3563.69	3565.98	3571.47	3519.20	3527.04
Log Likelihood	-1770.05	-1775.13	-1770.01	-1751.74	-1751.72
Deviance	3540.10	3550.25	3540.01	3503.48	3503.45
Num. obs.	2600	2600	2600	2600	2600

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Table shows regression results (coefficients and standard errors) for probit models regressing adopter status in 2017 on adopter status in 2016 of up-, down-, cross-wind neighbors. Adoption is defined using the preferred dicamba use model and an absolute threshold on out-of-sample prediction error. All regressions exclude Kansas.

Table S10: Probability of adoption – Adoption based on intensity (low threshold)

	(1)	(2)	(3)	(4)	(5)
Upwind, but not downwind 2016 adopter	$\mathbf{0.56}^{**}$		$\mathbf{0.56}^{**}$		
	(0.21)		(0.21)		
Downwind, but not upwind 2016 adopter	$\mathbf{0.67}^{***}$		$\mathbf{0.67}^{***}$		
	(0.18)		(0.18)		
Crosswind 2016 adopter		0.22	0.24		0.34
		(0.33)	(0.33)		(0.33)
Up- or downwind 2016 adopter				$\mathbf{0.79}^{***}$	$\mathbf{0.80}^{***}$
				(0.12)	(0.12)
(Intercept)	$\mathbf{-0.49}^{***}$	$\mathbf{-0.47}^{***}$	$\mathbf{-0.50}^{***}$	$\mathbf{-0.51}^{***}$	$\mathbf{-0.59}^{***}$
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
AIC	3240.28	3258.74	3241.74	3214.62	3102.58
BIC	3257.87	3270.47	3265.19	3226.35	3120.17
Log Likelihood	-1617.14	-1627.37	-1616.87	-1605.31	-1548.29
Deviance	3234.28	3254.74	3233.74	3210.62	3096.58
Num. obs.	2600	2600	2600	2600	2600

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Table shows regression results (coefficients and standard errors) for probit models regressing adopter status in 2017 on adopter status in 2016 of up-, down-, cross-wind neighbors. Adoption is defined using the preferred dicamba use model and an absolute threshold on out-of-sample prediction error. All regressions exclude Kansas.

Table S11: Probability of adoption – Adoption based on intensity (high threshold)

B.3 Land use change models: alternative specifications

B.3.1 Treatment intensity

Farmers' decisions are probably sensitive to the density of adopters surrounding them rather than to a binary indication of adoption. To explore the effect of the intensity of the treatment, I therefore consider:

$$Y_{i,t\to t+1} = \alpha_1.d_{it} + \alpha_2.\left(d_{it} \times \mathbb{1}\left\{t \geq 2015\right\}\right) + \lambda_i + \lambda_t + \varepsilon_{it} \tag{S1}$$

with $Y_{i,t\to t+1}$ the net conversion between years t and $t+1$ to soybean and cotton from some other land use, d_{it} the dicamba use anomaly (in kg, kg/ha) compared to model predictions (see 3.1). λ_i, λ_t are county and year fixed effects, respectively. Errors ε_{it} are clustered at the state level. d_{it} is interacted with a post-DT seed release dummy, $\mathbb{1}\left\{t \geq 2015\right\}$, taking the value of 1 if t is 2015 or later (corresponding to herbicide applications made in 2015 or later, and land-use changes occurring between years 2015 and 2016 and subsequently), 0 otherwise.

	(1)	(2)	(3)	(4)	(5)	(6)
Anomaly x Post	-0.01					
	(0.03)					
Per-hectare Anomaly x Post		80.59				
		(56.03)				
Dicamba x Post			$\mathbf{0.08}^{**}$			
			(0.03)			
Dicamba per hectare x Post				$\mathbf{22268.42}^{***}$		
				(5391.32)		
Log Dicamba x Post					$\mathbf{352.51}^{***}$	
					(31.01)	
Log Dicamba per hectare x Post						$\mathbf{342.81}^{***}$
						(32.40)
R^2	0.00	0.00	0.00	0.00	0.01	0.01
Adj. R^2	-0.12	-0.12	-0.12	-0.12	-0.12	-0.12
Num. obs.	23473	23473	23473	23473	23465	23465

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Table shows regression results for net change in soybean and cotton area (in hectares).

Table S12: Net conversion with continuous treatment

B.4 Crop outcome models

B.4.1 Other outcomes: production and yield per harvested acre

In addition to crop failure and yields per planted area, two other outcomes are of interest: yields per harvested area (corresponds to the yield reported by the USDA) and production. The effect of being subjected to neighboring counties ("Treated") or farmers ("Adopted") adopting DT seeds on these two variables is reported in Table S13 and Table S14, respectively.

