

ABSTRACT

JONES, MICHAEL STEPHEN. Essays on the Economics of Novel Agricultural Biotechnologies. (Under the direction of Dr. Zachary S. Brown and Dr. Roderick Rejesus).

Recent technical innovation has renewed focus on the ability of biotechnology to address critical challenges in agriculture. Advances in genetic engineering have allowed developers to expand the application of biotechnology beyond alteration of crops to the engineering of insect pests themselves, with the goal of suppressing damaging populations or preventing the spread of crop disease. The complex and potentially far-reaching implications of these novel inputs, from consumer welfare to the optimal management of other production inputs, remain poorly understood. In this dissertation, I explore field to market-level economics of several plant-based and insect-based agricultural biotechnologies that are designed to control crop damage from insect pests. Heterogeneity in consumer preferences and farm production is a key theme that runs throughout the work, shedding light on understanding the implications of novel biotechnologies in agriculture. The second and third chapters draw from a nationally-representative survey of 1,018 U.S. adults to evaluate public perceptions and consumer welfare implications of releasing of genetically engineered (GE) ‘gene drive’ insects for agricultural pest control. I find majority support for releases which restrict the geographic spread of engineered traits, but find cautionary results for releases with more geographically extensive spread, as well as divisions in how organic consumers perceive interactions with current labeling requirements. Through a hierarchical Bayesian framework, results from an embedded discrete choice experiment also indicate that negative consumer valuation of GE insects in growing areas is less than that for a GE crop or high (vs. low) frequency pesticide spraying. Drive insect presence with simultaneous

reductions in pesticide use and prices may also fundamentally alter the consumer choice set. I find a net negative consumer surplus impact for fresh blueberries and statistically insignificant impacts in orange juice using parameterizations from the literature, and then characterize the conditions necessary for positive surplus impacts. In Chapter 4, I construct a complex bio-economic genetic model for releases of GE diamondback moths as part of a resistance management strategy to preserve the pesticidal value of a Bt crop. Within a static policy rule, Bt and GE insect releases have substitutable and complementary effects on population control and the net value of crop output, depending on the time horizon, Bt planting intensity, and GE insect release rates. While lower release rates may preserve susceptibility and Bt yield advantage, higher release rates may crash the insect population for extended periods and ultimately reduce the marginal pesticidal value of the Bt trait. In Chapter 5, I empirically examine how heterogeneous grower socioeconomic circumstances mediate the relative yield advantage of Bt crops in a developing country context. With panel data from Filipino maize farmers, I find that GE maize traits are substitutes with proxies for human capital and pest control knowledge. For every year *decrease* in formal education and maize farming experience, farmers realize significantly higher yield gains from planting GE maize.

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Essays on the Economics of Novel Agricultural Biotechnologies

by
Michael Stephen Jones

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APPROVED BY:

Dr. Zachary S. Brown
Committee Co-Chair

Dr. Roderick Rejesus
Committee Co-Chair

Dr. Walter Thurman

Dr. Fred Gould

DEDICATION

To my wife, for patience beyond measure and unwavering support.

To my daughter, you are the most beautiful thing I've ever seen and I hope you always know how much your mom and I love you.

To my parents, for lifelong support of the pursuit of dreams.

BIOGRAPHY

Mike received Bachelor's degrees in Food and Resource Economics and Political Science from the University of Florida and a Master's degree in Agricultural Economics from Purdue University. He completed his doctoral dissertation under the direction of Dr. Zachary Brown and Dr. Roderick Rejesus. His Ph.D. is in the field of agricultural economics, with an emphasis on consumer demand analysis and applied production analysis. His other research interests include agricultural biotechnology and applied micro-econometrics.

His doctoral training has been guided through a uniquely interdisciplinary environment in the Genetic Engineering and Society (GES) Center at North Carolina State University, with colleagues and mentors ranging from agricultural economists, to insect geneticists and molecular biologists, to policy administration scholars and anthropologists. He is grateful for funding through a National Science Foundation IGERT fellowship, with a cohort topic focus on genetically engineered agricultural pests.

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Chapter 1: Introduction

Agricultural technologies have profound impacts on the economics of food systems. The development of synthetic fertilizers, machinery, chemical pesticides, and improved seed technology has facilitated historic shifts in crop yields and redefined food production systems to support a growing global population (Pingali, 2012). Likely some of the more celebrated and vilified agricultural technologies in recent history are products developed through synthetic biotechnology. These products are known popularly as genetically modified organisms (GMOs, GM organisms) or genetically engineered (GE) organisms. Seed inputs generated through agricultural biotechnology exploit targeted genetic additions, deletions, or alterations to create products with an advantage in chemical tolerance, insect resistance, improved growth, or nutritional benefit (NASEM, 2016b). Advances in GE technology have also allowed developers to introduce targeted genetic alterations in insect pests themselves. Mass open releases of these engineered insects may attempt to spread traits that could disrupt reproduction and suppress populations or simply interrupt the ability of insects to transmit harmful pathogens (Thomas *et al.*, 2000; NASEM, 2016a). These far-reaching and complex technologies inherently require an interdisciplinary lens to evaluate usage feedbacks on biological, economic, and policy ecosystems (NASEM, 2016a; Baltzgar *et al.*, 2018).

In this dissertation, I explore field to market-level economics of several agricultural biotechnologies that are designed to control crop damage from insect pests. Given my training background within NC State's Genetic Engineering and Society Center, the topics discussed and approaches taken are largely interdisciplinary in nature and this work is meant for consumption by an interdisciplinary audience. In the chapters which follow, the technologies I examine include both 'traditional' plant-based biotechnologies, insect-based biotechnologies, and the

interaction between the two. The main goal of this dissertation is to provide an economic lens through which to view these complex, novel, and experimental agricultural biotechnology products, and to understand how biological designs of these technologies can have profound effects on the economic dynamics of the systems into which they are introduced. While this evaluation inherently includes some methods distinct to the field of economics, I have attempted to reduce feared economics jargon to an extent that most of this work could be accessible to readers without a graduate-level economics background.

The second and third chapter analyze results from a nation-wide survey of US adults to gain insights on public perceptions and consumer reactions to releases of genetically engineered ‘gene drive’ insects as a novel, chemical-free pest control strategy. Generally developed through novel CRISPR-Cas9 gene editing technology, agriculturally-relevant ‘gene drive’ insect species may be engineered in the lab to carry a trait which is either deleterious to reproduction or provides a genetic resistance to crop pathogens. In a gene drive system, these engineered genetic traits are passed on with ‘Super-Mendelian’ inheritance to most or all offspring instead of the typical ~50%; this potentially allows a gene without a biological advantage for the insect to quickly spread through a large-scale population (Esveld *et al.*, 2014). This technology may be very efficient in landscape-level control of highly damaging invasive pests, in such a way that both reduces the need for chemical insecticides and reduces prices via avoided pest control expenses and crop losses (Brown, Jones and Mumford, 2019). However, public preferences for use of a wide-spreading insect biotechnology are unknown. The demand-side impacts of this biotechnology input in conventional and certified organic markets have also yet to be explored.

In Chapter 2, I present survey results examining broad-level public preferences for gene drive insect use in agriculture, reporting from an original dataset of 1,018 US adults drawn from

a probability-based sample. We find majority support for use of some gene drive insect designs that limit the geographic extent of the spread of engineered traits, but this support declines significantly when drive systems allow for uncontrolled, ‘self-sustaining’ spread of traits throughout insect populations. We also find that consumer avoidance of plant-based biotechnologies negatively (but only partially) correlates with support for use of insect-based biotechnologies. Further, we report potentially cautionary data for certified organic producers and certification bodies, as about one-third of organic consumers express concern about USDA organic certification credibility when gene drive insects are present in and around growing areas.

In Chapter 3, I present results of a consumer discrete-choice experiment embedded in the same national survey. Through examples with blueberry and orange juice product choices, we draw inferences on the consumer welfare impacts of gene drive insects through a Bayesian lens. Consumers negatively value gene drive insect presence in growing areas (i.e. have a negative ‘willingness-to-pay’), though consumers penalize this presence less than they penalize high (vs. low) frequency insecticide spraying or a crop that is genetically engineered to resist insects. However, the nature of the gene drive technology creates simultaneous impacts such as reduced production costs (and thus, potentially, reduced prices), reduced need for insecticide spraying, and potentially wide-spread or complete presence of these genetically engineered insects in growing areas of host crops. Thus, methodologically, a complete assessment of welfare impacts requires an expansion beyond estimation of marginal willingness-to-pay. When gene drive insects can spread through conventional and organic fields, changes in the choice set result in a statistically significant net welfare loss for blueberry consumers and statistically insignificant welfare impacts for orange juice consumers. We estimate large consumer welfare gains from

using spatially limited (vs. spatially unlimited) drive insect systems, helping to inform both policy makers and technology developers about optimal design of any potential release program.

In Chapter 4, we adopt a transdisciplinary approach to examine the interaction between plant-based and insect-based biotechnologies as part of an integrated pest management (IPM) strategy. Millions of acres of GE crops are engineered to carry insecticidal genes for *Cry* proteins derived from the ‘Bt’ bacteria *Bacillus thurengiensis* (Tabashnik, Brévault and Carrière, 2013; NASEM, 2016b). A major concern in the use of GE crops with Bt toxins is evolved resistance which could render this valuable input obsolete (Tabashnik, Brévault and Carrière, 2013). One traditional component of resistance management programs is the inclusion of proximate non-Bt ‘refuge’ zones that reduce selection pressure for Bt resistance and allow insects to pass on alleles for susceptibility, thus potentially extending the functional life of Bt inputs by many years (Gould, 1998). We examine a proposed combination of traditional non-insecticidal refuge planting with releases of (non-gene-drive) GE insects that are susceptible to Bt and contain a repressible gene which results in near-complete lethality for females. We extend previous work (e.g., Alphey *et al.*, 2007; Zhou *et al.*, 2019) to combine age- and sex-specific insect genetic profiles of the world-wide pest Diamondback Moth with the economic value of Bt broccoli yield over long time horizons. This follows demonstrated caged field trials in this plant/pest system which suggest efficacy (Harvey-Samuel *et al.*, 2015). Within a static policy rule, Bt and GE insect releases have substitutable and complementary effects on population control and the net value of crop output, depending on the time horizon, Bt planting intensity, and GE insect release rates. This suggests potentially asymmetric program design incentives for growers, GE insect developers, and Bt seed sellers. While lower GE insect release rates help preserve susceptibility

and the relative yield advantage of Bt (vs. non-Bt) crops, higher release rates may crash the insect population and ultimately reduce the marginal pesticidal value of the Bt trait.

In my last chapter, I examine a plant-based biotechnology system in a novel growing environment within a developing country setting. This context is especially important to examine as a majority of global GE crop acreage is now in developing countries (ISAAA, 2017) and many developing-world policy makers are actively weighing the risks and benefits of legalizing ‘traditional’ and next-generation GE crop production (NASEM, 2016b; Wolt, Wang and Yang, 2016). We evaluate the heterogeneity in GE herbicide-tolerant and Bt maize yields accruing to producers with varying levels of human capital. We view Bt and stacked traits as *simplifying* input components, removing much complexity in farmer pest control needs. With panel data from the Philippines, we test whether these traits serve as substitutes or complements to human capital. Results indicate GE maize traits are substitutes with proxies for human capital and pest control knowledge. For every year *decrease* in formal education and maize farming experience, farmers realize significantly higher yield gains from planting GE maize. This evidence provides additional insights about ‘pro-poor’ claims of many biotechnology proponents, given small-scale, poor farmers tend to have lower levels of education.

Taken together, this dissertation provides valuable economic evidence for policymakers considering novel applications of both experimental and previously existing biotechnologies. I hope this work is both thought-provoking and useful for the global agricultural biotechnology research and policy community.

Chapter 2: Does the US Public Support Using Gene Drives in Agriculture? And What Do They Want to Know?

(with Jason A. Delborne, Johanna Elsensohn, Paul D. Mitchell, and Zachary S. Brown)

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2.1 Introduction

Rapidly advancing research in gene drives has sparked intense debate among scientists, regulators, and NGOs. Gene drives can alleviate a pest or disease by using preferential inheritance to generate self-sustaining spread of genetic traits that either suppress a species population or render the organism less harmful (Burt, 2003; NASEM, 2016a). Important applications of drives have been proposed for human health, environmental management, and agriculture (Esveld *et al.*, 2014).

Acknowledging potentially significant benefits and risks of gene drive technologies, and the diverse array of stakeholders, the US National Academies of Sciences, Engineering and Medicine (NASEM) recommended in 2016 that gene drive research continue in concert with ecological risk assessment and early-stage engagement with the public (NASEM, 2016a). In response, several sponsors of drive research have committed to ethical principles based on NASEM recommendations, including two-way public engagement and to ensuring ‘the perspectives of those most affected are taken into account’ in research and development (Emerson *et al.*, 2017). However, to date, there is no published research systematically assessing public views and questions about the application of gene drives in any domain, despite calls for

such information (NASEM, 2016a; Delborne *et al.*, 2018; Mitchell, Brown and McRoberts, 2018).

While much publicity and social debate has highlighted the opportunities and risks of gene drive pursuits for vector-borne human disease control (Sinkins and Gould, 2006; Pennisi, 2015) and biodiversity conservation (Webber, Raghu and Edwards, 2015; Esvelt and Gemmell, 2017), potentially useful and risky agricultural applications are also under development. An early attempt was to control Huanglongbing or citrus greening, a bacterial disease (*Candidatus liberibacter* spp.) vectored by the Asian citrus psyllid (*Diaphorina citri*) and other psyllid species, which is devastating the citrus industry globally (da Graça *et al.*, 2016). A proposal funded by the US Department of Agriculture (USDA) attempted to develop a *population replacement* drive – the self-sustaining spread of an insect strain incapable of transmitting the disease to replace the existing population (CRDF, <https://citrusrdf.org/nupsyllid-page-2>). Similarly, spotted wing drosophila (*Drosophila suzukii*), an invasive fruit fly from Eastern Asia, has established in Europe and the Americas, where it causes extensive damage to ripening berry and stone fruits and dramatically increases control costs (Asplen *et al.*, 2015). Research funded by the USDA and grower associations is seeking a *population suppression* drive (Li and Scott, 2016; Buchman *et al.*, 2018), a system that causes population collapse by spreading a trait that inhibits normal reproduction (Esvelt *et al.*, 2014). While not yet directly funding agricultural gene drives, the US Department of Defense (DOD) is funding development of gene drives for biodiversity conservation, as well as measures for controlling and reversing the effects of gene drives (DARPA, 2017). The DOD is also funding other genetic pest management (GPM) techniques for agricultural applications, for example “insect-delivered horizontal genetic alteration” of crops to increase resistance to environmental stressors and disease (DARPA, 2017;

Reeves *et al.*, 2018). The DOD’s support of horizontal genetic alteration technologies has raised concerns about possible dual-use (Reeves *et al.*, 2018). Private industry is also developing GPM techniques for area-wide pest control and crop protection (Jin, Walker, Fu, Harvey-Samuel, Dafa’alla, *et al.*, 2013). However, one of the primary firms active in this area, Oxitec, has so far steered away from producing gene drives (Intrexon, 2016), and the holder of a patent for a key molecular biology tool for gene drive development has prohibited its use for this purpose in licensing agreements with private firms (Guerrini *et al.*, 2017).

Public perceptions about gene drive applications in agriculture can inform policy. Somewhat distinct from vector-borne disease and biodiversity conservation, agricultural applications raise direct economic questions about possible consumer responses to food produced using gene drives (Mitchell, Brown and McRoberts, 2018). These questions are particularly relevant given prior controversies about genetically modified organisms (GMOs) in agriculture (Costa-Font, Gil and Traill, 2008) and evolving attitudes about GMOs in food supplies given recently revised labeling laws (Kolodinsky and Lusk, 2018). But gene drive perceptions may diverge in important ways from prior GMO controversies due, for example, to the genetic manipulation of pests instead of food products and to their intentional – and potentially uncontrolled – spread. One economically relevant subgroup to consider includes purchasers of certified organic food products, who accounted for US food sales of \$38.4 billion in 2015 (Willer and Lernoud, 2017). Release of gene drive pests in non-organic farms would spread to organic farms in the same area, providing non-chemical pest control benefits but also resulting in genetically modified pest residue on organic produce. It is unclear how current organic standards would handle such a situation. For example, the USDA’s organic certification standards do not directly address presence of genetically modified insect material, and some

researchers have asserted that direct or indirect support from grower groups in release programs may complicate farmer claims of ‘adventitious’ presence (Reeves and Phillipson, 2017). This ambiguity presents an opportunity to inform policy with ex-ante views among organic consumers on how this technology should interact with organically certified agriculture.

To investigate US public perceptions of potential gene drive applications in agriculture, we analyze original data from a web-based questionnaire administered to a population-based sample of the US general public. We developed the questionnaire based on three exploratory focus group discussions and our own survey pretesting, and then obtained the population-based sample from the GfK Knowledge Panel. These samples have been validated in other peer-reviewed academic research (Powell, Schnabel and Apgar, 2017).

A primary challenge with using a survey to elicit ex-ante attitudes towards gene drives is the public’s current unfamiliarity with these technologies (confirmed by our data). Following social science literature that seeks informed values about public goods (Johnston *et al.*, 2017), our objective in this research is to characterize the views from an otherwise average member of the public who happened to be reasonably informed about the basic purpose, function, feasibility, and risks of gene drives in specific agricultural applications. We devoted significant effort in each focus group discussion (FGD) and survey pre-testing in explaining the technology to participants, using the citrus psyllid and spotted wing applications described above as concrete examples to identify points of engagement and confusion. Although it is impossible to judge an information frame as perfectly ‘balanced’ or ‘objective,’ we intentionally provided content detailing the risky and uncertain nature of the drive technology, as well as its potential to replace traditional control measures that are not working well or economically for the specific pests considered. Based on FGDs and pretests, we committed an extensive portion of the survey – a

median 27% of total questionnaire time – interactively providing information about gene drives. All respondents first received a basic explanation of the technology and illustrations of the two proposed applications, including discussion about the failure of many current control strategies for these invasive species and their economic impact on the respective industries and growers. Respondents then had the option of selecting any of seven frequently-asked-questions (FAQs) identified in the FGDs and pretesting. While over 85% had never heard of gene drives before the survey, respondents appeared highly engaged with learning about the technology and over 89% selected at least one FAQ.

One limitation of this approach to informing respondents about gene drives is that subsequent reported attitudes on gene drive applications may be anchored to the specific applications considered. Since both of the applications presented have been proposed for pests causing significant economic damage and for which conventional pest control is very costly or failing, it may be best to characterize respondent attitudes as judging the acceptability of drive approaches in these contexts. Since many drive proposals will likely focus on intractable, invasive pests which are highly destructive, results may still be generalizable to a large relevant pool of future candidate species. To further account for anchoring effects, we include in our statistical analysis control variables for whether respondents consume the relevant agricultural products for the described applications (orange juice for the citrus psyllid and fresh blueberries for spotted wing drosophila).

Following this description of the technology, example applications, and FAQ provision, respondents then indicated their extent of support for or opposition to 8=2³ types of gene drives for agricultural pest control, which varied according to three binary factors: (a) whether the drive would suppress or replace the target pest population, (b) whether spread of the drive would be

limited, and (c) whether the species to be controlled was native to an area. These factors were identified in FGDs and survey pretesting as potentially important determinants of public support. Control of drive spread is particularly important, as ‘spread’ may be explicitly desired in some contexts and biomathematical models have suggested difficulty in controlling potential invasiveness of some drive systems (Marshall and Hay, 2012; Dhole *et al.*, 2018; Noble *et al.*, 2018). Respondents then indicated support or opposition for whether gene drive pest residue be allowed on organically certified food.

Respondents also indicated the relative importance they attributed to each of 10 scientific and policy uncertainties surrounding the use of gene drives in agriculture. The items on this list (described below) were adapted from the uncertainties the NASEM report (NASEM, 2016a) recommended be resolved prior to gene drive deployment, aggregated and simplified based on FGDs and survey pretests. Finally, respondents indicated the trust they placed in different entities to responsibly conduct research into agricultural applications of gene drives. The survey also elicited a variety of respondent characteristics (for example, whether they purchased or sought out organically certified or non-GMO food). We examine these characteristics vis-à-vis the above attitudinal indicators.

We first provide a detailed explanation of the relevant survey instrument sections and focus group data collection methods. We discuss statistical methods employed. Then, we describe survey results on support for the different types of gene drives considered, and for whether to allow gene drive pest residues in organic certification. We then analyze the selection of different FAQs, and the levels of importance attributed to different uncertainties. Finally, given the involvement of private enterprises, universities, the USDA and the DOD in gene drive

development, we analyze *who* the public trusts to responsibly handle research into these uncertainties.

2.2 Survey Data Collection

Results are based on a nationally representative survey of 1,018 of US adults (18 and older), conducted by the survey firm GfK from October 17 to November 14, 2017. Respondents were drawn from GfK's KnowledgePanel®, a widely used national probability-based online panel validated in other peer-reviewed research (Powell, Schnabel and Apgar, 2017). The sampling frame is unique compared to other web-based survey panels, in that GfK combines address-based sampling, random digit dialing, and both laptops and internet access are provided to active members when necessary.

A total of 2,269 panel members were sampled, of which 1,356 entered the Qualtrics-based online survey instrument and 1,189 consented to complete the survey. For recruitment, after emailing initial invitations at survey launch, email reminders were sent by GfK to non-responders on day three of the field period. Additional email reminders to non-responders were sent on day seven of the field period. The response rate was 45% and the completion rate was 75%. Median response time among qualified completes was 23 minutes. Of those consenting, 77 had incomplete responses at survey close. A total of 90 respondents were excluded via real-time quality control metrics. Metrics included excessive speeding in the four-panel information frame, with a threshold set at ten times an assumed average reading speed of 200 words-per-minute and assessed at total time on four information panels (full information frame wording in Appendix B) or failure of >1 (of 2) trap questions. Trap questions included failure to follow an embedded directive to select 'disagree' in an early question, as well as indicating household purchase of

‘fresh ackee fruit’ from a fruit product list, as this is illegal to import in the United States (Jones, House and Gao, 2015). Four additional respondents were excluded ex-post due to total completion times less than 25% of the survey-wide median. This resulted in 1,018 qualified completes used for analysis. Post-stratification statistical weights were prepared by GfK as standard and used for all reporting of results here¹.

2.3 Focus Groups and Survey Questionnaire

Design of the survey questionnaire consisted of the following steps: (1) three 2.5 hour exploratory FGDs about public attitudes and comprehension of agricultural applications of gene drive insects, conducted with a total of 21 primary grocery shoppers recruited at grocery stores in Durham, Raleigh and Dunn, North Carolina in spring 2017 (Appendix F, Fern (2001)), (2) using FGD analysis, survey instrument drafting in Qualtrics and initial pretesting with students and colleagues, (3) revision by researchers of Qualtrics instrument and pretesting with Amazon Mechanical Turk ($n=300$), (4) revision of Qualtrics instrument to address open-ended feedback in pretests, adhere to KnowledgePanel® requirements and reduce median completion time to 25 minutes or less, and experimental design of BWS subsets, and (5) finalize and launch survey instrument with KnowledgePanel® sample.

After a brief introduction and informed consent, the survey instrument contained the following sections analyzed in this paper (presented in this order): (I) respondent consumer

¹ The following benchmark distributions of 18+ US general population from the most recent March 2017 Current Population Survey (CPS) were used for the adjustment of weights: Gender (Male, Female) by Age (18-29, 30-44, 45-59, 60+), Race/Ethnicity (White/Non-Hispanic, Black/Non-Hispanic, Other/Non-Hispanic, Hispanic, 2+ Races/Non-Hispanic), Census Region (Northeast, Midwest, South, West), Metropolitan Status (Metro/Non-Metro), Education (Less than High School, High School, Some College, Bachelor or higher), Household Income (under \$25K, \$25-\$49,999, \$50K-\$74,999, \$75K-\$99,999, \$100K-\$149,999, \$150K and over). The breakdown of benchmark distributions for demographic covariates used in regression models, in raw qualified completes vs. adjustment with survey weights, is detailed in Appendix Table A.1.

characteristics; (II) general textual and visual information about how gene drives work, followed by description of the potential applications of a Spotted Wing Drosophila repression drive and a Asian Citrus Psyllid replacement drive; (III) FAQs; (IV) BWS exercise on gene drive uncertainties; (V) respondent knowledge of current organic certification requirements; (VI) views on allowing gene drives within organic certification; (VII) elicit support/opposition to the eight types of gene drives in Figure 2.1; (VIII) religiosity, elicited at the end to avoid any impacts (e.g. due to saliency or availability bias) of this question on preceding responses.

Part (I) included relevant respondent characteristics not automatically collected in the KnowledgePanel®, described below. The information provision in (II) began with the following consequentiality statement, to retain attention and reduce hypothetical bias (Herriges *et al.*, 2010): “Your responses to questions about this information will inform policy decisions at the US Department of Agriculture.” The full informational text and illustrations for (II) are in Appendix B. Wording of the FAQs in (III) is in Appendix C; these FAQs were crafted based on FGD findings, open-ended feedback on survey pretests, as well as a previous FAQ webpage published by the Wyss Institute at Harvard (<https://wyss.harvard.edu/staticfiles/newsroom/pressreleases/Gene%20drives%20FAQ%20FINAL.pdf>). Respondents could select as many as they wished to view (including none), with presentation order randomized to avoid order effects. Each unselected FAQ was still shown to respondents with one-third probability.

The BWS exercise in (IV) follows methods in (Finn and Louviere, 1992; Flynn *et al.*, 2007); this survey methodology was selected because of its lower cognitive demand and faster completion than elicitation of a full rank order, and as compared to a set of Likert scales it avoids between-respondent scale differences and higher likelihood of ties. The exercise was preceded

by the following instructions (further details in Appendix E and example question in Appendix Figure A.1):

Many questions remain to be answered before deciding whether gene drive insects should be used to control agricultural pests. Policy makers want to know how the public feels about these issues and which research questions are most important to answer. We need your help to inform these decisions.

Here, we will show you a short series of questions. We would like to know which you feel is the ‘most important’ and which is the ‘least important’ to answer.

The selection and wording of the uncertainties included in the BWS exercise are based on the 2016 NASEM report conclusions (NASEM, 2016a) combined with FGD and survey pretest feedback; Appendix E describes this in detail. The experimental design of the BWS exercise followed a Balanced Incomplete Block Design to guide choice set construction (Flynn *et al.*, 2007). With 10 items to rank, the full design contained 15 sets of 4 items each, with each item occurring 6 times and co-occurring 2 times with each other item. The SAS software package (version 9.4, with macro %mktbibd) was used to identify a statistically efficient 3-block design limited to 5 sets for each individual respondent to reduce survey fatigue and completion time. Respondents were randomly assigned to a block and every respondent saw each item at least once. Choice set order, as well as item order within each choice set, was randomized to avoid order effects.

Knowledge of organic certification in (V) consisted of the single question, “Please indicate the extent to which you believe the following statement is true or false: *Food that is certified ‘USDA organic’ can be produced applying certain types of insecticides* [Image of USDA organic label shown].” Responses consisted of a scale ranging from “Definitely False”, “Probably False”, “Probably True”, to “Definitely True” and included a “Don’t know” option. We define ‘awareness’ of pesticide allowances within organic certification, as used in Figure 2.3, as selection of “Probably True” or “Definitely True.” In (VI), two questions on support for organic certification allowing gene drive insects (“in the area” for one question, and “on or in the crops” for the second) were elicited on a five-point Likert scale ranging from “Strongly disagree” to “Strongly agree”.

Part (VII) elicited respondents’ levels of support or opposition to the eight possible combinations of three binary factors for gene drive insect applications: intended for suppression/replacement, self-limiting/unlimited spread, and native/non-native target species. These factors were chosen based on the 2016 NASEM report recommendations (NASEM, 2016a) and related feedback from FGD participants. Particularly motivating was report recommendation 9-3: “The distinguishing characteristics of gene drives—including their intentional spread and the potential irreversibility of their environmental effects—should be used to frame the societal appraisal of the technology, and they should be considered in ecological risk assessment, public engagement, regulatory reform, and decision making” ((NASEM, 2016a), p. 178). The terminology for these factors was simplified to aid comprehension by respondents about these unfamiliar technologies. The description of these factors preceding this set of questions read as follows (emphases in instrument):

After reading about gene drives for agricultural uses, we would like to hear how you feel.

Specifically, we want to know how you feel about gene drives **to reduce** populations of pests vs. **to alter** pests to prevent them from carrying a crop disease.

We also want to know how you feel about gene drives used on insects which are **native** to an area vs. insects which are **not native** to an area. (Note: both the berry and citrus pest examples are invasive species not native to the United States).

Finally, some scientists have proposed trying to control how far a gene drive can spread. We would like to know how you feel about gene drives when scientists try to **limit how far a gene drive can spread** vs. gene drives which are **allowed to potentially spread to the global population** of the insect species.

Following this preamble, respondents were then asked, for each of the eight applications: “Overall, to what extent would you personally support or oppose the use of gene drives to control agricultural insect pests in the following applications: …” [emphasis in instrument]. Support or opposition to each of the eight applications (randomizing their order) was assessed for every respondent, on a 5-point scale from 1 = “Strongly Oppose” to 5 = “Strongly Support,” and including both a “Neither Support or Oppose” and a “Don’t know” option (aggregated together here, but tested in robustness).

2.4 Demographic and Consumer Characteristics

We include in our statistical analysis standard demographic variables that may relate to public opinion of agricultural gene drive applications. The following variables were provided by GfK (not asked in survey instrument): *Female* is coded 1 = ‘female’ and 0 = ‘male’ (51.8% female). *Age* is measured in years (M=50.7; SD=16.2; Weighted Mean = 47.3). For race, *White* is coded 1 = ‘white’ and 0 = ‘otherwise’ (64.0% white). GfK provides up to 21 levels for *Income*, coded 1 = “Less than \$5,000”, 2 = “\$5,000 to \$7,499”, 3 = “\$7,500 to \$9,999”, 4 = “\$10,000 to \$12,499”, 5 = “\$12,500 to \$14,999”, 6 = “\$15,000 to \$19,999”, 7 = “\$20,000 to \$24,999”, 8 = “\$25,000 to \$29,999”, 9 = “\$30,000 to \$34,999”, 10 = “\$35,000 to \$39,999”, 11 = “\$40,000 to \$49,999”, 12 = “\$50,000 to \$59,999”, 13 = “\$60,000 to \$74,999”, 14 = “\$75,000 to \$84,999”, 15 = “\$85,000 to \$99,999”, 16 = “\$100,000 to \$124,999”, 17 = “\$125,000 to \$149,999”, 18 = “\$150,000 to \$174,999”, 19 = “\$175,000 to \$199,999”, 20 = “200,000 to \$249,000”, and 21 = “\$250,000 or more” (Median = 13).

We collected additional education information at a more granular level than the standard GfK-provided indicators, in order to examine the potential importance of an undergraduate and graduate education with a topic as potentially complex as gene drives. The base level is “No College” (40.0%). Next, separate variables are coded for *Some college* as 1 = ‘some college’ and 0 = ‘otherwise’ (28.6% some college), *Bachelor Degree* as 1 = ‘Bachelors’ and 0 = otherwise (17.8% bachelor), and *Graduate Degree* as 1 = ‘Masters’ or ‘PhD’ and 0 = otherwise (13.7% graduate). While not part of the GfK-supplied demographic information, *Religiosity*, or “how much guidance does religion provide in your everyday life?”, has been shown to impact US public opinion on some human genome editing applications (Scheufele *et al.*, 2017). This

variable is measured on an 11 point scale from 0 = “No guidance at all” to 10 = “A great deal of guidance” (M=6.32; SD=3.68; Weighted Mean=6.41).

As gene drive insect applications in agriculture are inherently focused on commercial food products, consumer characteristics are a key focus for public opinion research. In the explanation of potential drive applications, both a major soft berry pest (Spotted Wing Drosophila) and a major citrus pest (Asian Citrus Psyllid) were discussed. Therefore, consumers of berries and citrus may view a gene drive insect as more personally beneficial to reduce damage to consumed products, or, perhaps, more threatening since the gene drive insect may interact with their food. We ask respondents if their household purchased several fruit and juice products in the last six months, including fresh blueberries and orange juice. *Household buys blueberries* and *Household buy O.J.* are each coded 1 = ‘yes’ and 0 = ‘no’ (Blueberries: 56.8% yes; O.J.: 70.4% yes). *Primary Shopper* is coded 1=’yes’ and 0=’no’ (79.1% yes). Finally, specialty consumers who purchase USDA-Organic labeled, ‘non-GMO’-labeled, or locally grown products may have distinct values about food production which impact their support for the use of gene drive insects in agriculture. Buyers of certified organic and ‘non-GMO’ –labeled foods may be particularly sensitive to the use of any genetic engineering in the food supply (Costa-Font, Gil and Traill, 2008). Respondents were asked “the extent they agree or disagree with the following statements about food shopping”, including questions “I regularly purchase food labelled ‘USDA-Organic’”, “I regularly search for food labeled ‘non-GMO’ or ‘GMO-free’”, and “I regularly purchase locally grown food.” Responses were reported on a 5-point scale, from 1 = “Strongly Disagree” to 5 = “Strongly Agree”. Each variable *Buys USDA-Organic foods*, *Buys non-GMO/GMO-free labeled foods*, and *Buys ‘local’ foods* is coded 1 for ‘buys’ if

responding “Strongly Agree” or “Agree” and 0 otherwise (Org: 22.7% buys; non-GMO: 21.7% searches; Local: 43.4% buys).

2.5 Statistical Analysis

The survey responses analyzed by design as dependent variables in this study are: support for agricultural gene drive applications (five-point Likert-scale responses), support for gene drive inclusion in organic certification (five-point Likert-scale), FAQ selection, and perceived relative importance of gene drive uncertainties (BWS indicators for most/least important). For concise interpretation, in Figs. 2.1, 2.2 and 2.3, and Table 2.1 we aggregate in the main text the five-point Likert scales for support (with a ‘don’t know’ option), into a three-point ‘agree’ [Strongly Agree + Agree], ‘neutral’ [Neither + DK], and ‘disagree’ [Strongly Disagree + Disagree] scale (following condensing in Scheufele *et al.* (2017)). Our statistical analysis employs Wald tests of differences in subgroup means of these responses and generalized linear regression models to estimate the marginal effects of different gene drive factors and respondent characteristics on these outcomes.

Ordered logit regression models were used to obtain statistical estimates for the ordinal, Likert-scale responses in Figure 2.1 and Table 2.1. Given concerns about violations of the proportional odds assumption in ordered logit models, which are common in empirical work (Long and Freese, 2014; Williams, 2016), partial proportional odds (PPO) ordered logit models were employed where appropriate with the *gologit2* command in Stata. In a PPO ordered logit model, some beta coefficients may be constrained to be the same across dependent variable levels (as in a standard ordered logit model) while others may be allowed to vary if the proportional odds assumption is rejected at the 0.05 confidence level. In an example from

(Williams, 2016), with j dependent variable levels, betas for X_1 and X_2 may be constrained while betas for X_3 vary:

$$P(Y_i > j) = \frac{\exp(\alpha_j + X_{1i}\beta_1 + X_{2i}\beta_2 + X_{3i}\beta_{3j})}{1 + (\exp(\alpha_j + X_{1i}\beta_1 + X_{2i}\beta_2 + X_{3i}\beta_{3j}))}, j = 1, 2, \dots, M - 1$$

Ordinary least squares (OLS) models were used as robustness checks against the ordered logit models (Appendix Table A.9). OLS was also used to estimate marginal effects on the count of selected FAQs (Table 2.1), with a tobit model used in robustness checks (Appendix Table A.5).

All estimation was done in Stata® version 14. Standard errors for all regression coefficients (in Table 2.1 and used to estimate statistical precision in Figures 2.1, 2.2, and 2.3) account for GfK-provided survey weights and within-respondent clustering. Marginal effects for ordered logit regressions are obtained with Stata's *margins* command, which estimates standard errors using the Delta method.

The exposure of every respondent to the complete factorial of the three binary gene drive factors in eliciting general support ensures that these factors are not correlated with observed or unobserved respondent characteristics, reducing statistical bias and imprecision in estimates of these effects. The experimental design of the BWS exercise, and random assignment of respondents to the three blocks in this exercise, ensures the subsamples presented with each block are statistically indistinguishable. The random ordering of different drive types and the BWS sets protects against bias from order effects in these measurements. Weighted least squares regression is used to statistically rank uncertainty items (Flynn *et al.*, 2007). For this estimation procedure, the dependent variable is the total (sample-level) log frequency of the

$10*(10-1)=90$ possible most-least important pairs (i.e. ‘best-worst’ pairs). The log selection frequency for each pair is a linear function of the difference in utility (Flynn *et al.*, 2007). Independent variables are $10-1=9$ items (‘Cost-effectiveness’ used as reference), which are coded ‘1’ for the pair’s ‘most important’ item and ‘-1’ for the pair’s ‘least important’ item. The regression weights are the frequencies each pair appears in the balanced incomplete block design.