	Soybean			Cotton			Wheat			Corn		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treated x Post	-0.25			$\mathbf{0.12}^{*}$			-1.34			$\mathbf{-5.41}^{*}$		
	(0.77)			(0.06)			(1.22)			(2.41)		
Placebo x Post		-0.99			0.15			$\mathbf{-9.19}^{**}$			4.95	
		(2.10)			(0.13)			(3.24)			(6.81)	
Adopted x Post			$\mathbf{0.93}^{*}$			-0.07			-0.29			$\mathbf{-5.19}^{***}$
			(0.38)			(0.04)			(0.71)			(1.28)
R^2	0.30	0.30	0.30	0.08	0.08	0.08	0.10	0.10	0.10	0.32	0.32	0.32
Dep. var. mean	42.78	42.78	42.78	1.80	1.80	1.80	55.00	55.00	55.00	141.60	141.60	141.60
Num. obs.	11903	11903	11903	2771	2771	2771	9380	9380	9380	13478	13478	13478

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Table shows regression results for fixed-effect models regressing production outcomes on dicamba use anomaly at the county level, for four major crops, for two of which DT technology is available (cotton, soybean), the other two (wheat, corn) are relatively tolerant to dicamba, owing to their being monocotyledones. Areas are expressed in acres, production in bushels (soybean, wheat, corn) or pounds (cotton), and yields are accordingly in bushels or pounds per acre. Includes weather controls.

Table S13: Yield models (harvested)

	Soybean			Cotton			Wheat			Corn		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treated x Post	13901.50			**24498.51*****			-77737.24			-387586.72		
	(84234.37)			(4081.19)			(82163.94)			(251919.31)		
Placebo x Post		-255568.60			4533.60			-341977.13			160166.86	
		(230326.90)			(9115.05)			(218166.51)			(711788.83)	
Adopted x Post			**712071.80*****			**12010.80*****			**−146176.72****			**554196.19*****
			(40254.85)			(3133.91)			(48200.53)			(133021.48)
R^2	0.09	0.09	0.14	0.18	0.17	0.18	0.09	0.09	0.09	0.09	0.09	0.09
Dep. var. mean	2490910	2490910	2490910	43751	43751	43751	929694	929694	929694	8089558	8089558	8089558
Num. obs.	11903	11903	11903	2771	2771	2771	9380	9380	9380	13478	13478	13478

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Table shows regression results for fixed-effect models regressing production outcomes on dicamba use anomaly at the county level, for four major crops, for two of which DT technology is available (cotton, soybean), the other two (wheat, corn) are relatively tolerant to dicamba, owing to their being monocotyledones. Production in bushels (soybean, wheat, corn) or pounds (cotton). Includes weather controls.

Table S14: Production models

B.4.2 Alternative specifications

Similar to the analysis presented in the body of this paper, I consider chiefly two outcome variables: yield (in physical quantity per *planted*[47] acre), and the planted-to-harvested ratio, to account for the fact that farmers observing damage beyond repair do not harvest those fields. The difference with the specifications presented above resides in the de-discretization of the treatment, i.e. the use of the anomaly itself *in the county of interest*, as the regressor:

$$Y_{it} = \alpha_1.\mathrm{d}_{it} + \alpha_2.\left(\mathrm{d}_{it} \times \mathbb{1}\left\{t \geq 2015\right\}\right) + \mathbf{X_{it}}\theta + \lambda_i + \lambda_t + \varepsilon_{it} \tag{S2}$$

with Y_{it} the yield (bushel/acre for soybeans, lb/acre for cotton) or planted-to-harvested ratio for the focal crop (soybean, cotton, and two non-target crops, wheat and corn), d_{it} alternatively: the dicamba use anomaly (kg, kg/ha) compared to model predictions (see 3.1), dicamba use (in kg, in levels or logs), and dicamba use per hectare (in levels or logs). $\mathbb{1}\left\{t \geq 2015\right\}$ is a dummy variable that is given a value of 1 in 2015 and thereafter. $\mathbf{X_{it}}$ are weather controls. λ_i, λ_t are county and year fixed effects, respectively. Errors ε_{it} are clustered at the state level.

The reason why the interaction with a "post" dummy still makes sense in these cases is that dicamba use, as levels or as anomalies, is expected to be different pre- and post-DT because the anomaly post-DT is attributed to the in-crop use required by DT seeds (i.e. spraying dicamba during the growing season) while pre-DT it should be confined (by law and for agronomic reasons) to the pre-planting period; their magnitudes also differ vastly.

The results are reported in the tables S15-S16 below.

[47] USDA NASS reports yield per harvested acre.

	Soybean	Soybean	Soybean	Soybean	Soybean	Soybean	Cotton	Cotton	Cotton	Cotton	Cotton	Cotton
Anomaly x Post	**−0.00*****						−0.00					
	(0.00)						(0.00)					
Per-hectare Anomaly x Post		**−0.17****						−0.21				
		(0.06)						(0.26)				
Dicamba x Post			**−0.00*****						−0.00			
			(0.00)						(0.00)			
Dicamba per hectare x Post				**−18.49*****						−17.16		
				(5.45)						(25.27)		
Log Dicamba x Post					**−0.32*****						−0.07	
					(0.06)						(0.39)	
Log Dicamba per hectare x Post						**−0.33*****						−0.08
						(0.06)						(0.35)
R^2	0.13	0.13	0.14	0.13	0.14	0.14	0.29	0.29	0.29	0.29	0.29	0.29
Dep. var. mean	97.98	97.98	97.98	97.98	97.98	97.98	92.58	92.58	92.58	92.58	92.58	92.58
Num. obs.	13196	13196	13196	13196	13196	13196	3064	3064	3064	3064	3064	3064