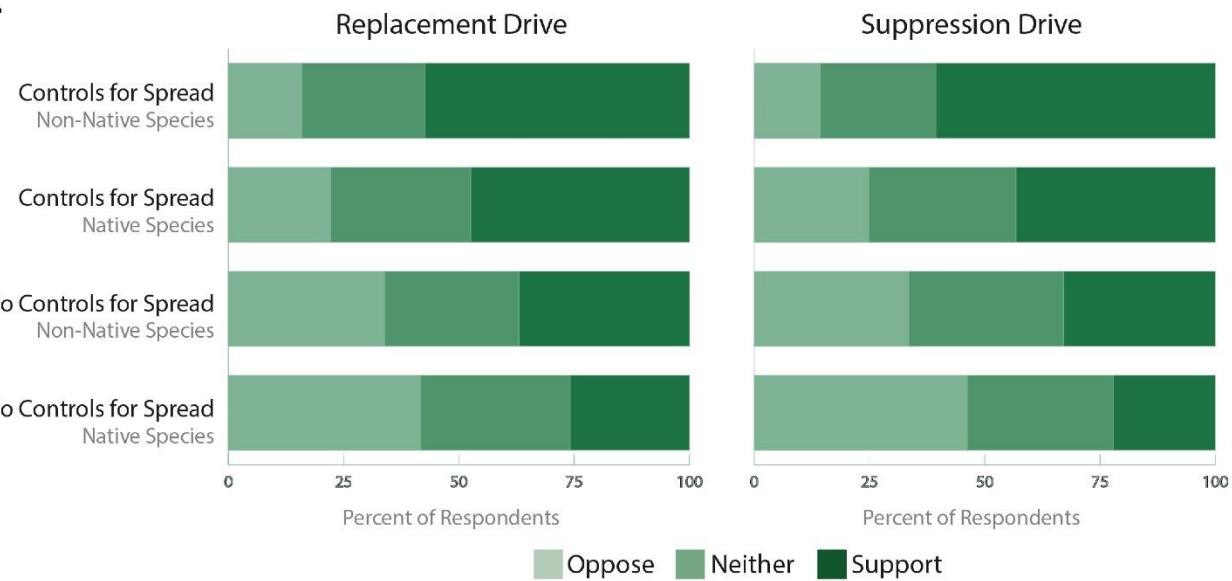
2.6 Results

Our data indicate that a majority of the US public, when provided information about potential benefits, risks and actually proposed examples of the technology, would currently support use of an agricultural gene drive targeting non-native species, if mechanisms limit drive spread. As Figure 2.1 illustrates, this result holds for population suppression (61% support, 14% oppose) and replacement (57% support, 16% oppose). However, even in non-native species, drives that spread freely have considerably less support, whether for suppression (33% support, 34% oppose) or replacement (37% support, 34% oppose). The distinction between unlimited and self-limiting drives is the most important factor analyzed, reducing the likelihood of public support by 22.1 percentage points ($p<0.001$). Targeting native v. non-native species have less support (11.5 percentage point reduction, $p<0.001$), as do drives to suppress rather than replace pest populations (1.9 percentage point reduction, $p = 0.010$) (Appendix Tables A.2 & A.3). These statistics are essentially equivalent when controlling for respondent covariates (Table 2.1).

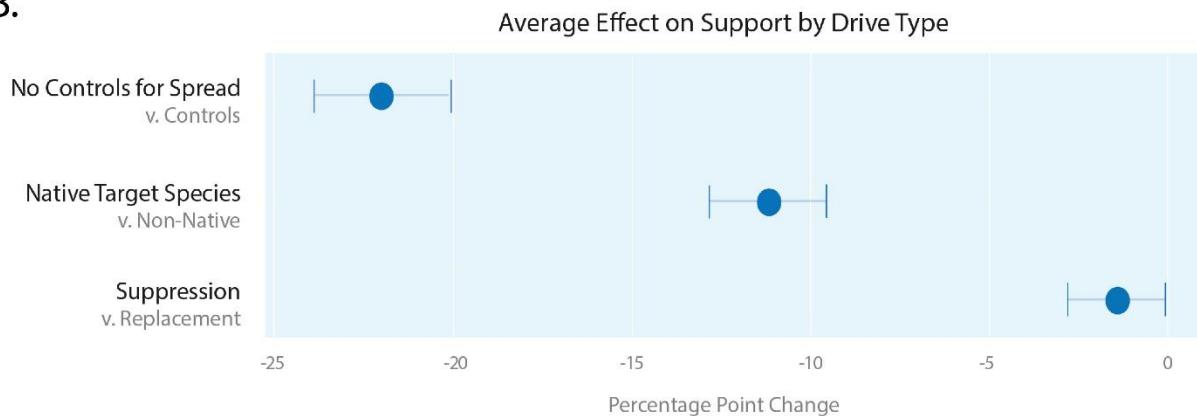
Figure 2.1: Support for Gene Drive Use in Agriculture

Note: Respondents were asked whether they support or oppose the use of gene drives to control agricultural insect pests in each of eight applications. **(A)** Condensed Likert response frequencies varying 1) whether the drive would reduce populations or alter populations to not carry a crop disease, 2) whether controls are in place to limit the extent of drive spread, and 3) whether the target species was native to an area. **(B)** 95% CIs shown for average marginal effects of estimates from a pooled ordered logit model with standard errors clustered by respondent (full model Appendix Table A.2 & A.3, respondent covariates in Table 2.1)

A.



B.



Statistical analysis also shows that attitudes towards agricultural gene drive insects vary significantly between respondent subgroups and their level of awareness about existing pest control practices and regulations. As hypothesized, respondents regularly seeking out non-GMO (or ‘GMO-free’) labeled products are statistically significantly less supportive of gene drive insects in agriculture, with an 8.8 percentage point reduction in support (Table 2.1). However, as shown in Figure 2.2 a substantial portion of those seeking non-GMO food do still support some types of gene drive insect use. Of the roughly one-fifth of the US population who search for non-GMO labeled foods, a majority support gene drive applications in non-native species with controls for drive spread. Respondents regularly buying certified organic foods are not statistically significantly less likely to support drives. More educated respondents are more likely to take a supporting or opposing position, with undergraduate and graduate degree holders 18.0 percentage points less likely to select a neutral or ‘don’t know’ position than respondents with no college exposure. While the survey questions about drive support were not specifically framed in terms any specific pest species, as noted above the spotted wing and psyllid applications described in the information frame likely increased the salience of the technology for consumers of the associated citrus and berry crops. Enhanced salience could have the effect of increasing or decreasing support, depending on whether perceived benefits from reduced crop damage (ensuring availability of affordable produce) outweigh perceived risks. We find blueberry consumers are 4.2 percentage points more likely to support gene drives (Table 2.1). Similarly, given the citrus psyllid case description, orange juice consumers are 5.4 percentage points more likely to support drive use.

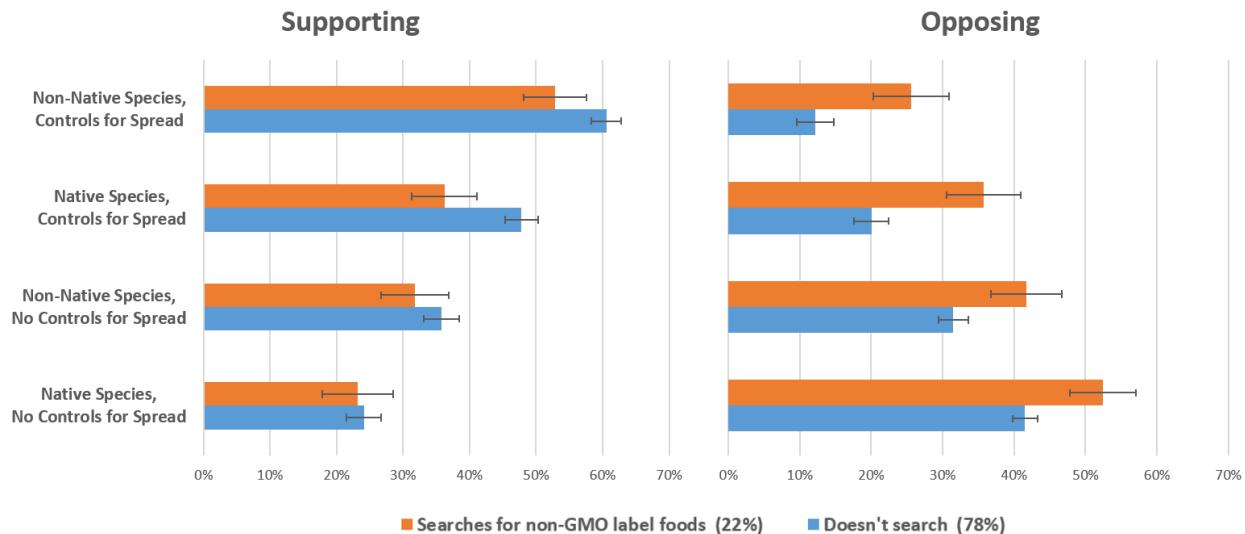
Table 2.1: Average marginal effects of gene drive attributes and respondent characteristics on support and FAQ selection.

Note: Drive support estimating using a partial proportional odds (PPO) ordered logit regression model. FAQ selection estimated using ordinary least squares. Includes survey sampling weights. ** $P < 1\%$, * $P < 5\%$, † $P < 10\%$.

	Marginal Effect on Probability of Drive Use Position			Number of FAQs Selected
	Oppose	Neither	Support	
<i>Gene drive attributes</i>				
No Controls for Spread [v. controls]	0.190** (0.0102)	0.0297** (0.00535)	-0.220** (0.0107)	-
Native Species [v. non-native]	0.0890** (0.00927)	0.0316** (0.00730)	-0.121** (0.0101)	-
Suppression [v. replacement]	0.0164* (0.00653)	0.00255* (0.00111)	-0.0189* (0.00754)	-
<i>Demographic variables</i>				
Female	0.0341† (0.0178)	0.00531† (0.00291)	-0.0394† (0.0205)	0.427*** (0.149)
Age	-0.000436 (0.000545)	-6.79e-05 (8.41e-05)	0.000504 (0.000628)	0.0031 (0.0044)
White	0.0453† (0.0237)	-0.0588* (0.0265)	0.0135 (0.0257)	-0.563*** (0.159)
Income	-0.00314 (0.00235)	-0.000489 (0.000375)	0.00362 (0.00271)	0.0140 (0.0182)
<i>Post-secondary Education</i> (base=No college)				
Some college or Assoc. Degree	0.0312 (0.0281)	-0.113** (0.0316)	0.0818** (0.0298)	0.352† (0.181)
Bachelor Degree (only)	0.0922** (0.0310)	-0.181** (0.0303)	0.0891** (0.0328)	0.520* (0.210)
Graduate Degree	0.0960** (0.0322)	-0.180** (0.0322)	0.0842* (0.0354)	0.321 (0.228)
Religiosity Scale	-0.00294 (0.00243)	-0.000457 (0.000400)	0.00339 (0.00282)	0.0172 (0.0202)
<i>Consumption variables</i>				
Primary Shopper	-0.0377* (0.0190)	-0.00587† (0.00321)	0.0436* (0.0220)	0.279† (0.154)
Buys Blueberries	-0.0361* (0.0177)	-0.00562† (0.00301)	0.0417* (0.0205)	0.0611 (0.155)
Buys Orange Juice	-0.0469* (0.0215)	-0.00731* (0.00371)	0.0542* (0.0250)	0.356* (0.176)
Buys ‘Local’ Foods	0.0541* (0.0216)	-0.0607** (0.0220)	0.00658 (0.0227)	0.237 (0.147)
Buys ‘USDA-Organic’ Foods	0.0204 (0.0234)	0.00318 (0.00367)	-0.0236 (0.0270)	0.372† (0.202)
Seeks ‘non-GMO’ Labeled Foods	0.0762** (0.0250)	0.0119** (0.00410)	-0.0881** (0.0285)	0.371† (0.203)
Constant	-	-	-	1.879** (0.379)
Respondents	1,000			1,001
Observations	7,997			1,001
(McFadden’s) R ²	0.0723			0.092
<i>Wald test p-value for joint significance</i>				
Drive Attributes	p<0.0001			-
Demographic Variables	p<0.0001			p=0.0004
Consumption Variables	p<0.0001			p<0.0001

Figure 2.2: Drive Support and Opposition by Whether Seeking Non-GMO Food.

Note: Level of Support and Opposition to Gene Drive Insect Applications for Seekers and Non Seekers Non-GMO Labeled Food (95% CIs shown; Suppression and Replacement applications combined [see Appendix Table A.6]). While those searching for non-GMO labeled food are relatively less supportive and more likely to explicitly oppose drive applications (Table 2.1), a slight majority (53%) still support applications in non-native species with controls for drive spread with 26% opposing.

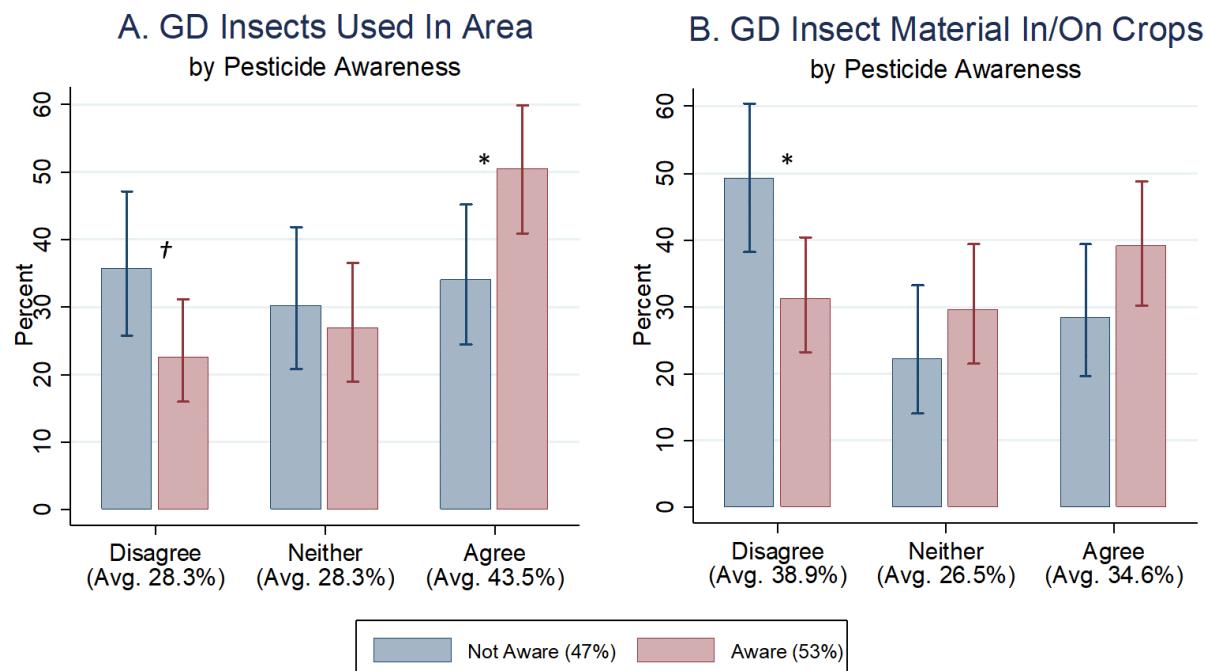


Around one in five respondents also report ‘regularly’ purchasing USDA organically-certified food (regular organic purchase exhibits a 0.485 correlation with seeking non-GMO labeled food). When asked whether USDA organic certification standards should allow gene drive insects (without specifying adventitious or intentional presence), 43% of these consumers agree that farmers should be able to retain certification when drive insects are present “in the growing area” (Figure 2.3). Agreement drops to 35% when gene drive insect material is “in or on crops,” a reasonable expectation given current organic regulations. Focus groups suggested organic consumers may have different views depending on awareness that certification standards permit some insecticide use. Only 57% of those regularly purchasing certified organic foods are

aware that “certain types of insecticides” are allowed by organic certification standards. Among these ‘aware’ individuals, 50% agree that certification should allow for drive insects “in the growing area” (Figure 2.3). Those unaware of standard guidelines are 18 percentage points more likely to disagree that standards should permit modified insect material “in or on crops” ($p=0.012$).

Figure 2.3: Organic certification attitudes when drive insects present.

Note: Level of agreement (with 95% CI) that a farmer should be able to retain organic certification in the presence of gene drive insects, among affirmed regular purchasers of certified organic food products ($n=228$), by whether the respondent is aware that some types of insecticides are allowed under organic regulations (57% of regular organic consumers aware). Asked separately by whether (A) gene drive insects are used in the area to control a damaging insect species or (B) that use of drive insects in results in genetically modified insect material ‘getting in or on crops’. ** $P < 1\%$, * $P < 5\%$, † $P < 10\%$ for Adjusted Wald Tests of equivalent response means.



To understand what additional information different groups want to know about these technologies, we analyze respondents' voluntary selection of seven FAQs about agricultural gene drives (Figure 2.4a). The most popular – “What are some possible risks of gene drives?” – was selected by 70%, suggesting widespread concern over unintended consequences. Women, non-whites, household primary shoppers, and bachelor degree holders more frequently sought additional FAQ items (Table 2.1).