	Wheat	Wheat	Wheat	Wheat	Wheat	Wheat	Corn	Corn	Corn	Corn	Corn	Corn
Anomaly x Post	0.00						0.00					
	(0.00)						(0.00)					
Per-hectare Anomaly x Post		0.15						−0.04				
		(0.20)						(0.11)				
Dicamba x Post			0.00						0.00			
			(0.00)						(0.00)			
Dicamba per hectare x Post				20.40						−5.52		
				(19.64)						(10.65)		
Log Dicamba x Post					**0.49***						0.01	
					(0.24)						(0.11)	
Log Dicamba per hectare x Post						**0.50***						0.02
						(0.25)						(0.11)
R^2	0.05	0.05	0.05	0.05	0.05	0.05	0.09	0.09	0.09	0.09	0.09	0.09
Dep. var. mean	81.17	81.17	81.17	81.17	81.17	81.17	86.63	86.63	86.63	86.63	86.63	86.63
Num. obs.	10270	10270	10270	10270	10269	10269	14920	14920	14920	14920	14919	14919

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Table shows regression results for fixed-effect models regressing production outcomes on dicamba use anomaly at the county level, for four major crops; for two of them (soybean, cotton), the DT technology is available and absent the DT trait, they are extremely vulnerable to dicamba, while for the other two (wheat, corn) the DT technology is not available but they are relatively tolerant to dicamba. Includes weather controls.

Table S15: Harvested-to-planted models

	Soybean	Soybean	Soybean	Soybean	Soybean	Soybean	Cotton	Cotton	Cotton	Cotton	Cotton	Cotton
Anomaly x Post	**−0.00*****						−0.00					
	(0.00)						(0.00)					
Per-hectare Anomaly x Post		**−0.26****						0.01				
		(0.09)						(0.01)				
Dicamba x Post			**−0.00****						0.00			
			(0.00)						(0.00)			
Dicamba per hectare x Post				−10.74						0.90		
				(8.59)						(0.84)		
Log Dicamba x Post					**0.58*****						**0.04****	
					(0.09)						(0.01)	
Log Dicamba per hectare x Post						**0.75*****						0.02
						(0.10)						(0.01)
R^2	0.27	0.27	0.27	0.27	0.27	0.28	0.12	0.12	0.12	0.12	0.12	0.12
Dep. var. mean	42.09	42.09	42.09	42.09	42.09	42.09	1.70	1.70	1.70	1.70	1.70	1.70
Num. obs.	13196	13196	13196	13196	13196	13196	3064	3064	3064	3064	3064	3064

	Wheat	Wheat	Wheat	Wheat	Wheat	Wheat	Corn	Corn	Corn	Corn	Corn	Corn
Anomaly x Post	0.00						**−0.00*****					
	(0.00)						(0.00)					
Per-hectare Anomaly x Post		−0.08						**−2.07*****				
		(0.17)						(0.31)				
Dicamba x Post			0.00						**−0.00*****			
			(0.00)						(0.00)			
Dicamba per hectare x Post				9.80						**−183.52*****		
				(16.77)						(29.83)		
Log Dicamba x Post					**0.81*****						−0.28	
					(0.20)						(0.30)	
Log Dicamba per hectare x Post						**1.21*****						0.39
						(0.21)						(0.32)
R^2	0.07	0.07	0.07	0.07	0.07	0.07	0.29	0.29	0.29	0.29	0.29	0.29
Dep. var. mean	46.38	46.38	46.38	46.38	46.38	46.38	124.39	124.39	124.39	124.39	124.39	124.39
Num. obs.	10270	10270	10270	10270	10269	10269	14920	14920	14920	14920	14919	14919

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Table shows regression results for fixed-effect models regressing production outcomes on dicamba use anomaly at the county level, for four major crops; for two of them (soybean, cotton), the DT technology is available and absent the DT trait, they are extremely vulnerable to dicamba, while for the other two (wheat, corn) the DT technology is not available but they are relatively tolerant to dicamba. Areas are expressed in acres, production in bushels (soybean, wheat, corn) or pounds (cotton), and yields are accordingly in bushels or pounds per acre. Includes weather controls.