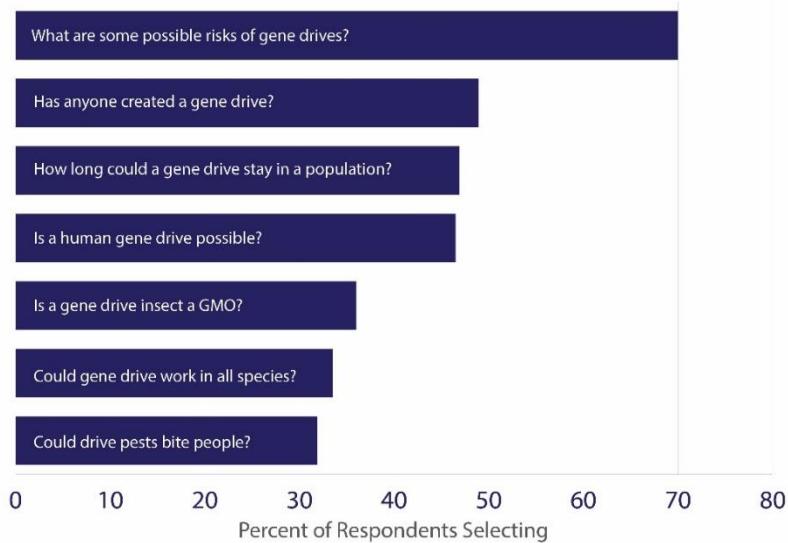
Respondents also selected what they believed to be the most and least important uncertainties to resolve “before deciding whether gene drive insects should be used to control pest damage to crops” (see Appendix E for uncertainty item construction and exact phrasing). This survey exercise is known as Best-Worst Scaling (BWS) (Finn and Louviere, 1992), and was implemented in the survey by presenting each respondent with five subsets of the 10 uncertainties shown in Figure 4b, from which respondents selected the most and least important items in each subset. The subsets are experimentally controlled and randomized across respondents so that the frequency an item is selected as most (or least) important provides an unbiased statistical estimator of that item's (un)importance within the population. Analysis of these data imply that potential human health impacts and ecological consequences of species removal are most frequently viewed as the highest priorities (Figure 2.4b). Even though NASEM recommends human health risk assessment only on drives for human disease vectors, this suggests the question of human health remains important to the public in any application (NASEM, 2016a). Uncertainty about the ecological consequences of species removal emerged as more important than economic impact and technical feasibility ($p < 0.001$, Appendix Table A.7), suggesting the NASEM report's recommendations for ecological risk assessments (NASEM, 2016a) align with public concerns. These results are also in line with a recent Pew Research

Center study showing high public acceptance of genetically engineered mosquitos for vector control, but also high concern about risks to the environment and ecosystem impact among dissenters (Funk and Hefferon, 2018). “Reversal drives”, or the possibility of releasing a second gene drive to overwrite and reverse unintended effects of a previous drive have received much attention in debates (DiCarlo *et al.*, 2015; NASEM, 2016a). However, reversibility was among the lowest ranked priorities. Taken with our evidence of public support for self-limiting drives (Figure 2.1), this suggests the public tends to prefer avoiding the need for reversal drives.

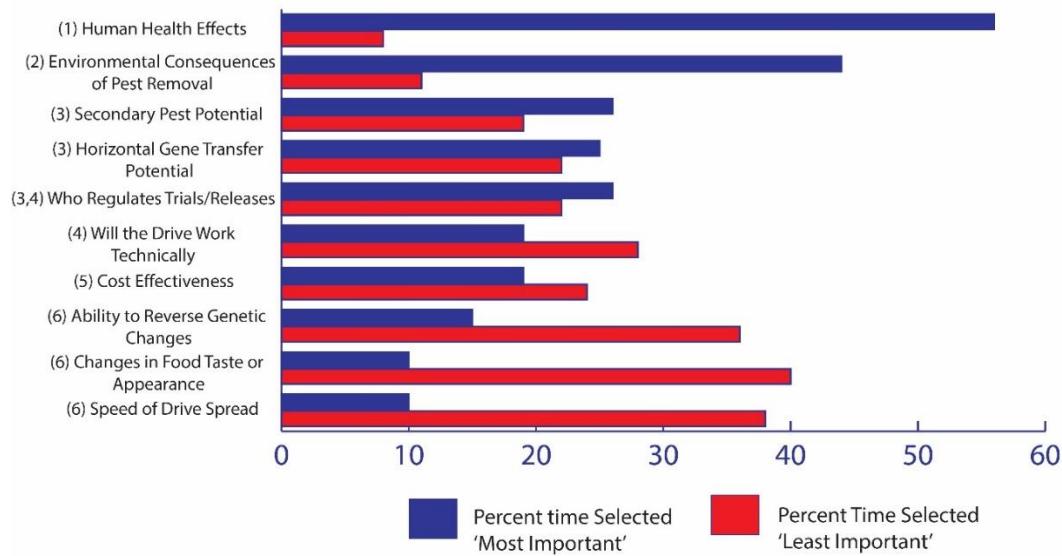
Figure 2.4: What does the public want to know about agricultural gene drives?

Note: (A) Voluntary respondent selection frequency from seven-item FAQ list. Question wording abbreviated for exposition. (B) Respondents selected the ‘most important’ and ‘least important’ among iterative four-item subsets of the ten alternatives to resolve “before deciding whether gene drive insects should be used to control pest damage to crops” (numbers denote statistical ranking via weighted least squares regression and Wald tests of linear hypotheses; full item wording found in Appendix E, WLS model results in Appendix Table A.7; example choice scenario in Appendix Figure A.1).

A. ‘Frequently Asked Question’ Selection Frequency



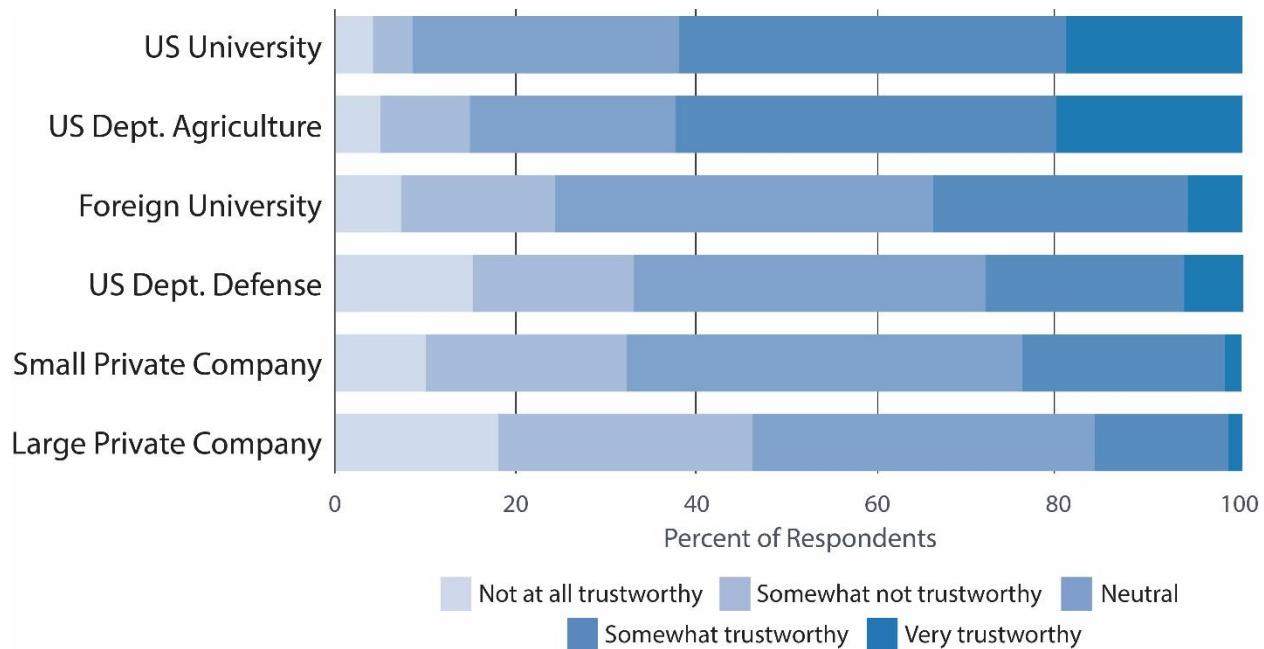
B. Ranking Uncertainties to Resolve before Use Decisions



The US public will also likely scrutinize who develops and assesses the risks for agricultural gene drive applications. Our data indicate that 62% regard both US universities and the USDA as ‘somewhat’ or ‘very’ trustworthy to conduct “research on gene drive insects to control agricultural pests”, compared to 9% and 15% responding ‘somewhat not’ or ‘not at all’ trustworthy, respectively (Figure 2.5). However, only 16% view large private companies as trustworthy drive insect researchers and 46% view them ‘somewhat not’ or ‘not at all’ trustworthy. Similarly, there is more public distrust in the US Department of Defense to conduct this research (18% ‘somewhat not’ and 15% ‘not at all’ trustworthy), which may be concerning given recent influxes of DOD funding for genetic pest management efforts in agriculture that have attracted scrutiny (Reeves *et al.*, 2018). However, in this study we do not explicitly measure differences between ‘conducting’ vs. ‘funding’ research.

Figure 2.5: Trust in institutions to conduct research on gene drive agricultural pests.

Note: Respondents indicated “how trustworthy [they] feel each type of institution would be conducting research on gene drive insects to control agricultural pests” (full question wording and raw data in Appendix Table A.8).



2.7 Discussion

This survey analysis provides an ex-ante portrait of US public attitudes at an important point in time, well before any field release and with sparse popular press coverage about these technologies. Our analysis suggests, in agricultural applications, developers are most likely to have strongest public support for self-limiting gene drive applications, the feasibility of which has been shown to depend on the biological mechanisms involved (Dhole *et al.*, 2018). More research may be merited in operationalizing self-limiting applications given public concerns. Given surprisingly high levels of gene drive support we find among those seeking non-GMO labeled foods, there appears to still be scope for productive engagement between developers of gene drives and those skeptical of using genetic engineering in food production.

The type and trustworthiness of the information about gene drive insects – and about the problems they are intended to solve – is also clearly important to the public in forming their views. Our analysis of voluntary engagement with FAQs shows strong demand for further information about gene drive risks. Our analysis also suggests that in some cases respondents carefully weigh information about the benefits of gene drives relative to alternative pest control options. For example, we find that organic food consumers' knowledge of whether pesticides are used in organic agriculture is a significant determinant of their permissiveness of gene drive insect residue in organic certification. Lastly, the relatively greater trust the US public places in universities and the USDA to conduct research on agricultural gene drives suggests, for example, that the Broad Institute's decision in 2017 to prohibit drive applications when licensing patented CRISPR technology to large agribusiness firms aligns with prevailing public attitudes (Guerrini *et al.*, 2017).

To maintain public support for gene drive applications, researchers and policymakers should weigh these reported attitudes when deciding whether and what type of application to deploy, the extent and prioritization of risk assessments and stakeholder engagement, and the organizations conducting this work. Furthermore, public attitudes towards gene drives can change as events occur to increase the salience of perceived risks, as has been seen with GMOs in Europe in the 1990s (Frewer, Miles and Marsh, 2002). In addition, potential movement of drive species and agricultural trade will require discussions among international publics with heterogeneous values and market environments. This will require continued public engagement both over time and beyond immediate release areas. Qualitative information from focus groups and quantitative analysis of survey data will be important for disentangling the nuance and

diversity of attitudes towards these unfamiliar technologies, and for identifying questions these publics want answered.

Chapter 3: Landscape-Level Pest Control Externalities When Consumer Preferences Are Non-Neutral

(With Zachary S. Brown)

3.1 Introduction

Agricultural technologies which enhance productivity should, in theory, generate consumer surplus benefits (Taylor, 1980; Norton and Davis, 1981; Frisvold, Sullivan and Raneses, 2003). However, there is a large evidence base documenting that some consumers prefer to avoid food produced using specific agricultural technologies, such as pesticides or biotechnology, if they can afford to do so and are aware of underlying production technology attributes (Costa-Font, Gil and Traill, 2008; Frewer *et al.*, 2011, 2013; Lusk, McFadden and Wilson, 2018). However, new agricultural technologies that are distasteful to some consumers could still improve welfare on average if existing choices available to consumers are unaffected by a technology's introduction. Some new forms of agricultural biotechnology, in particular the landscape-level release of certain forms of genetically engineered insects, may reduce yield losses and management costs and provide a broad productivity-enhancing benefit (Thomas *et al.*, 2000; NASEM, 2016a; Scott *et al.*, 2018; Brown, Jones and Mumford, 2019). However, the broadest-reaching designs for genetically engineered insect releases may in fact limit the ability of consumers to opt out of purchasing certain food products grown in the presence of these technologies (Esvelt *et al.*, 2014; Noble *et al.*, 2018). If a new technology reduces the consumer choice set, there will be some associated welfare loss that must be accounted for in assessing the ex-ante impact of deployment. For such technologies, it is therefore important to be able to evaluate the tradeoffs between productivity improvements – or, in the case of pest control, avoided damages – and losses in consumer choice.

We introduce a novel and practical approach for assessing non-marginal welfare tradeoffs from productivity-enhancing technologies that may limit consumer choice, allowing for heterogeneous preferences and estimation of the statistical precision of these welfare estimates.

We apply this approach to an ex-ante consumer welfare analysis of a newly developed agricultural biotechnology – gene drives – with a particularly high potential for limiting consumers’ ability to opt out. ‘Gene drive’ insects are a class of genetically engineered insects that are released to reduce or eliminate pest populations or inhibit the ability of pest populations to transfer crop diseases (Esveld *et al.*, 2014). Traditional designs of gene drive insects could facilitate the self-sustaining spread of genetically engineered traits throughout an entire landscape’s species population, potentially reaching the national or global range of that pest species (NASEM, 2016a). This distinct component of gene drives as novel forms of agricultural biotechnology require specific investigation into potential consumer reactions. In doing so, researchers can help inform developers and policymakers at early stages about the potential downstream impacts of these novel approaches vis-à-vis other pest management alternatives.

We examine two proposed species for gene drive application that are invasive and highly damaging in the United States: the Asian citrus psyllid (*Diaphorina citri*) in orange juice markets and Spotted-wing Drosophila (*Drosophila suzukii*) in fresh blueberry markets.

The objective of this paper is to: (1) examine the potential demand effects of gene drive insect use in growing environments against other chemical and biotechnological approaches to pest management; (2) extend the analysis to measure the consumer surplus impacts of drive insect deployment in currently proposed contexts; and (3) estimate the value of geographically limited vs. unlimited gene drive insect releases through the lens of consumer welfare gains. Because gene drives have not been deployed in agriculture, consumer preferences over these

technologies cannot be revealed through analysis of food purchases, and we therefore must rely on ex ante valuation methods. We address these questions through a survey administered to a nationally representative probability sample of U.S. adults ($n=1,018$). We believe this is the first study of any genetically engineered insect's impact on consumer demand for an agricultural good, thus our study provides an important perspective on public values and preferences for mobile genetically engineered organisms in growing environments.

The next section provides a background of gene drives, broad genetically engineered insect development in agriculture, regulatory developments for agricultural biotechnology and organic certification, and consumer preferences for biotechnology in food production. We then describe the experimental procedures and survey data. We go on to present marginal results from a Hierarchical Bayesian analysis of a discrete choice experiment, as well as non-marginal consumer surplus simulations of drive insect deployment under varying contexts of pest damage levels. We then use the estimates to infer the consumer surplus value of deploying geographically restricted (versus unrestricted) genetically modified insects. Finally, the last section concludes and discusses policy implications.

3.2 Background

3.2.1 Gene Drive Insects

Effective and acceptable management of damaging, invasive species that threaten crops is a continual challenge for the agricultural sector. Biotechnology advances and CRISPR-based gene editing capabilities may soon facilitate a novel approach to pest management with the development of genetically engineered insects. This approach could have substantial applications in agriculture, addressing devastating pest problems while reducing environmental damages from pesticides. A type of strategy some scientists are pursuing is called a 'gene drive'

(Barrangou, 2014; NASEM, 2016a), in which scientists may be able to modify the genes of insect pests to prevent transmission of serious crop diseases or reduce their populations by disrupting normal reproduction (Hammond *et al.*, 2016). As outlined in Figure 3.1, Gene drive systems are distinct in that engineered modifications could be intentionally spread through entire populations of a pest species, as modified individuals pass on genetic changes that are inherited by up to 100% of their offspring (see: Burt (2003), Sinkins & Gould (2006)).

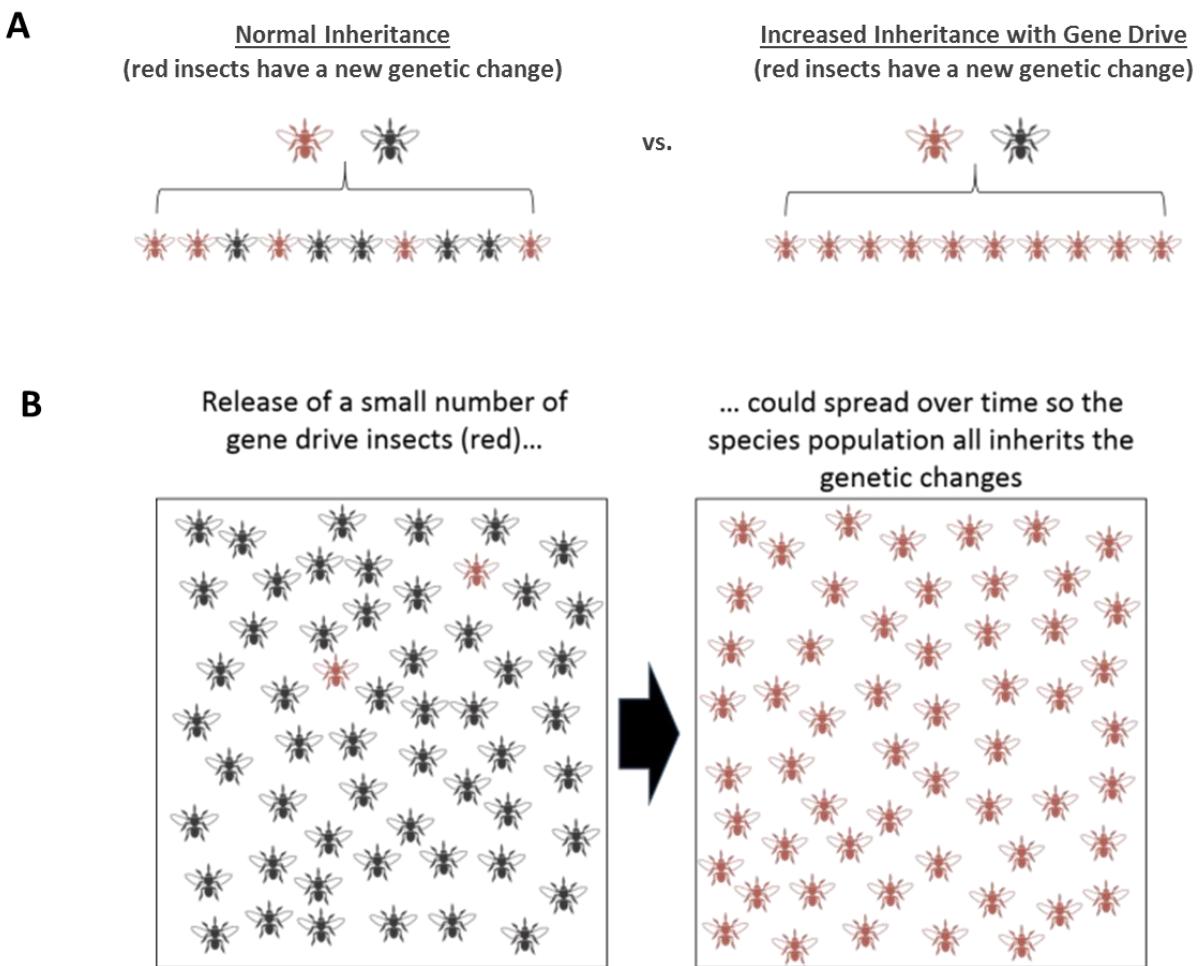
While no gene drive insect has been released in the environment to date, researchers have actively pursued this strategy for some time. One of the first gene drive attempts in an agricultural pest was to control Huanglongbing or citrus greening, a bacterial disease (*Candidatus liberibacter* spp.) which has devastated the \$3.3 billion U.S. citrus industry, with declines of 21.5% in Florida bearing acreage and 25.8% in yield since the disease was found in 2005 (USDA-NASS, 2017a). The bacterium is vectored by the Asian citrus psyllid, an invasive species from East Asia. The proposed gene drive, funded by a grant from the US Department of Agriculture (Turpin *et al.*, 2012), would have spread a strain of the citrus psyllid that would no longer be able to transmit the bacterium. This type of gene drive is referred to as a *replacement drive*, in which genetic modifications permeate through an insect population over time and leave an altered version of the pest species that remains in the environment.