Table S16: Yield models

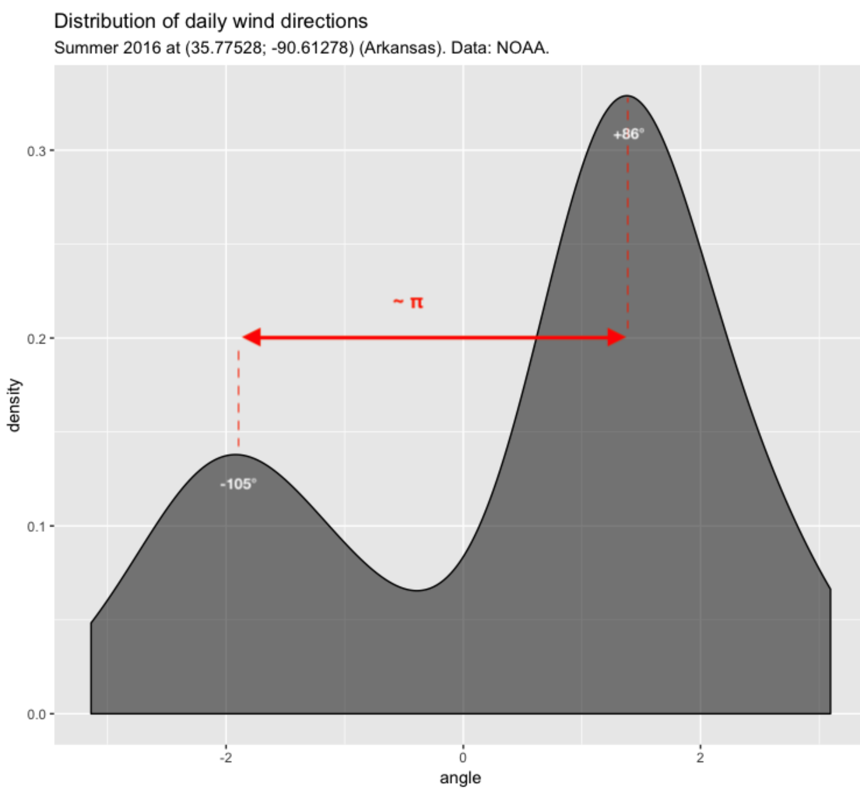
C Other additional material

C.1 On wind direction

Wind direction is central to this paper. Indeed, the proposed adoption mechanism relies on the physical transportation of herbicide particles from a source to an endpoint, where they may or may not cause observable effects, which may or may not action by farmers. Determining whether farmers indeed take action is the crux of the paper. Therefore handling the wind data properly and in accordance with their empirical manifestation is crucial.

While the effect of counties identified as "downwind" from the focal county on their adoption of the DT seeds can at face value be surprising, a closer look at wind patterns reveals a possible explanation. Indeed, the wind-neighboring relationships were obtained using monthly data, which conveniently provides a single value for wind speed and direction at every location, but observation of daily data over the course of a month, a season (see Figure S14), a year, provides a more complex picture: in a large share of the counties, the distribution of wind direction is bimodal.

Figure S14: Example: a location in Arkansas

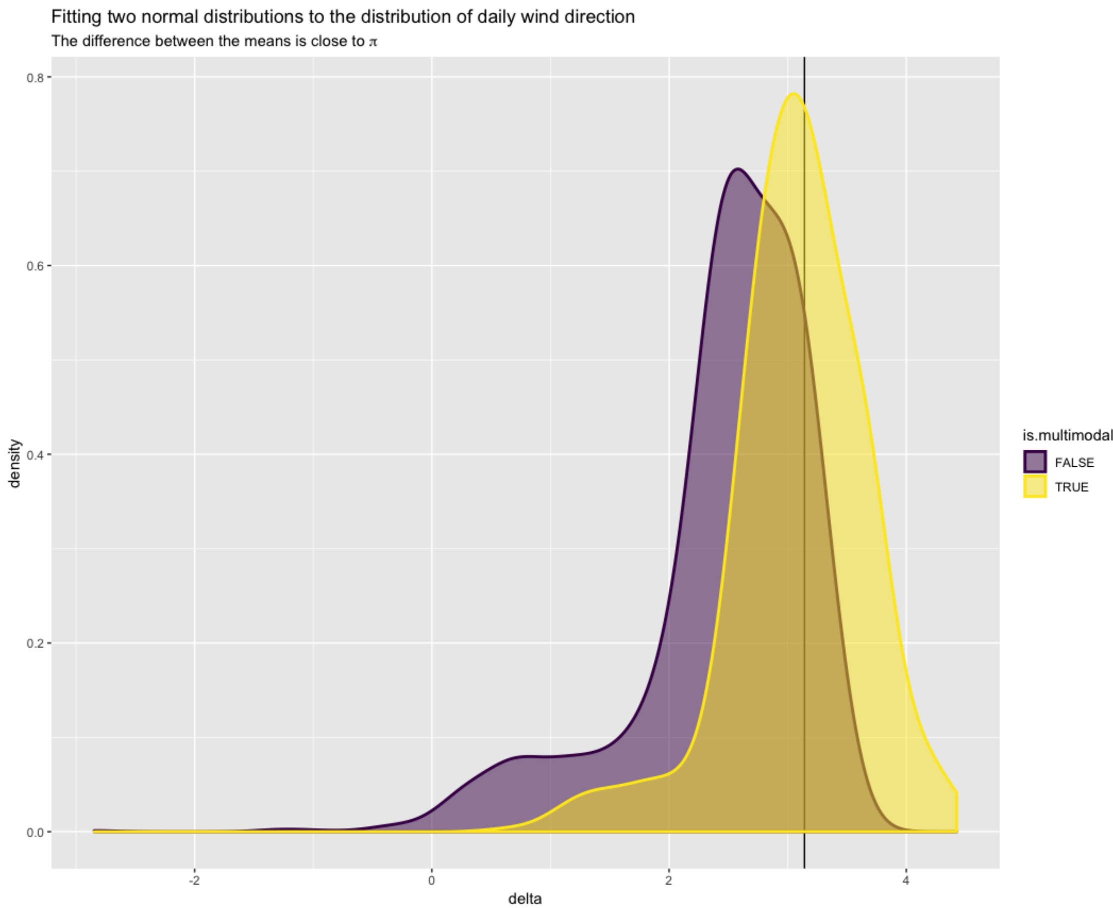


Notes: Graph shows the daily distribution of wind directions during the summer of 2016 (May through August, total of 123 days) at a data point of the NOAA dataset (latitude $\sim 36°$, longitude $\sim -91°$). The data were then fitted to a mixture of two normal distributions, whose means are $\hat{\mu}_1 \simeq -1.8$ and $\hat{\mu}_2 \simeq 1.5$ (converted to degrees on the graph); the difference between the means of the fitted underlying normal distributions is about π or 180°. Which means that at this location in Arkansas, the wind tends to circulate along a specific corridor, most of the time in a certain direction, and in the opposite direction a significant share of the time.

For instance, in 2016, the distribution of direction was bimodal at about 42.4% of the points in the NOAA dataset and located within the boundaries of a U.S. county (in yellow on Figure S15). I fitted the distributions at each point over the course of the year to a mixture of two normal distributions, and calculated the difference between the estimated means: as shown on Figure S15, the overwhelming majority of them differed by π (even when the distribution was not formally diagnosed as bimodal, purple curve), that is to say, while the dominant winds may blow in a direction α most of the time (e.g. 1.5 radians on Figure S14), they also blow in the exact opposite direction $\alpha \pm \pi$ (-1.8 radians) a significant part of the time.

Therefore that adoption in downwind counties should matter to counties upwind from them should not come as a surprise.

Figure S15: Testing a multimodal distribution of wind direction



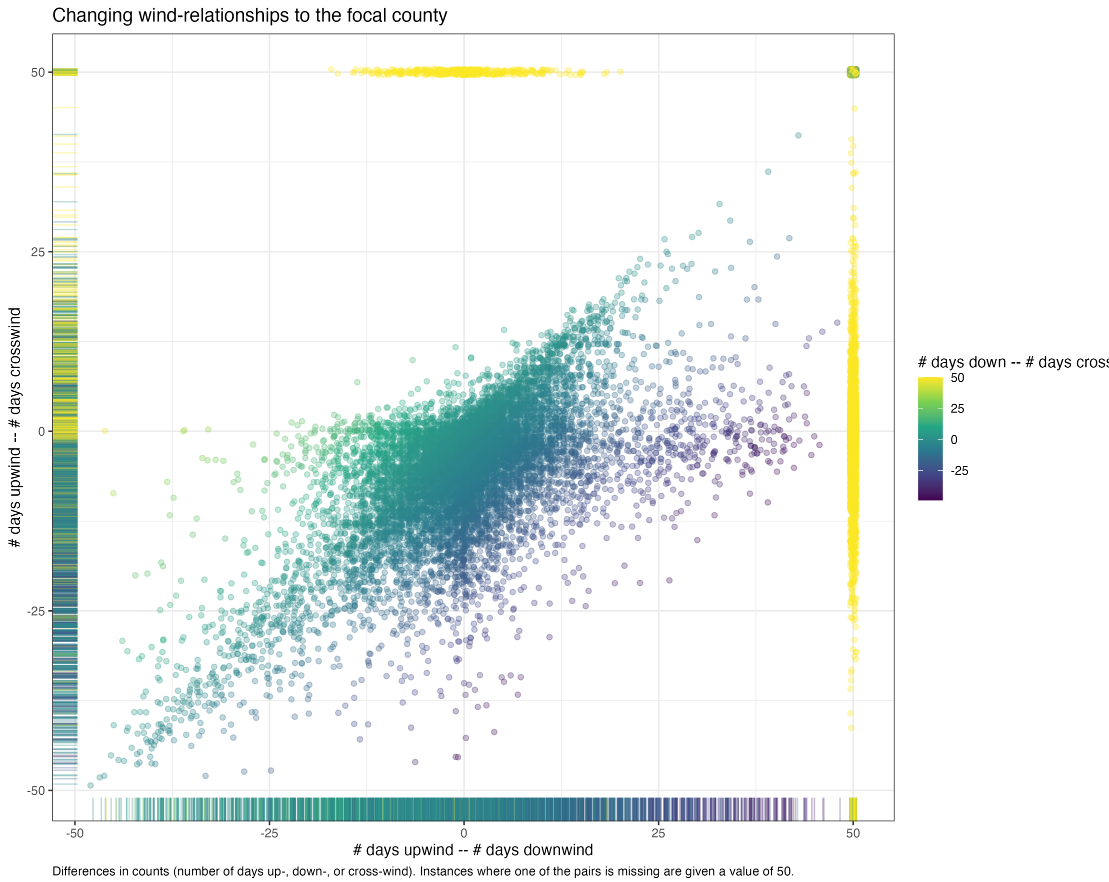
Notes: Graph shows kernel density (band width= 0.2) of $\hat{\mu}_2 - \hat{\mu}_1$ for both points diagnosed with a multimodal distribution of their daily wind directions (yellow), and the others (purple). Both wind direction distributions (in radians) were fitted with two normal distributions, whose means ($\hat{\mu}_1$, $\hat{\mu}_2$), standard deviation ($\hat{\sigma}_1$, $\hat{\sigma}_2$) and weights ($\hat{w}_1 + \hat{w}_2 = 1$) were estimated. The vertical black line indicates pi, that is to say, the point where the wind typically oscillates between a certain direction $alpha°$ and $alpha + 180°$.