In another application, researchers funded by the USDA (Li and Scott, 2016), and separately by grower associations (Buchman *et al.*, 2018), are seeking to design a *suppression drive* for Spotted-wing Drosophila. Spotted wing is an invasive species in the United States that dramatically increases control costs and causes extensive damage to ripening berry and cherry crops worth over \$4 billion in 2016 (Asplen *et al.*, 2015; USDA-NASS, 2017b). Where the suppression drive spreads, a trait could be passed that inhibits reproduction of the pest, leading to

eventual population collapse (Burt, 2003). A suppression drive would leave genetically engineered variants of the insect in the environment for some extended period of time, but potentially these too would dissipate in the long-run in the event of a ‘successful’ population collapse. Given these first investments in gene drive target pests, we focus our analysis on fresh blueberries and orange juice to provide the most relevant data to inform the current debate.

Figure 3.1: Biased inheritance in gene drive (A) and potential for population spread (B)

Note: Images created by the authors and present in a modified form in fielded survey to the public (see Appendix B for complete survey materials and wording).



3.2.2 Public Policy and Consumer Considerations

Recognizing the potential for unintended consequences with such a powerful technology, experts and funders have called for precaution, transparency, and early engagement with the public (NASEM, 2016a; Emerson *et al.*, 2017). The complex environment into which drive insects may be deployed is fraught with challenges in terms of technical difficulty, public opinion, governance and regulatory hurdles, as well as need for broad cooperation across geographic and trade landscapes where the insects may travel (Baltzegar *et al.*, 2018; Kuzma *et al.*, 2018; Friedman, Marshall and Akbari, 2020) .

Public views on gene drives are also unlikely to be independent from previous controversy involving genetically modified organisms (GMOs) in food supplies (Costa-Font, Gil and Traill, 2008; Baltzegar *et al.*, 2018), though one may reasonably expect distinctions. The genetic manipulation of pests instead of food products may in fact reduce consumer apprehension. However, the intentional – and potentially uncontrolled – spreading of genetic modifications through pest populations, rather than (somewhat) field-isolated genetically modified material in GM crops, may increase public concern, as has been expressed by gene drive researchers and evaluators (NASEM, 2016a). If gene drive insects are deployed across a wide enough geographic area, especially with the potential for self-sustaining spread, these releases could fundamentally alter the choice sets that consumers face. Releases could lead to widespread reductions in needs for pesticide applications and help efficiently reduce associated management costs and pest losses, increasing agricultural productivity and ultimately reducing retail prices. However, the short, medium, or long-term ubiquitous presence of gene drive insects in growing areas currently hosting that pest species means that consumers could no longer face a ‘gene drive insect free’ product alternative (Noble *et al.*, 2018). Trade-offs between

likely perceived environmental ‘bads’ like chemical control and biotechnology products, along with utility associated with price reductions, will ultimately determine the net consumer welfare impacts of these interventions. Thus, analyses of nuanced and heterogeneous consumer preferences surrounding program impacts of gene drive releases in agriculture may ultimately be as consequential and complex as risk assessments of ecological impacts.

Building on the stylized framework outlined by Mitchell, Brown, & McRoberts (2018), if gene drives work as intended, marginal costs of pest management would significantly decline in crop host environments. This is characterized by a welfare-increasing increase in agricultural productivity. However, ignoring demand-side effects would be highly naïve in a context of polarized debates on genetic modification in agriculture and growing public interest in production practices. Negative consumer reactions could partially or significantly attenuate net benefits from cost reductions, and have been mentioned in the US popular press such as *The Atlantic* when discussing even non-drive releases of genetically modified crop pests (Zhang, 2017). This is especially relevant when regional, area-wide deployment of gene drive insects could maintain a self-sustaining spread that could result in near ubiquitous presence of modified insect strains where the species population is present. While effective in reducing the biological pest threat, the spread of drive insects may ultimately reduce consumer choice, and this could carry notable welfare implications when consumer preferences towards genetically modified insects are non-neutral. While we do not attempt to estimate total surplus changes across the system due to lack of data on projected supply curve shifts from major pest removal, we examine consumer preferences that may drive surplus changes with potentially ambiguous net impacts on consumers and producers alike.

In addition, heterogeneous demand and segmented markets for target fruit products may – potentially – disproportionately impact markets with high sensitivity to genetically engineered organisms in growing environments. This includes areas under certified organic production, where, for example, control of Spotted-wing Drosophila infestations is possible but difficult and costly due to limited effective control methods available (Van Timmeren and Isaacs, 2013; Farnsworth *et al.*, 2017). As a gene drive approach could decrease pest and disease pressure without the need for pesticide applications, this could provide benefits to organic production systems. However, consumer demand impacts and secure preservation of market price premium for organic labeling are paramount to understand before release decisions. As such, consumer studies may be particularly relevant for certified organic growers to understand the nature of market risk with drive insect releases, as some authors (e.g. Reeves, & Phillipson (2017)) have expressed concern about the impact of genetically engineered insect presence on certification retention under certain release contexts and the underscored the role of public reaction. Under current regulations 7 CFR § 205.105:

“Allowed and prohibited substances, methods, and ingredients in organic production and handling”, excluded production methods include: “A variety of methods to genetically modify organisms or influence their growth and development by means that are not possible under natural conditions or processes and are not considered compatible with organic production. Such methods include cell fusion, microencapsulation and macroencapsulation, and recombinant DNA technology (including gene deletion, gene doubling, introducing a foreign gene, and changing the positions of genes when achieved by recombinant DNA technology). Such methods do not include the use of traditional breeding, conjugation, fermentation, hybridization, in vitro fertilization, or tissue culture (7 CFR § 205.2-Terms defined) ”.

Further, USDA Policy Memos on the National Organic Program have detailed responses to questions about incidental adventitious presence of genetically modified material in the crop:

“The NOP regulations prohibit the use of excluded methods (i.e., “GMOs”) in organic operations. If all aspects of the organic production or handling process were followed correctly, then the presence of a detectable residue from a genetically modified organism alone does not constitute a violation of this regulation... As long as an organic operation has not used excluded methods and takes reasonable steps to avoid contact with the products of excluded methods as detailed in their approved organic system plan, the unintentional presence of the products of excluded methods should not affect the status of the organic operation or its organic products” (McEnvoy, 2012).

Authors Reeves and Phillipson (2017) have argued that the cooperation of organic producers within mass release programs of GM insects, as well as the implicit assumption of full geographic coverage for GM insect suppression programs, would challenge basic tenants of reasonable exclusionary practices to avoid GMOs. This may be coupled by grower associations (that include organic members) actively funding GM insect research, for example, in current gene drive Spotted-Wing research (Buchman *et al.*, 2018). Regulatory agencies have yet to issue firm guidance on this issue.

However, even if the organic standard is determined legally secure in the short term, consumer perception of the product attributes denoted by the USDA-organic label may be even more important than final legal decisions about standard guidelines. Recent research has found USDA-organic and ‘Non-GMO Project’ labels are strong substitutes in apples (McFadden and Lusk, 2018), so it is unclear if this ‘GMO aversion’ also includes genetically engineered insects in the growing area. In the United States, considerable effort and expense has been invested to achieve goals for ‘co-existence’ between conventional (GM and non-GM) and certified organic production systems (Greene, C., Wechsler, S.J., Adalja, A. & Hanson, 2016). Given tension already surrounding the use of genetically engineered crops in close proximity to organic production environments, these niche market demand effects merit attention from policy makers

in discussions about gene drive insect release, especially if these attitudes translate to a strong contraction in WTP for certified organic products when drive insects are present.

Gene drive insects may also cause structural changes in product availability. As drive insects are released and spread, the ‘absence’ of drive insects in growing areas may simply not be an option in the short, medium, or long term depending on context. This structural change in product availability is not new. In fact, pest management requirements can drastically change as invasive species – such as Spotted-wing Drosophila or Citrus Psyllid – enter growing environments. After an invasive species enters a region, spray requirements to combat infestation may mean lower frequency conventional pesticide treatments may no longer be possible and consumers may only be faced with high frequency spray options. Further, in extreme cases organic production may no longer be cost-effective and producers may revert to conventional production or simply exit host crop cultivation.

Pertinent policy questions which require more detailed welfare analysis include:

1. How much would you have to pay a representative consumer after the introduction of high spraying regimens to return them to their original utility level?,
2. How dramatic of an impact on crop prices must an invasive pest cause for gene drive insects to deliver a positive net consumer surplus change?, and
3. What is the value of limiting drive insect releases geographically, such that consumers retain product alternatives that were not grown in the presence of these modified insects?

3.3 Experimental procedures and survey data

In this study, we employ a discrete choice experiment (DCE) to investigate consumer responses to gene drive insect use in area-wide pest management regimes. We use the DCE approach for several reasons. First, because no foods have yet been produced using gene drive insects, a revealed preference elicitation method such as experimental auctions is not feasible (barring the use of deception). Second, DCEs are shown to have design advantages over other stated preference methods, such as contingent valuation, by more closely simulating a real purchasing scenario (Lusk and Hudson, 2004).

The DCE was embedded within a larger web-based survey fielded in October and November 2017 through the survey firm GfK's KnowledgePanel®, a representative probability sample of U.S. adults, which resulted in 1,018 completes for analysis. All respondents received a basic explanation of gene drive technology, illustrations of the citrus psyllid and spotted-wing Drosophila applications described above, and respondents selected from seven frequently-asked-questions (full wording in Appendix B & C). Respondents then reported attitudes on various contexts of gene drives for agricultural pest control and specific views on use in organic agriculture, which is summarized in Jones *et al.* (2019). The DCE was only completed by respondents whose households purchased fresh blueberries or orange juice in the last six months². From 1,018 total respondents, we draw WTP data from 457 fresh blueberry consumers and 408 orange juice consumers who completed a (single) DCE. Following convention to

² In the case of households purchasing both products in the last six months, respondents were randomized at a ratio of 2:1 to the blueberry (v. orange juice) DCE. This is based on pretesting in Amazon MechanicalTurk (n=300, within US) indicating more frequent sole consumption of orange juice vs. blueberries and a desire to achieve roughly equivalent DCE sub-sample sizes. Consumption of blueberries was somewhat higher in the GfK sample than the Amazon MechanicalTurk pretest sample.

reduce potential hypothetical bias in WTP estimates, a cheap talk script³ was adopted in the DCE introduction (Cummings and Taylor, 1999; Lusk, 2003) and a consequentiality statement was included at the beginning of the survey (Herriges *et al.*, 2010).

For both products, we include attributes of gene drive insect presence in the growing area, crop genetic modification to resist pests, price, and varied traditional pest management regimes, which include a high conventional spray level, low conventional spray level, and the USDA-organic seal. Product attributes and corresponding levels are outlined in Table 3.1. Respondents were instructed to imagine they are making a regular shopping trip in a grocery store and indicate which of two options, if any, they would purchase. A D-efficient design powered to estimate main effects and interaction between gene drive insect presence and other current pest management practices was generated and fielded to a pretest sample via Amazon MechanicalTurk (n=300) to validate the instrument. Given current organic regulations, we excluded the possibility of a genetically modified plant appearing in the same alternative as the USDA-organic seal to keep choices realistic. Estimated coefficients from pretest models were used to generate more efficient, unique designs for each product for the main round (Ferrini and Scarpa, 2007), which yielded a total of 18 choice tasks. These were optimally blocked into two groups of nine choice sets for each respondent to avoid survey fatigue.

Table 3.1: DCE Attributes and Levels for Fresh Blueberries and Orange Juice products

Attributes	Levels
Gene Drive Insects	Present in the growing area to control pest damage; Not present in the growing area
Plant Type	Genetically modified to resist pest damage; Not genetically modified

³ Cheap talk script within the DCE introduction: “When making your choices, please consider the price of the product carefully compared to your household’s grocery budget. (In questions about hypothetical purchase choices, people often tend to overstate their willingness to purchase some products.)”

Pest Management Regime	USDA-Organic [seal shown]*; Low Conventional Spray Level; High Conventional Spray Level
Price	
Fresh Blueberries (\$/pint)	1.06; 2.12; 4.25; 5.31
Orange Juice (\$/half-gallon)	2.95; 4.07; 5.21; 6.34

Note: **Plant Type Wording** – “The plant and fruit are genetically modified to resist pest damage” [genetically modified; GM_Plant], “The plant and fruit are not genetically modified” [non-genetically modified]. **Pest Management Regime wording** – *Blueberries*: “Conventional insecticides applied only when pest populations are high” [low conventional spray; Low_Conv_Spray]; “Conventional insecticides applied every five days for several weeks while fruit ripens” [high conventional spray; High_Conv_Spray] – *Orange Juice*: “Conventional insecticides applied in the field 1-2 times per year” [low conventional spray; Low_Conv_Spray]; “Conventional insecticides applied in the field 11-14 times per year” [high conventional spray; High_Conv_Spray]. Low v. high spray regimes represent predominate pest management regimes before and after the arrival of spotted-wing Drosophila (blueberries) or citrus psyllid (orange juice). See Appendix Figure A.2 for choice scenario examples.
 *Due to USDA-organic regulations, to keep the choice tasks realistic, the organic attribute was restricted to never appear in the same attribute set as a GM plant.

3.4 Empirical Analysis

DCEs are grounded in random utility models (RUMs), allowing researchers to estimate the WTP for attributes describing product profiles in an experimental setting. Crucially for our purposes, there are also well-established methods for using RUMs for estimating the welfare effects of adding, subtracting, or jointly altering alternatives in the choice set. Given appropriate specifications of the RUM, we can also estimate the statistical precision of these welfare impacts.

The remainder of this section describes our preferred RUM used in this paper: a mixed logit model, which allows for unobserved heterogeneity in individual preferences, estimated using a Hierarchical Bayes (HB) method, which facilitates estimation of our welfare measures. While other RUMs are available that more flexibly allow for individual heterogeneity (e.g., the generalized multinomial logit model, or GMNL, Fiebig *et al.* (2010)), the mixed logit model is most amenable to estimation via the HB method with currently available software tools. In turn, the HB method greatly eases the burden of obtaining statistical precision of our estimated

welfare effects, as compared to classical maximum likelihood (ML) estimation. In appendices (Appendix Tables A.12 – A.15), we compare the HB mixed logit model to estimates from other ML-estimated RUMs, and show that the mixed logit model generally performs as well or better than these alternative models in terms of statistical fit and parsimony. Appendix Table A.12 – A.15 also show the estimated regression coefficient and marginal WTPs do not tend to differ substantively between the models (implying approximately the same estimated welfare impacts).

3.4.1 The Mixed Logit Random Utility Model

Random utility theory (Manski, 1977) treats an individual's utility as a random latent variable, because the researcher has incomplete information and cannot directly observe utility. In a DCE, an individual I is assumed to select an alternative j in each choice scenario t that maximizes their utility given the available alternatives. We follow the conventional approach, and specify utility linearly as:

$$(1) \quad U_{ijt} = \boldsymbol{\beta}'_i \mathbf{X}_{jt} + \varepsilon_{ijt}$$

where $\boldsymbol{\beta}'_i \mathbf{X}_{jt}$ is the deterministic component of utility, itself composed of a vector of attributes \mathbf{X}_{jt} defining alternative j in scenario t and a conformable parameter vector $\boldsymbol{\beta}_i$ that defines the marginal utilities associated with each attribute in \mathbf{X}_{jt} . The component ε_{ijt} is the random utility term unobservable to the researcher. The conditional probability that individual i selects alternative j over all other alternatives k in choice scenario t is therefore:

$$(2) \quad \pi_{jt}(\boldsymbol{\beta}'_i) = \text{Prob}\{\boldsymbol{\beta}'_i \mathbf{X}_{jt} + \varepsilon_{ijt} \geq \boldsymbol{\beta}'_i \mathbf{X}_{kt} + \varepsilon_{ikt} ; \mathbf{X}_{kt}, j \neq k, j, k \in t\}$$

In our application, \mathbf{X}_{ijt} is a vector of fresh blueberry or orange juice attributes (Table 3.1), with:

$$\mathbf{X}_{jt} = [Price_{jt}, GM_Plant_{jt}, GD_Insects_{jt}, Organic_{jt}, Low_Conv_Spray_{jt}, (Organic * GD_Insects)_{jt}, (Low_Conv_Spray * GD_Insects)_{jt}]$$

Note in the above that we interact the gene drive insects with the ‘organic’ and ‘low spray’ pesticide attribute levels. This was included in the experimental design of the DCE, and allows for example the marginal utility and WTP for the organic attribute to potentially depend on the presence or absence of gene drive insects.

By assuming that ε_{ijt} is distributed iid Extreme Value Type I over all individuals and choice scenarios, we obtain from (2) the familiar logit specification for the choice probabilities, conditional on preference parameters $\boldsymbol{\beta}_i$:

$$(3) \quad \pi_{jt}(\boldsymbol{\beta}_i) = \frac{e^{\boldsymbol{\beta}'_i \mathbf{x}_{jt}}}{\sum_{k \in t} e^{\boldsymbol{\beta}'_i \mathbf{x}_{kt}}}$$

Conditional on the marginal utilities, $\boldsymbol{\beta}_i$, the joint likelihood of observing consumer i selecting a sequence of alternatives $\mathbf{Y}_i = \{j_{i1}, \dots, j_{iT}\}$ over T different scenarios, is therefore:

$$(4) \quad L(\mathbf{Y}_i | \boldsymbol{\beta}_i) = \prod_{t=1}^T \pi_{j_{it}}(\boldsymbol{\beta}_i)$$

Assuming marginal utilities to be distributed according to some parametric probability density function (pdf) $\phi(\boldsymbol{\beta}_i | \boldsymbol{\Theta})$ with a vector of so-called ‘hyper-parameters’ (e.g. mean and

variance) Θ , we integrate $L(\cdot)$ over β_i 's pdf to obtain the unconditional likelihood for the mixed logit model (Revelt and Train, 1998):

$$(5) \quad P_i(Y_i|\Theta) = \int L(Y_i|\beta_i)\phi(\beta_i|\Theta)d\beta_i$$

The goal of the mixed logit model is to estimate the hyper-parameter vector Θ governing the distribution of β_i .

The marginal utilities β_i have no meaningful units, and economic analysis of the model normally focuses on marginal willingness to pay (MWTP) of the non-monetary attributes in X_{jt} . For a given attribute x , with marginal utility $\beta_{i,x}$, individual i 's MWTP for a unit of attribute x is given by:

$$(6) \quad MWTP_{i,x} = \frac{\beta_{i,x}}{\beta_{i,price}}$$

where $\beta_{i,price}$ is the marginal utility for the price attribute in X_{jt} .

3.4.2 Welfare evaluation of complex changes to the consumer choice set

While the MWTP metric in (6) provides a useful measure of how much an increment in a given attribute is worth to consumers, *ceteris paribus*, one key advantage of discrete choice RUMs is the ability to economically evaluate non-marginal changes in the composition of the choice set, either from addition or removal of alternatives or from simultaneous changes to multiple alternatives' attributes. A standard economic valuation measure for such changes is *compensating variation* (CV), or the amount of money needed to return an individual to their

baseline utility *after* a change in prices, attributes, or availability. Small & Rosen (1981) show how to obtain ex-ante CV estimates for the logit RUM via the now familiar log-sum formula. When income effects are negligible (as we would strongly expect them to be in our blueberry and OJ applications), then this measure is approximately equivalent to consumer surplus (McConnell, 1995).

Suppose we wish to evaluate the ex-ante CS for a change from a baseline choice scenario t_0 to a new scenario t_1 . Then the log-sum formula for individual i 's CS from this change in the logit RUM is:

$$(7) \quad CS_i(t_0, t_1, \beta_i) = \frac{1}{\beta_{i,price}} \left[\ln \sum_{j \in t_1} e^{\beta_i' X_{jt_1}} - \ln \sum_{j \in t_0} e^{\beta_i' X_{jt_0}} \right]$$

This formula provides a theoretically consistent way of evaluating complex changes to the menu of options available to consumers and avoids erroneous aggregation of multiple changes, e.g. by simply summing the MWTP values (Lancsar and Savage, 2004). Population-level welfare measures of the mean and variation in CS are obtained from the individual-level measure in (7) by integrating over β_i 's pdf. This tool for welfare evaluation using discrete choice RUMs has been applied extensively across environmental economics (e.g. *ibid.*; English *et al.*, 2018), transportation economics (e.g. Niemeier, 1997; Allcott, 2013), and somewhat in health economics (Lancsar and Savage, 2004). It has been used in limited contexts in agricultural economics to analyze potential bans on food production methods (Lusk and Marette, 2010) and labeling requirements (e.g. *ibid.*; Marette, Roosen and Blanchemanche, 2008)

Yet we have found no previous published examples of applying this welfare measure to discrete choice RUMs analyzing consumer food choices with respect to biotechnology and

product availability. This is surprising given more than a decade of extensive research conducting discrete choice experiments to measure consumers' WTP for genetically modified food (Lusk, Jamal, *et al.*, 2005; Costa-Font, Gil and Traill, 2008; Costanigro and Lusk, 2014). This apparent under-utilization of non-marginal welfare measures to evaluate the consumer impacts of agricultural biotechnology may have been due to the plausible argument that prior agricultural biotechnology could be assumed to have little substantive effect on the food options available to consumers (beyond potential questions surrounding information and food labeling; see Lusk *et al.* (2005) and Costanigro and Lusk (2014)).

However, new forms of agricultural biotechnology – gene drives being a prime example – can no longer be plausibly claimed to be neutral regarding consumer choice and product availability. If gene drive insects are released and spread as intended, the ‘absence’ of drive insects in growing areas may simply not be an option in the short, medium, or long term depending on context. This follows changes already in place during fluctuating pest management requirements as invasive species – such as Spotted-wing Drosophila or Citrus Psyllid – enter growing environments. After an invasive species enters a region, the frequency and breadth of pesticide applications may increase considerably across the infestation region (Farnsworth *et al.*, 2017; Stansly *et al.*, 2019) and any previous ‘low frequency’ conventional pesticide regime may largely no longer be available to consumers.

Thus, the potential welfare change from the introduction of gene drives for agricultural pest control is complex: The gene-drive-free, status quo choice scenario would likely be one of increased prices (relative to pre-infestation levels), and in extreme cases would completely obviate some production practices desirable to consumers, such as low-spray or organic production systems. A plausible choice scenario with gene drives, in contrast, could at least

partially offset pest-induced price increases and maintain the viability of low-spray and organic systems. However, if spread of the drive was uncontrolled it could forestall the ability of consumers to purchase non-gene-drive products. Welfare evaluation comparing these complex choice scenarios requires the type of metric in (7).

3.4.3 Hierarchical Bayes Estimation

To estimate the mixed logit model in (3) – (5), we employ a Hierarchical Bayes (HB) algorithm, generalized by Train (2001) and implemented using his available MATLAB code (Train, 2009). We use this method instead of a classical maximum likelihood (ML) in order to more easily estimate statistical precision of CS in (7). For example, mean CS for the sampled population in the mixed logit model is obtained from (7) as:

$$(8) \quad \omega(\Theta) = \mathbb{E}_{\beta_i}[CS_i(t_0, t_1, \beta_i)|\Theta] = \int CS_i(t_0, t_1, \beta_i)\phi(\beta_i|\Theta)d\beta_i$$

That is, mean CS can be expressed as a nonlinear function $\omega(\Theta)$ of the hyper-parameters Θ . This function in general will not have a closed form, in which case we require numerical computation of the integral in (8) either via quadrature or simulated resampling of β_i 's from its pdf.

If we estimate the mixed logit model using ML (or, more precisely, using maximum *simulated* likelihood), we obtain an estimate $\widehat{\Theta}_{ML}$ with its statistical precision given by an asymptotically normal distribution, $\mathcal{N}\left(\widehat{\Theta}_{ML}, \frac{\widehat{\Omega}_{ML}}{N}\right)$, where $\widehat{\Omega}_{ML}$ is the asymptotic covariance matrix of the ML estimates and N is the sample size. The corresponding point estimate of mean CS is given by $\omega(\widehat{\Theta}_{ML})$. The standard ways of obtaining the statistical precision of the CS

estimate in an ML framework is the Delta method or bootstrapping. The former implies an asymptotically normal distribution with variance given by $\widehat{\omega}'_{\Theta} \widehat{\Omega}_{ML} \widehat{\omega}_{\Theta}$, where $\widehat{\omega}_{\Theta}$ is the column-vector gradient of $\omega(\cdot)$ evaluated at $\widehat{\Theta}_{ML}$. This gradient itself requires multi-dimensional numerical integration, in light of (7) and (8), which combined with the computation required to integrate (8) compounds multiple levels of numerical approximation error. Alternatively, bootstrapping $\omega(\widehat{\Theta}_{ML})$ requires repeated maximum simulated likelihood estimation using the bootstrap resamples, which is also highly time-consuming for mixed logit models with correlated random coefficients (which is necessary here based on additional statistical tests). Applying these methods in a ML framework with sufficiently low levels of numerical error is therefore time-consuming and tedious (Train, 2009).

HB facilitates an easier approach to obtaining the statistical precision of $\omega(\Theta)$, because this method's primary estimation output, instead of a point estimate, is a posterior pdf, $K(\Theta)$, for the hyper-parameters. Given $K(\cdot)$, the HB estimate of mean CS is given by $\widehat{CS}_{HB} = \int \omega(\Theta) K(\Theta) d\Theta$ and the statistical precision can be obtained for example from its estimated variance, calculated as $\widehat{Var}(CS_{HB}) = \int [\omega(\Theta) - \widehat{CS}_{HB}]^2 K(\Theta) d\Theta$. These integrals can easily and directly be approximated by HB, because the method as applied to mixed logit provides a set of simulated draws of Θ from $K(\Theta)$, as well as simulated draws of the marginal utilities β_i conditional on each draw of Θ .

We specify and estimate our mixed logit model via HB as follows: The marginal utilities for the non-price base attributes are assumed to be distributed across consumers as random normal with mean vector b and variance Ω ; full correlation in these parameters is allowed within Ω . That is, the hyper-parameter vector Θ referred to above in this specification consists of all the elements in b and Ω . As is standard in economic applications, the marginal utility on the

negative of price is assumed to be distributed lognormally, its mean and covariances included within \mathbf{b} and Ω (and also correlated with the other parameters). This allows the marginal utility of price to vary across consumers but restricts it to be negative. We also impose fixed coefficients on the included attribute interactions.

HB estimation exactly follows Train (2009, Ch. 12): We assume an uninformative normal prior distribution on \mathbf{b} and a diffuse prior inverted Wishart distribution for Ω , which are well-known to comprise a conjugate prior $k(\mathbf{b}, \Omega)$ with the assumed multivariate normal distribution for β_i . The posterior $K(\mathbf{b}, \Omega)$ is obtained from Bayes' rule as:

$$(9) \quad K(\mathbf{b}, \Omega) \propto \prod_i \int L(Y_i | \beta_i) \phi(\beta_i | \mathbf{b}, \Omega) d\beta_i \cdot k(\mathbf{b}, \Omega)$$

Draws from this joint posterior are obtained via Gibbs sampling. A sequence of draws for one set of parameters is taken conditional on other model parameters, according to the following hierarchy: First, draws of $\mathbf{b} | \beta_i, \Omega$ are taken, followed by draws of $\Omega | \mathbf{b}, \beta_i$ and then a Metropolis-Hastings algorithm is used to take draws of $\beta_i | \mathbf{b}, \Omega$. This hierarchical process greatly speeds sampling from $K(\mathbf{b}, \Omega)$. Beginning at arbitrary initial values, a burn-in of 100,000 draws was specified and thrown out, after which 1,000 draws were retained, thinning along every 100th draw to minimize the impact of autocorrelation, and verifying convergence visually (Train, 2009). As the mean (and variance) of a Bayesian posterior distribution of a parameter with a diffuse prior is asymptotically equivalent to a maximum likelihood estimator of that parameter, estimates from the HB model may be interpreted similar to classical procedures (Train, 2009). To check robustness, we compare the HB and ML mixed logit regression estimates (Appendix Tables A.12 – A.15). The posterior draws of the mean and standard deviations are presented.

3.4.4 Modeling Drive Insect Release Scenarios and the Status Quo

Unlike many field-level pest management strategies, the area-wide mass release of gene drive insects may lead to their presence in the short, medium, or long term wherever that species is found. Self-limiting strategies to restrict the extent of drive spread have received significant research attention due to ecological and policy concern about unlimited spread (Dhole *et al.*, 2018; Kandul *et al.*, 2019). However, ‘homing endonuclease’ drive systems are the classic design example in gene drive debates and the topic is widely discussed in the context of a self-sustaining, unlimited spread through the species population (NASEM, 2016a). The area-wide supply side benefits to growers in reduced losses and control costs will thus depend on the extent to which drive insects can spread.

For consumers, this translates to expansion or restriction of the product choice set. If releases are self-sustaining and drive alleles spread freely, consumers may be forced to trade off drive insect presence in growing areas for the resulting decrease in spraying and, ultimately, lower prices with reduced losses and control costs. If releases are limited, product alternatives may be available which were grown in or outside of release zones. To measure consumer welfare implications of release scenarios, we can model a prevailing status-quo (SQ) of a high price, high spray, choice set with no drive insect presence (outlined in Table 3.2)⁴. Self-sustaining releases simultaneously change multiple attributes in the choice set, modeled as moving to lower (pre-infestation) prices, lower (pre-infestation) spray levels, and ubiquitous drive insect presence in growing areas. These two scenarios are the primary comparison of interest. Geographically

⁴ 1) Status-quo (SQ): Price + pesticide increases because of pest damage; no GD; Alts: a) High Spray/High Price; b) Organic/High Price; c) Opt-out.

2) Gene Drive self-sustaining releases (GD): GD options with lower prices, pesticides only; no non-GD alts; Alts: a) Low Spray/GDIs/Low price; b) Organic/GDIs/Low Price; c) Opt-out.

3) Limited Drive Releases with both regime products available (GD+SQ): GD options with lower prices, pesticides; retain non-GD alts with higher prices; Alts: a) High Spray/High Price; b) Organic/High Price; c) Low Spray/GDIs/Low price; d) Organic/GDIs/Low Price; e) Opt-out.

limited releases would result in localized reduced spraying and thus a geographic disparity in producer control costs and losses. We additionally model a speculative scenario where consumers can choose between lower prices and spraying from release areas *as well as* higher price and spray options where releases do not occur. The practical concurrent availability of both scenarios, as well as retail price disparity between these options, may or may not occur depending on market structure. However, we examine this from a perspective of public preferences to focus on the value of evolving consumer choice given this novel, area-wide pest control strategy.

Table 3.2: Summary of Drive Insect Release Scenarios on Modeled Consumer Choice Alternatives

Scenario/regime	Description	Alternative Availability		
		Pesticide Spraying	Drive Insect Presence	Prices
Status Quo (SQ) Alternatives only	No releases	High levels & Organic only	Not present	Higher
Gene Drive (GD) Alternatives only	Self-sustaining, unlimited spread	Low levels & Organic only	Present	Lower (pre-invasion levels)
Both (GD + SQ) Alternatives	Limited releases	High (where no drive insect releases), Low (where drive insect releases), and Organic.	Not present (where no drive insect releases) and Present (where drive insect releases)	Higher (where no drive insect releases) and Lower (where drive insect releases)

With fixed individual RUM coefficients, the consumer surplus of the GD over SQ scenario is positive, i.e. $CS(GD, SQ) > 0$, if prices decrease and drive insect preferences are a neutral. If drive insect preferences are non-neutral, the sign is ambiguous. Further, $CS(GD + SQ, SQ) > CS(GD, SQ)$ and the difference $CS(GD + SQ, GD)$ can be viewed as the consumer benefits of keeping gene drives spatially limited.

3.5 DCE Estimation Results

In Table 3.3 & Table 3.4, we present our preferred specification of the Hierarchical Bayes mixed logit model with correlated random main effect coefficients and a log-normally

distributed random price coefficient⁵. We clearly see that both blueberry and orange juice consumers, on average, negatively value genetically modified plant alternatives and gene drive insect presence, while positively valuing organic and low conventional pesticide spray levels (versus high conventional spray levels). This conforms with a large literature on consumer preferences of genetically modified organisms and pest management practices (well summarized in Costa-Font, Gil and Traill (2008)). However, while Table 3.5 illustrates a high positive correlation between GM plant and GD insect presence coefficients (BB: 0.789; OJ: 0.564), we see from both sets of WTP estimates that consumers do not have equivalent preferences for biotechnology inputs. In fresh blueberries (Table 3.3), the mean of the WTP posterior distribution for a GM plant is over 2.8 times that of GD insect presence; in orange juice (Table 3.4), the GM plant mean is almost 2 times higher. This also aligns with intuition, given that those concerned with ingesting genetically modified organisms would face this personal ‘risk’ with certainty given a GM plant versus some likely low yet non-zero probability with gene drive insect presence. Comparing chemical control to drive insects, the mean WTP impact of moving from low to high conventional spray regimes in blueberries is about 1.5 times that of drive insect presence; in orange juice, this disparity rises to a factor of three. In Figure 3.2, we present a summary of these mWTP main effects for each product (using column 3 WTP results from Table 3.3 & Table 3.4). For both blueberries and orange juice, the means of the WTP posteriors for GD insect interactions are generally negative (as hypothesized) but the 95% credible interval always includes zero. The positive coefficient for the orange juice interaction between GD insects and the organic seal is very nearly zero and imprecisely measured. Thus, on average, GD

⁵ Model choice was guided by significant gains in log-likelihood compared to modeling price as fixed. Base model - Blueberries LL: price fixed (-3075) vs. log-normal (-2883), gain of 6.24%; Orange Juice LL: price fixed (-2851) vs. log-normal (-2675), gain of 6.17%. Results for HB mixed-logit with fixed price presented in Appendix Tables A.10 & A11.

insect presence does not significantly reduce WTP for organic or low conventional spraying vis-à-vis high conventional spray regimes.

Our results show that consumers do not view biotechnology interventions monolithically. For both products, modifying the plant for insect resistance has a larger negative effect on WTP. For blueberries, there is no statistically significant difference between shifting from a low to high conventional spray regime and gene drive insect presence. In orange juice, however, drive insects have lower impact on WTP. Therefore, when evaluating strategies to combat damaging invasive species, a consistent and robust finding is that drive insects have a lower or equivalent impact on mean consumer WTP for conventional food products compared to alternative biotech approaches and heavily increased insecticide spraying.

Table 3.3: Hierarchical Bayes Mixed Logit Coefficients and mWTP – Blueberries

Note: *indicates the 95% CI for WTP does not contain zero. WTP units are in USD per pint. Price Coefficient modeled as random and log-normally distributed. The mean and standard deviation of the posterior distributions are presented for coefficient mean and coefficient standard deviations.

Variables	<u>Coefficients</u>				<u>Willingness-to-Pay</u>	
	(1) Without Interactions		(2) With GD Interactions		(3) Without Interactions	(4) With GD Interactions
	Mean (SD)	SD (SD)	Mean (SD)	SD (SD)	Mean (SD) [95% CI]	Mean (SD) [95% CI]
GM Plant (v. not GM)	-1.220 (0.168)	5.216 (0.911)	-1.231 (0.171)	2.295 (0.212)	-1.432* (0.229) [-1.91, -0.99]	-1.445* (0.234) [-1.92, -1.02]
GD Insects (v. none)	-0.429 (0.124)	2.566 (0.454)	-0.331 (0.168)	1.620 (0.141)	-0.504* (0.153) [-0.82, -0.21]	-0.388 (0.199) [-0.76, 0.01]
Organic (v. Conv. High Spray)	1.774 (0.201)	9.422 (1.434)	1.825 (0.230)	3.096 (0.246)	2.082* (0.294) [1.53, 2.71]	2.142* (0.322) [1.52, 2.81]
Conv. Low Spray (v. Conv. High Spray)	0.710 (0.176)	4.563 (0.978)	0.771 (0.198)	2.165 (0.241)	0.835* (0.226) [0.41, 1.30]	0.907* (0.249) [0.45, 1.42]
Optout ASC	-4.969 (0.374)	37.015 (4.852)	-4.929 (0.417)	6.0829 (0.409)	-5.806* (0.345) [-6.50, -5.15]	-5.753* (0.332) [-6.41, -5.13]
Price	-0.865 (0.061)	1.032 (0.065)	-0.852 (0.062)	1.032 (0.066)		-0.162 (0.214) [-0.60, 0.24]
GD Ins. X Organic			-0.138 (0.183)			-0.176 (0.249) [-0.67, 0.27]
GD Ins. X Conv. Low Spray			-0.147 (0.210)			
Log-Lik	-2882.80		-2882.33			

Table 3.4: Hierarchical Bayes Mixed Logit Coefficients and mWTP – Orange Juice

Note: *indicates the 95% CI for WTP does not contain zero. WTP units are in USD per half-gallon. Price Coefficient modeled as random and log-normally distributed.