C.2 Alternative specification using daily wind direction for treatment assignment

To refine the empirical approach, I construct a different measure of exposure relying on the number of days a given county (focal) is downwind (or upwind, or crosswind) from an adopter county in the previous year.

Indeed, there is a variety of situations and variability in wind-positions (e.g., see Figure S16): only the dots with large positive or negative values exhibit constant behavior throughout the growing season.

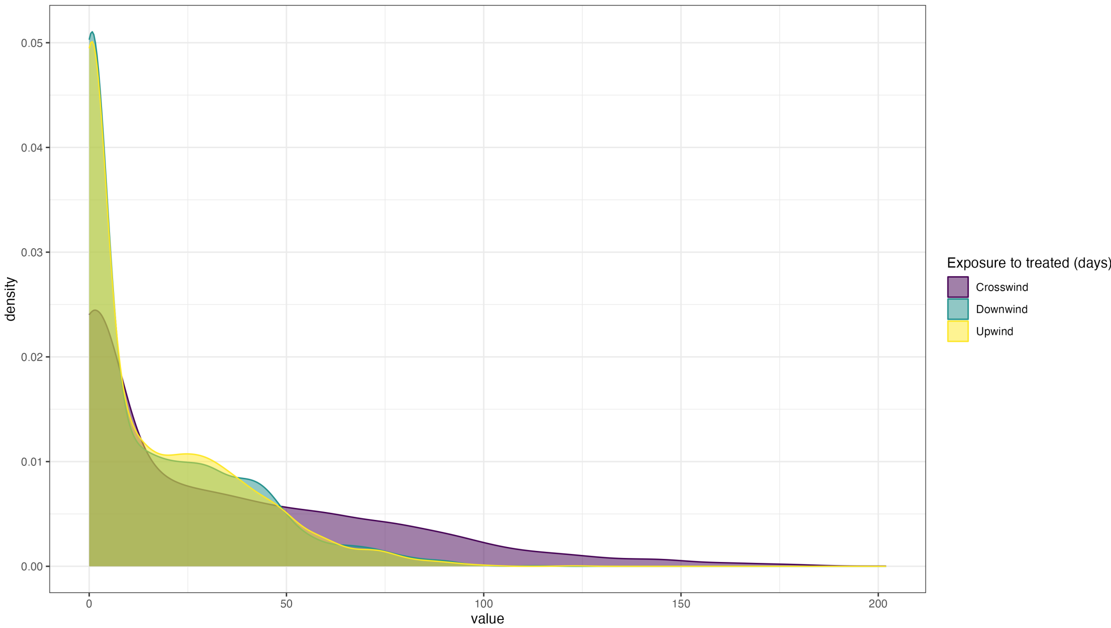
Figure S16: Changing wind-relationships to the focal county



Notes: Graph shows the variability in neighbor relationships (2016 growing season daily wind speed and direction data), i.e., conditional on the existence of a wind-county pair, how many times is the second (non-focal) county up-, down-, and cross-wind from the first (focal)? The horizontal axis shows the difference between number of days spent upwind and downwind, the horizontal axis the difference between number of days spent upwind and crosswind, and finally the color scale maps to the difference between number of days spent downwind and crosswind. Marginal distributions on the sides of the plot. Note that the sample consists of all the counties of the conterminous United States (not just the counties that grow soybean or cotton). Date range: June 1st, 2016 to July 31st, 2016. The value 50 (yellow on the color scale) is attributed to differences where at least one of the directions has not been observed at all, i.e. no variability. Jittering is added for clarity.

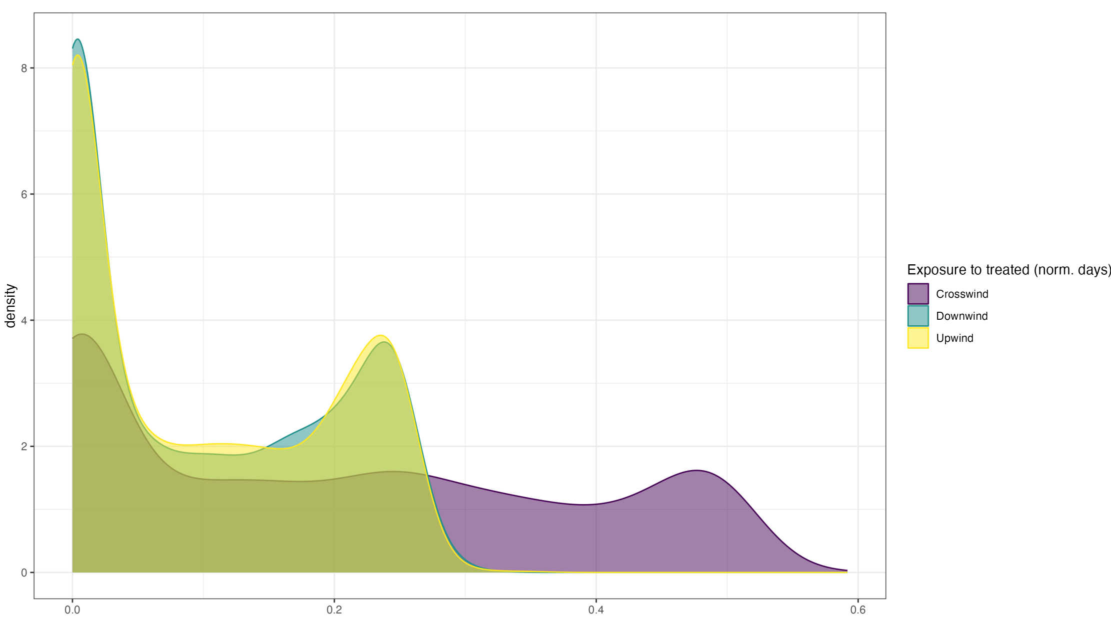
Exposure is now measured as the *number* of days a county spends downwind (upwind, crosswind) from an adopter (Figure S17), or alternatively, the *share* of the days where any wind-neighbor is found that a county spends downwind (upwind, crosswind) from an adopter (Figure S18), during the 2016 growing season for both.

Figure S17: Exposure to treated county (in number of days)



Notes: Graph shows exposure of focal counties to treated (adopter) counties; the metric is the number of instances of matching in the specified wind direction (up-, down-, or crosswind). Since a county can be matched to several counties in a given direction on a given day, certain exposure values exceed 61 days (or 122 days for crosswind).

Figure S18: Exposure to treated county (normalized by the total number of days with wind-neighbors)

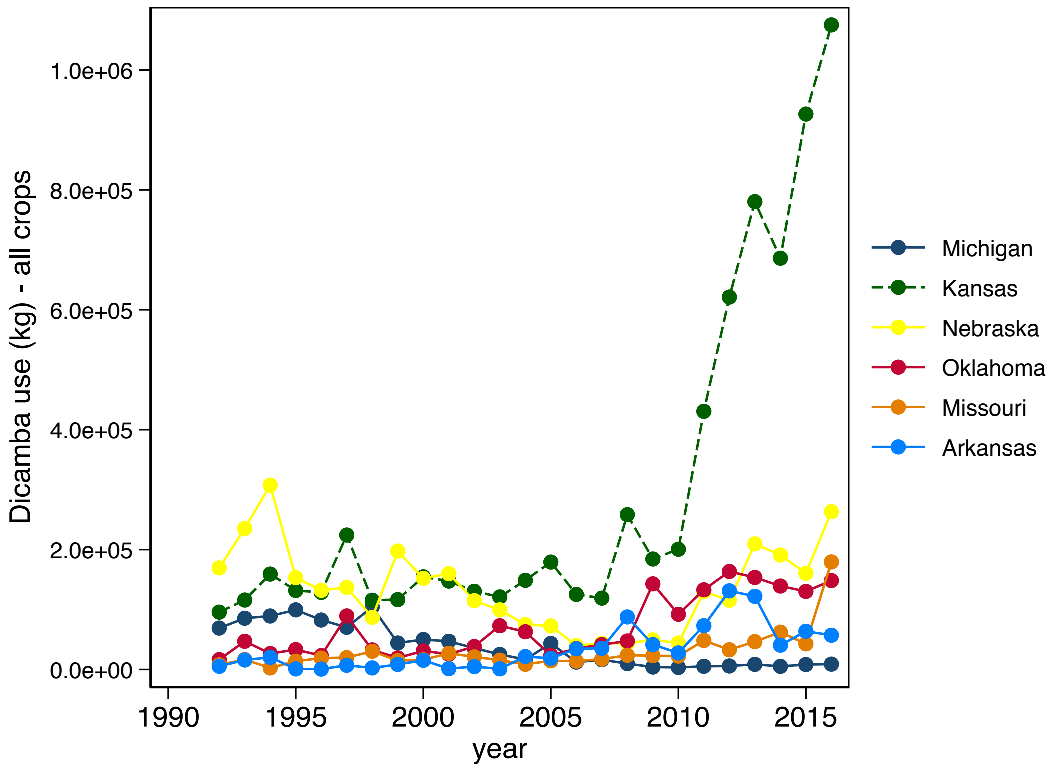


Notes: Graph shows exposure of focal counties to treated (adopter) counties; the metric is the number of instances of matching in the specified wind direction (up-, down-, or crosswind) out of the total number of matching instances for that county.