Variables	<u>Coefficients</u>				<u>Willingness-to-Pay</u>	
	(1) Without Interactions		(2) With GD Interactions		(3) Without Interactions	(4) With GD Interactions
	Mean (SD)	SD (SD)	Mean (SD)	SD (SD)	Mean (SD) [95% CI]	Mean (SD) [95% CI]
GM Plant (v. not GM)	-0.949 (0.168)	2.318 (0.200)	-0.933 (0.166)	2.310 (0.020)	-0.848* (0.167) [-1.20, -0.54]	-0.826* (0.163) [-1.16, -0.51]
GD Insects (v. none)	-0.487 (0.137)	1.601 (0.140)	-0.420 (0.187)	1.576 (0.135)	-0.437* (0.134) [-0.72, -0.19]	-0.374* (0.173) [-0.71, -0.06]
Organic (v. Conv. High Spray)	1.875 (0.236)	3.157 (0.255)	1.859 (0.252)	3.137 (0.234)	1.673* (0.234) [1.21, 2.14]	1.643* (0.251) [1.18, 2.16]
Conv. Low Spray (v. Conv. High Spray)	1.529 (0.172)	2.093 (0.182)	1.639 (0.183)	2.091 (0.192)	1.364* (0.174) [1.03, 1.72]	1.448* (0.188) [1.09, 1.84]
Optout ASC	-7.587 (0.513)	6.792 (0.525)	-7.631 (0.510)	6.707 (0.503)	-6.748* (0.330) [-7.42, -6.13]	-6.72* (0.315) [-7.36, -6.13]
Price	-1.134 (0.084)	0.955 (0.060)	-1.130 (0.082)	0.955 (0.057)		
GD Ins. X Organic			0.040 (0.235)			0.036 (0.207) [-0.38, 0.42]
GD Ins. X Conv. Low Spray			-0.233 (0.192)			-0.204 (0.169) [-0.54, 0.13]
Log-Lik	-2674.96		-2674.01			

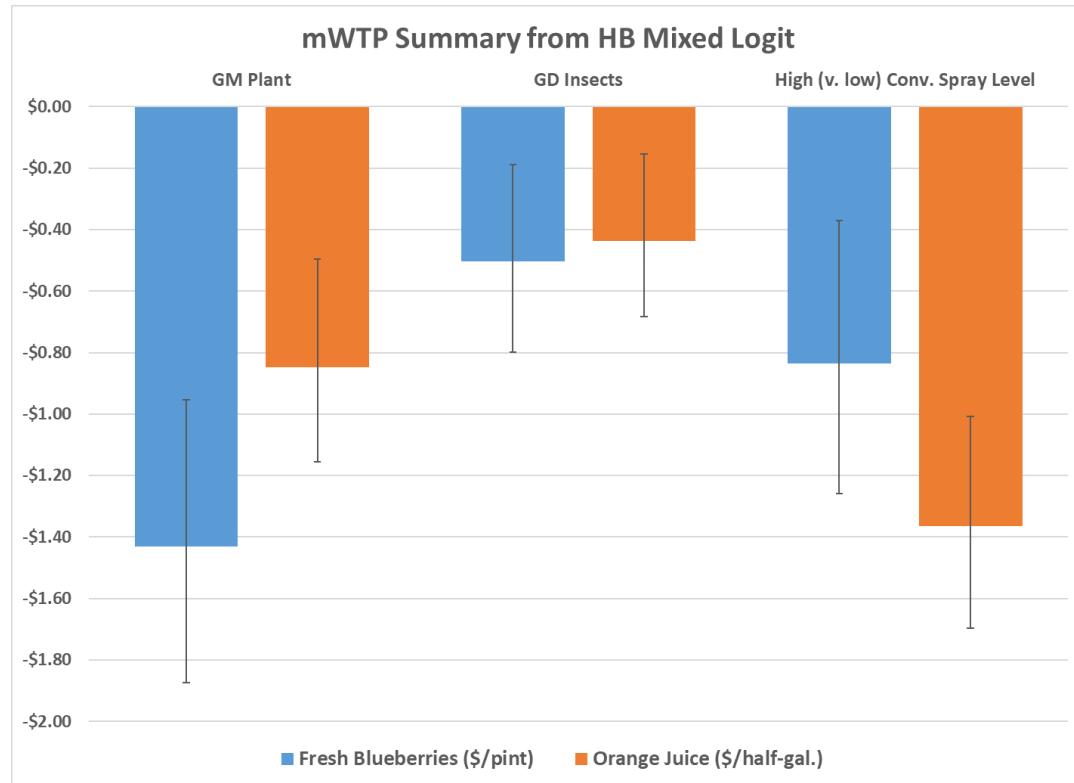
Table 3.5: Correlation between Random Coefficients – Price Coefficient as Random Lognormal

Note: C.H. = Conventional High Spray. Non-price attributes modeled as random normal.

	GM Plant	GD Insects	Organic (v. C.H.)	Conv. Low (v. C.H.)	Opt-out ASC	Price
Fresh Blueberries						
GM Plant	1.000					
GD Insects	0.789	1.000				
Organic (v. Conv. High Spray)	-0.380	-0.134	1.000			
Conv. Low (v. Conv. High Spray)	-0.613	-0.420	0.773	1.000		
Opt-out ASC	-0.568	-0.421	0.717	0.778	1.000	
Price	-0.389	-0.332	0.404	0.485	0.599	1.000
Orange Juice						
GM Plant	1.000					
GD Insects	0.564	1.000				
Organic (v. Conv. High Spray)	-0.366	0.154	1.000			
Conv. Low (v. Conv. High Spray)	-0.401	0.106	0.862	1.000		
Opt-out ASC	-0.550	-0.364	0.626	0.629	1.000	
Price	-0.403	-0.405	0.264	0.235	0.643	1.000

Figure 3.2: Comparing mWTP Estimates of Escalated Pest Management Strategies

Note: HB Mixed Logit model with correlated random main effects, price as random lognormal (Col. 3 of Table 3.3 & Table 3.4). Coefficient comparisons are only appropriate between attributes of the same product.



3.6 Welfare analysis

3.6.1 Consumer surplus impacts of drive insect releases to reduce pesticides and prices

We now simulate consumer surplus impacts of drive insect releases across scenarios outlined in Table 3.2, in which gene drive insect releases simultaneously reduce conventional pesticide spraying and retail prices. Among other factors, the impact of releases on retail prices is a function of the level of pest-specific avoided yield loss and management costs. Therefore price impacts will naturally vary across market context and target species. The more damaging the pest species, ceteris paribus, the greater the potential surplus generated from drive insect releases. Drive insect releases may also disproportionately reduce management costs and losses

for organic producers, as pests generally have a greater impact on prices in the organic (vs. conventional) sector due to limited and potentially inadequate control options (Van Timmeren and Isaacs, 2013; Farnsworth *et al.*, 2017; Burrack *et al.*, 2019).

We obtain estimates of the price impacts from pest damage from previously published research. Farnsworth *et al.* (2017) provide a rich analysis of retail price impacts of spotted-wing Drosophila in California raspberries, differentiating between organic and conventional markets. We use their estimates as the only available proxy for spotted-wing in the fresh blueberry market. Farnsworth *et al.* (2017) report that spotted-wing has a disproportionately greater impact on organic retail prices. The authors also divide analysis between “early” and “late” periods of spotted-wing infestation: in the “early” days of invasion, growers had less experience managing the pest, and the impact on prices was about a 6% increase in conventional markets and about a 7% increase in organic markets. In the “late” period, control methods were refined and pest-induced price increases for conventionally produced products settled back to less than 1%, though the 7% price impact persisted in organic markets. For orange juice, we use estimates from Moss *et al.* (2014) of psyllid-vectored citrus greening on fresh orange field box prices. Moss *et al.* estimate that these prices increased about 12% due to citrus greening. They do not differentiate organic and conventional price impacts. We maintain that assumption here. Allowing for higher psyllid-induced price impacts in organic orange production would potentially increase our consumer welfare impacts of gene drives for citrus psyllid. However, these effects would likely be small in this application, since the organic OJ market comprises less than 2% of total orange juice sales (FDC, 2020).

3.6.2 Unlimited Drive Releases

In Table 3.6 & Table 3.7, we present a summary of the simulations from the literature's empirical price change estimates, with consumer surplus changes expressed in annual per-capita terms⁶. The hierarchical Bayesian framework easily facilitates measurement of statistical precision of mean and median surplus estimates. Statistical criteria indicate the superiority of random log-normal (vs. fixed) specifications for the price coefficient, though we present both to elucidate factors driving results.

For blueberries, simulation results in Table 3.6 for an unlimited drive insect release (i.e., $\Delta CS(GD, SQ)$) suggest a mean \$8.94 consumer surplus *loss*, which is about the current average retail value of 2.5 pints of fresh berries. For comparison, this drive release estimate is quite close in magnitude to our estimates of mean consumer welfare loss from the original spotted-wing introduction, at \$7.59. The median loss estimate of \$1.61 is much smaller and, while still negative, only about 1/3 the estimated median \$4.63 loss from spotted-wing introduction. The difference between mean and median surplus estimates is driven by subpopulations with higher aversion to drive insect presence. While median estimates are less sensitive to price coefficient specification as fixed or random lognormal, mean estimates are quite sensitive. Aside from lognormal distributional skew, this is driven in part by the negative correlation between the price and drive insect attribute coefficients (see: Table 3.5), where those with highest aversion to gene drive insect presence derive less utility from co-incident price reductions.

The state of the world when drive insects are released is also important when considering market impacts and net consumer welfare. As growers and researchers have improved

⁶ Assuming weekly shopping trips to convert our DCE “shopping trip” simulation to meaningful terms. Note that our ‘per-capita’ population are those who have consumed the product at least once in the six months before Nov/Dec 2017.

management practices between “early” and more recent “late” or “current” stages of spotted-wing infestation (Farnsworth *et al.*, 2017), the potential price impact from drive insect releases has declined. Thus, consumers may benefit less (or be harmed more) from this type of unlimited, area-wide intervention to manage invasive species if releases are delayed past periods of improved management innovation and adoption. Given the complexity of designing and testing drive systems and the speed of reactions from industry and governmental bodies to attempt to cope with invasive threats, this delay is unlikely to be avoided.

In orange juice, simulation results in Table 3.7 for an unlimited gene drive citrus psyllid release suggest a small, statistically insignificant mean welfare loss of \$0.36. This is less than 10% the current average retail value of a half-gallon of orange juice. Welfare losses from unlimited releases are considerably lower than the estimated mean \$9.46 per capita loss from Asian citrus psyllid-vectored citrus greening. A plurality of consumers would benefit from drive insect releases, however, with a small, statistically significant median surplus gain of \$0.73. The finding of more positive results for orange juice (vs. blueberries) are driven, in part, by much greater relative disutility from increased insecticide versus drive insect presence (Table 3.3 & Figure 3.2). Estimates for orange juice consumers are less sensitive to model specification, though we note the significant mean welfare gain of \$2.76 when the price coefficient is fixed.

Table 3.6: Mean and Median Per-capita Annual Consumer Surplus Changes – Blueberries

Note: ^aUsing price movement estimates from (Farnsworth *et al.*, 2017) for SWD on California raspberries as a proxy, where “Early” uses higher price impacts in initial SWD infestation and “Late” or “current” uses attenuated price impacts after improved control regimes were established. Note: annual surplus based on weekly shopping trips; * indicates the 90% CI does not contain zero.

Scenario	V^1 Alternatives	V^0 Alternatives	Price Log-normal		Price Fixed (non-random)	
			Mean [90% CI]	Median [90% CI]	Mean [90% CI]	Median [90% CI]
$\Delta CS(SQ, \text{Pre-SWD})$ “current”	High spray & Organic, high prices (Conv. Price $\uparrow 0.04\%$; Org. Price $\uparrow 7.04\%^a$)	Low spray & Organic, low prices	-7.592* [-9.152, -6.188]	-4.628* [-5.148, -4.004]	-5.512* [-6.448, -4.576]	-4.784* [-5.096, -4.368]
Original estimated change due to SWD introduction, with current prevailing practices						
$\Delta CS(GD, SQ)$ “current” or “late”	Low spray & Organic, low prices, with ubiquitous gene drive insect presence	High spray & Organic, high prices (Conv. Price $\uparrow 0.04\%$; Org. Price $\uparrow 7.04\%^a$)	-8.944* [-11.960, -5.928]	-1.612* [-2.756, -0.676]	-0.676 [-1.924, 0.520]	-1.248* [-2.236, -0.468]
After SWD infestation and <u>current</u> prevailing practices, release of GD SWD and ubiquitous presence						
$\Delta CS(GD, SQ)$ “early”	Low spray & Organic, low prices with ubiquitous gene drive insect presence	High spray & Organic, high prices (Conv. Price $\uparrow 5.8\%$; Org. Price $\uparrow 6.9\%^a$)	-8.008* [-11.128, -4.888]	-0.728* [-1.612, -0.052]	0.208 [-1.040, 1.508]	-0.780* [-1.664, -0.104]
After SWD infestation with <u>initial</u> management, release of GD SWD and ubiquitous presence						
$\Delta CS(GD+SQ, GD)$ “current” or “late”	High spray & Organic, high price + no GD insect presence; low spray & Organic, low price with GD insect presence	Low spray & Organic, low prices, with ubiquitous gene drive insect presence	25.064* [22.464, 28.132]	10.608* [9.412, 11.804]	12.488* [11.823, 13.189]	9.329* [8.574, 10.116]
Gain from limiting GD SWD presence given current prevailing practices						

Table 3.7: Mean and Median Per-Capita Annual Consumer Surplus Changes – Orange Juice

Note: ^a Using price movement estimates from (Moss *et al.*, 2014) for Florida orange field box prices, where conventional and organic oranges are undifferentiated. Note: annual surplus based on weekly shopping trips; * indicates the 90% CI does not contain zero.

Scenario	V^1 Alternatives	V^0 Alternatives	Price Lognormal		Price Fixed (non-random)	
			Mean [90% CI]	Median [90% CI]	Mean [90% CI]	Median [90% CI]
$\Delta CS(SQ, \text{Pre-ACP})$	High spray & Organic, high prices (All Price ↑11.99% ^a)	Low spray & Organic, low prices	-9.464*	-8.216*	-7.124*	-7.384*
Original estimated change due to ACP introduction			[-10.296, -8.632]	[-8.996, -7.436]	[-7.592, -6.604]	[-8.06, -6.708]
$\Delta CS(GD, SQ)$	Low spray & Organic, low prices with ubiquitous gene drive insect presence	High spray & Organic, high prices (All Price ↑11.99% ^a)	-0.364	0.728*	2.756*	1.560*
After ACP infestation, release of GD ACP and ubiquitous presence			[-1.924, 1.300]	[0.260, 1.352]	[2.028, 3.484]	[0.988, 2.184]
$\Delta CS(GD+SQ, GD)$	High spray & Organic, high price with no GD insect presence; Low spray & Organic, low prices with gene drive insect presence	Low spray & Organic, low prices with ubiquitous gene drive insect presence	10.712*	2.444*	5.252*	2.288*
Gain from limiting GD ACP presence			[9.360, 12.272]	[1.924, 2.964]	[4.836, 5.668]	[2.028, 2.548]

We next address the question: “How damaging would a pest species have to be for unlimited gene drive insect releases to increase mean consumer surplus?” To answer, we generalize our simulation along a wide range of potential conventional and organic price increases from spotted-wing Drosophila and citrus psyllid invasion in Figure 3.3 adding context to the literature’s empirical parameter estimates driving results in Table 3.6 & 3.7. Guided by the literature, we assume pests cause equal or greater price increases in organic vs. conventional markets (Van Timmeren and Isaacs, 2013; Farnsworth *et al.*, 2017; Burrack *et al.*, 2019).

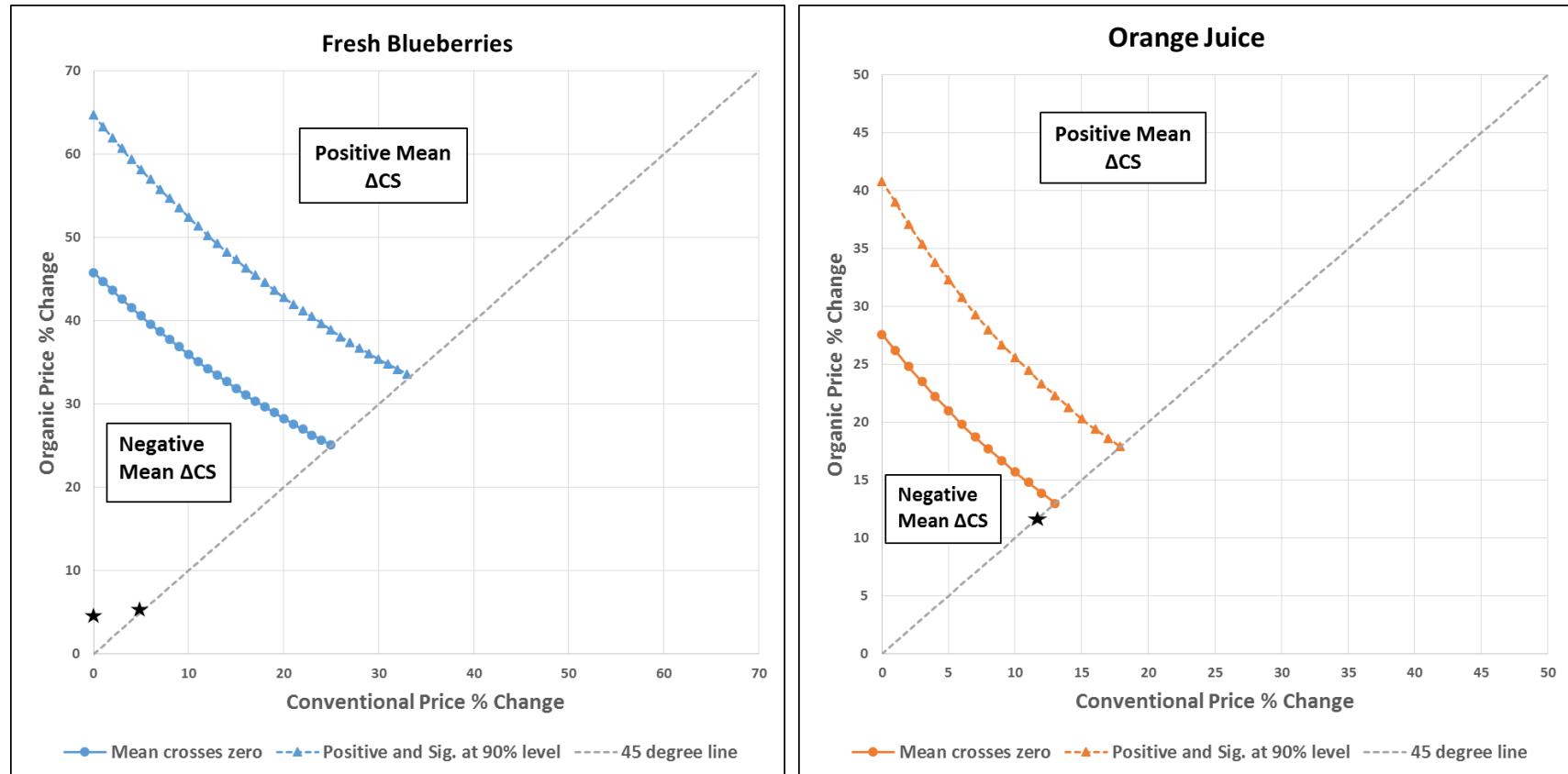
Results in Figure 3.3 indicate that spotted-wing Drosophila must increase fresh blueberry prices by 25% before drive insect releases with unlimited spread provide a positive mean gain in consumer welfare. For this positive welfare impact to be statistically significant at the 90% level, a more drastic price increase of about 33% would be necessary. Allowing for differential impacts in conventional and organic production, unchanged prices in the conventional market would require a simultaneous organic price impact of about 45%. These breakeven points are much higher than the (starred) spotted-wing price impacts estimated by Farnsworth *et al.* (2017).