C.3 On reasons for excluding Kansas from all analyses

Most analyses exclude Kansas; while the results hold with the inclusion of Kansas, the fact that the entire state appears as an outlier as far as dicamba is concerned *before* the advent of the DT seed technology, as evidenced by Figure S19, exhorts to prudence.

Figure S19: Dicamba use by state, total for all crops, selection of states



Notes: Graph shows total dicamba use as reported by the USGS (see section 2.2) by state and by crop, aggregated over all crops, for a selection of Midwestern states at the heart of the DT seed boom. It appears clearly that while the other states are only starting in 2016 to see, for some of them, an uptake in dicamba use due to the commercialization of DT seeds, dicamba use in Kansas amorced a steep increase from 2010 onwards, with a fivefold increase over the course of 5-6 years, with no change in land-use to match (not shown).

I therefore excluded Kansas from the dicamba use model. While the results are not very different from those obtained without Kansas (see Table 1), including Kansas (Table S17) seems to nudge the coefficients upwards in particular for wheat (of which Kansas is the U.S.'s largest producer) and to degrade the quality of the fit – both consistent with an atypically large use of dicamba in the state.

Absent obvious explanations I questioned the agricultural extension at Kansas State University: glyphosate-resistant kochia (a weed) has appeared 2007, and has been reported in Kansas since about 2010, and dicamba has been a prominent part of the arsenal against it (Burton et al., 2014; Kumar et al., 2019) from the beginning; the problem has been particularly prevalent in the western part of the state, with fallow land and no-till practices being particularly favorable to the proliferation of glyphosate-resistant kochia. Note that the increased use of dicamba to overcome glyphosate-resistant weeds *is not* accompanied by a decrease in glyphosate use (i.e., no substitution): glyphosate, being a broad-spectrum herbicide, is used to kill all unwanted plants, and other herbicides are *added* to take care of those that resist.[48]

[48] Personal communication, August 12th, 2019.

	(1)	(2)	(3)	(4)
Cropland (ha)	**0.016*****	**0.009*****	**0.009*****	**0.004*****
	(0.000)	(0.000)	(0.000)	(0.001)
Wheat (ha)		**0.029*****	**0.024*****	**0.031*****
		(0.001)	(0.001)	(0.001)
Pasture/hay (ha)			**0.002*****	**0.002*****
			(0.000)	(0.000)
Corn (ha)				**0.011*****
				(0.001)
(Intercept)	**252.906*****	**337.354*****	**230.416*****	**244.805*****
	(18.377)	(17.971)	(19.054)	(19.092)
R^2	0.140	0.192	0.202	0.205
Dep. var. mean	928.7	928.7	928.7	928.7
Num. obs.	19718	19718	19718	19718
RMSE	1960.445	1900.347	1888.061	1884.575

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Table shows results for regression of dicamba use (in kg) at the county level against agricultural land uses to obtain in years 2008-2014 to obtain typical per-hectare dicamba use (kg/ha). The models in columns (2)–(4) further add crop acreage for two land uses that are major receivers of dicamba according to USDA statistics, namely wheat (column 2), hay/pasture (column 3), and corn (column 4). Includes Kansas.

Table S17: Dicamba use models – Including Kansas

C.4 Technical appendix

Units

Useful units and orders of magnitude:

- hectare (ha): by definition, a surface equivalent to 100 m x 100 m, i.e. $10^4\,\mathrm{m}^2$ or about 2.47 acres. A quarter-quarter section (small field) corresponds to 16 ha.

- kilogram per hectare (kg/ha): $1\,\mathrm{kg.ha}^{-1} \simeq 0.89\,\mathrm{lb.A}^{-1}$. Typically dicamba is applied at a rate of 0.5 to 1 lb ae (acid equivalent.) per acre (or 11 to 22 fl oz per acre), hence about 0.56 to 1,12 kg/ha.

Determination of wind-neighbors procedure, detail

The data obtained from NOAA consists in a set of points identified by their latitude and longitude and associated at each time period with a value of u-wind and v-wind (in meters per second). To produce the one-to-many mapping of focal counties with their up-, down- and cross-wind neighbors, I proceeded as follows.

First, I projected the vectorial sum of the $\vec{U}$ and $\vec{V}$ vectors from the original latitude and longitude: this gives me the latitude and longitude of the place where a particle would land if it was lifted off by the wind at the origin location. This requires converting distances originally expressed in meters (the units of the wind data) to degrees of latitude and longitude.

The same procedure is repeated for $-\left(\vec{U}+\vec{V}\right)$ (upwind), $\vec{U}-\vec{V}$ and $-\vec{U}+\vec{V}$ (crosswind).

It then suffices to find in which counties (if any) the origin point and the up-, down-, and cross-wind destinations are located. Inevitably, some of these will fall into the ocean, abroad or in the same county as the origin point. These instances are removed, and the rest of the destinations are combined, and associated with their corresponding origin county to obtain the set of counties located up-, down-, and cross-wind from a focal county.