Figure 3.3 also illustrates that orange juice prices must increase about 13% due to citrus greening to achieve a positive mean welfare estimate, just above the (starred) empirical orange field box estimates from Moss *et al.* (2014). Allowing for differential impacts, if citrus greening led conventional orange juice prices to rise only 12.0%, organic prices would have to rise by at least 14.0% for a positive consumer surplus. For a statistically significant increase in welfare, prices must be higher, with an increase of at least 18%. More broadly, full simulations for per-capita mean and median estimates across original price impacts are presented in Appendix Figures A.3 & A.4. A majority of consumers would benefit from drive insect releases if spotted-wing had induced at least a 10% price increase in conventional and organic markets; if

conventional prices only rose 8%, organic prices must have risen at least 20%. With any non-zero price impact, median estimates for orange juice are always positive (Appendix Figure A.4).

Figure 3.3: Pest impact on prices and breakeven mean consumer surplus from drive insect releases

Note: The solid line denotes the estimated combination of organic and conventional price increases necessary for a self-sustaining gene drive insect intervention to result in break-even (mean zero) consumer surplus. The dotted line denotes the price increases necessary for a statistically significant positive consumer surplus (at the 90% level). For context, we include stars for empirical estimates of price impacts due to spotted-wing in berries (Farnsworth *et al.*, 2017) and the citrus psyllid in oranges (Moss *et al.*, 2014).



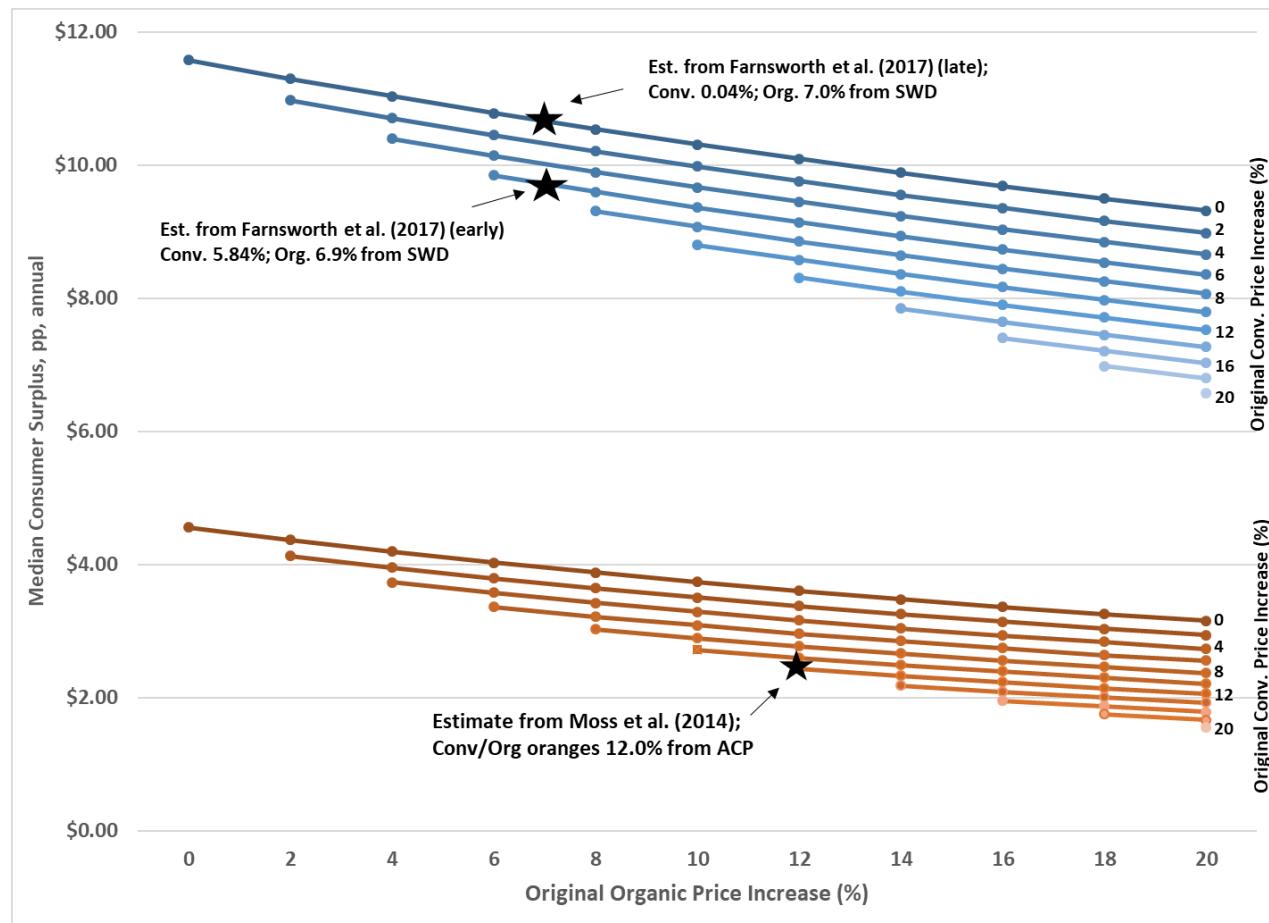
3.6.3 Limiting drive releases to retain market choice

Our econometric results imply considerable welfare gains associated with retaining market alternatives without drive insect presence, even when those alternatives have higher prices and pesticide spray levels. As the distribution of $\Delta CS(GD+SQ, GD)$ is censored at a zero and unbounded in the positive direction, we concentrate analysis on median estimates in Table 3.6 & Table 3.7. In blueberries, median welfare gains of \$10.61 are particularly driven by retaining a higher-priced organic alternative that was not grown in the presence of gene drive insects. For orange juice consumers, the impact of retaining non-drive insect presence is more modest, with a median \$2.44 welfare gain. In Figure 3.4, we provide analogous welfare ranges across possible initial price impacts of the pest infestations, placing empirical literature estimates in context. The value of additional high spray and/or higher-priced, non-drive alternatives clearly declines as the prices of those alternatives increase.

The structure of the choice model will always result in strictly positive consumer welfare gains from limiting drive releases to preserve greater consumer choice. However, the scale of the estimates can inform policy. Our results show that, when considering consumer welfare with drive insect releases, it is key to distinguish between both the consumer preferences for host crop-derived products and the actual impact the pest species has on crop prices. And while organic producers have disproportionately higher management costs and losses due to invasive pests, our analysis indicates that, on aggregate, there is significant consumer welfare gain to retaining organic options without any interaction with biotechnology products.

Figure 3.4: Median consumer surplus from retaining non-gene-drive products relative to gene drives with unlimited spread.

Note: Fresh Blueberries (top) and Orange Juice (bottom) The value of additional higher spray, higher priced non-drive alternatives declines as the price of those alternatives increases. HB MXL model, correlated random coefficients, price as random log-normal. No estimates contain zero in 90% CI. Blueberry empirical points proxied by CA raspberry estimates from (Farnsworth *et al.*, 2017). OJ empirical point proxied by FL orange field box prices from (Moss *et al.*, 2014).



3.7 Conclusions and Policy Recommendations

Increasingly successful scientific research is developing the use of gene drive insects to combat invasive agricultural pests which cause significant damage in U.S. growing environments. Researchers, funders, and policy makers have already begun a broad debate on the ethics and potential ecological impacts of such technologies (NASEM, 2016a; Emerson *et*

al., 2017; Baltzegar *et al.*, 2018), and market impacts will also be a key concern to address in deliberations over development investments and potential releases. The net market impacts of these technologies depend not only on the cost savings and yield improvement afforded to producers, but also how consumers will react in the marketplace.

We evaluate heavily informed consumer preferences for multiple strategies to address damaging invasive pests, including gene drive insects, crop genetic modification, and heavy conventional pesticide spraying regimes. Unsurprisingly, *ceteris paribus*, consumers prefer less insecticide and no use of biotechnology. However, the introduction of Spotted-wing Drosophila as a major invasive pest has already led to increased spraying and control costs (Burrack *et al.*, 2019). Similarly, the threat of citrus greening spread has spurred heavy spray programs to attempt to control Asian citrus psyllid (Stansly *et al.*, 2019). Thus, high-spray pesticide regimes are already almost ubiquitous in these growing environments. Our results consistently indicate, across both fresh blueberries and orange juice choice experiments, that consumers had lower or statistically equivalent reductions in mean mWTP with gene drive insect presence in growing areas compared to current high- (vs. low-) frequency spray regimes. On average, gene drive insects are also consistently preferred to crop genetic modification, providing insight into differential public and consumer perceptions of biotechnology interventions. This is an important consideration, especially given implementation of the National Bioengineered Food Disclosure Standard and evolving types of biotechnology inputs in food production. It is logical that the presence of a genetically engineered insect in the field would elicit a weaker consumer reaction than a genetically engineered product that is directly (and intentionally) consumed. We also examine potential impacts of drive insect presence on WTP for organic certification. While organic producers may in fact receive very high production benefits from gene drive insects to

reduce damage without chemical applications, it is reasonable to expect that some segments of their consumer base may be hesitant to accept this new technology. There is weaker evidence for mean mWTP declines for organic products when drive insects are in growing areas, though the effect may be more pronounced among sub-groups of the population.

However, the area-wide nature of gene drive insect releases, and likely large publicity to accompany mass releases of genetically modified insects (NOFA-NY, 2017; Zhang, 2017), mean fundamental changes to product choice sets are likely to be faced by consumers with non-neutral preferences. Unlimited drive insect releases may provide efficiency for lowest cost implementation of pest management programs, but grower benefits from reduced control costs and losses must be weighed against consumer and public welfare impacts. When compared to status quo prices and management, model specifications with the highest explanatory power indicate that mean and median surplus changes for fresh blueberry consumers would be negative under an unlimited gene drive insect release program. In orange juice, mean surplus changes are small, negative and statistically insignificant while median estimates are small, positive and significant. The value of retaining product alternatives in the choice set is quite large (relative to the market impacts of the pests considered) and should be carefully considered when weighing how (and if) to implement any release program for genetically engineered insects. Thus the ecological risk concerns already expressed by scientists and regulators with self-sustaining gene drive insect releases (NASEM, 2016a; Delborne *et al.*, 2018) are augmented by these marketplace concerns, given the inherently commercial nature of any agricultural gene drive pest application. However, just as the National Academy of Sciences, Engineering, and Medicine (2016) report emphasizes the need for case-by-case ecological risk assessment with gene drive

organisms, our analysis indicates that parallel case-by-case consumer research is paramount for host crop products.

There are some drawbacks to this study. Awareness of pest control measures will be important in extrapolating these results. Respondents in our experiments saw clearly labeled product features and in the survey received detailed information about gene drives, whereas such information is unlikely to be available to many consumers in the marketplace. Still, our analysis of well-informed consumer preferences regarding these technologies provides an important starting point for understanding consumer impacts. A related concern is how consumer preferences and welfare estimates might change in response to ‘shocks’ to public perceptions, e.g. from increased media coverage (Frewer, Miles and Marsh, 2002). While similar technologies for public health applications have received significant media coverage (see: Allen (2016), Servick (2016b, 2016a), and Kahn (2020)), proposed agricultural applications of gene drives has received little media attention .

Further research is needed to connect underlying values driving the consistently differential impacts of plant vs. insect-based biotechnology solutions. Also, while our information frame was delivered as objectively as possible, the public may receive information on gene drive insects through outlets encouraging either support or opposition. Investigating informational and framing effects on subsequent consumer decision-making would help to understand implications for market analysis.

Chapter 4: Genetically Modified Bt Crops and Genetically Modified Insect Releases: Input Complements or Substitutes?

(with Jennifer Baltzegar and Nicole Gutzmann)

4.1 Introduction

Pest control is an inherently challenging part of most agricultural crop production. As new pest management products and practices are implemented by producers, there is constant evolutionary pressure for insects to adapt and evolve resistance to these measures. As of 2013, there were over 11,000 records of pesticide resistance or “a genetically based decrease in susceptibility to a pesticide” within over 500 arthropod species (Whalon, Mota-Sanchez and Hollingworth, 2013; Tabashnik *et al.*, 2014). As novel pest control methods are introduced, scientists and regulators such as the Environmental Protection Agency (EPA) are keenly interested in preserving their efficacy by employing strategies for resistance management (Bates *et al.*, 2005; Gould, Brown and Kuzma, 2018).

Genetically engineered crops producing insecticidal crystalline (*Cry*) toxins from *Bacillus thuringiensis* (Bt) are also threatened by evolved resistance. With nearly 100 million worldwide acres planted to Bt crops in 2016, researchers have advocated for decades to preserve Bt benefits including pest reduction, decreased chemical insecticide use, and increased profits for producers (for a recent overview, see Tabashnik and Carrière (2017)). The most commonly employed strategy is reserving non-Bt plant ‘refuges’ in the immediate vicinity of Bt growing areas to decrease selection pressure and allow for genetic dilution of potential resistance alleles (Gould, 1998; Tabashnik, Brévault and Carrière, 2013). Alternative and complementary strategies have included ‘stacking’ Bt traits (i.e. inserting multiple types of Bt *Cry* toxin genes)

(Zhao *et al.*, 2003; Carrière, Crickmore and Tabashnik, 2015), and the mass release of irradiated sterile insects (or ‘SIT’) to suppress a potentially resistant insect population (Tabashnik *et al.*, 2010). Instead of decreasing selection pressure, these later strategies work by integrating multiple simultaneous control strategies. This prevents the survival of resistant insects, and thereby the spread of resistance alleles.

One proposed resistance management strategy is the release of genetically modified (GM) insects to maintain or reintroduce Bt susceptibility (Jin, Walker, Fu, Harvey-Samuel, Dafa’alla, *et al.*, 2013). Under the technique known as RIDL, or “Release of Insects with a Dominant Lethal,” genetically modified (GM) male insects are released to mate with wild females (Phuc *et al.*, 2007). The modified males are fully susceptible to Bt and carry a female-specific lethal gene which causes almost all of the female progeny to die (while males survive) (Thomas *et al.*, 2000)⁷. A recent experimental field trial with Bt broccoli and a major *Brassica* pest, Diamondback moth (DBM) (*Plutella xylostella*), provided the first proof-of-concept evidence that this may be possible (Harvey-Samuel *et al.*, 2015) and open field releases are furthering the technology’s practical potential (Shelton *et al.*, 2020)⁸. Developers of the RIDL strain have claimed their approach could be more cost-effective than irradiated sterile insect releases, while allowing for a reduction or elimination of refuge requirements (Alphey *et al.*, 2007; Alphey, Bonsall and Alphey, 2009).

While the practical potential for a genetically modified diamondback moth (GM-DBM) has been demonstrated, economic assessment so far remains limited (Brown, Jones and Mumford, 2019), and optimal management of GM crop resources in the presence of GM-DBM

⁷ This lethal gene is only active in the absence of the feed additive tetracycline, allowing mass-rearing in factories but mortality once released in the field (Thomas *et al.*, 2000).

⁸ See Appendix G for a full illustrated explanation of the GM-DBM RIDL system

insect releases remains an unresolved question. One possible reason for this is that such analysis requires the combination of detailed biological and economic modeling methods. A key feature of the GM insect design is that releases simultaneously decrease insect populations and increase Bt susceptibility. As the economic value of Bt vis-à-vis non-transgenic varieties is a function of total insect damage mitigated, this value is eroded with widespread resistance *as well as* drastic declines in the overall (susceptible) pest population. GM insect releases, therefore, may conceivably subsume the insecticidal role of Bt and render these toxins unnecessary, with a potentially fine line dictating the extent to which GM insect releases preserve the long-term *value* of Bt. This interaction is key to analyze in detail, since the value to developers of preserving the Bt trait is inherently linked to the product's market potential. While all actors may benefit from some combination of Bt and GM insect input use, optimal release rates may vary dramatically between growers, GM insect developers, and marketers of Bt crops.

In this article, we combine the modeling of age and sex-specific insect genetic profiles under GM insect releases in Bt crop zones with the economic value of crop yield preserved over long-term horizons. For illustration, we apply this model to the case of possible GM-DBM releases for Bt resistance management in broccoli, given the research and field trials with this system noted above (Alphey *et al.*, 2007; Harvey-Samuel *et al.*, 2015). We examine the dual roles that GM insect releases may play in mitigating pest populations and resistance. This has lead to insights on how various release strategies and uncertainties in the system ultimately impact the yield-preserving value of Bt toxins. In doing so, we contribute to both the literatures of the economics of insect resistance management and broader modeling literature of genetic management of agricultural pests.

4.2 Background

4.2.1 Diamondback Moth Distribution and Biology

Diamondback moth (DBM) is a well-studied, world-wide pest of economic importance in *Brassica* crops (e.g. cabbage, canola, broccoli, cauliflower), with an annual economic impact conservatively estimated to be between \$4 - \$5 Billion USD (Zalucki *et al.*, 2012). While canola dominates these totals, the impact on cauliflower and broccoli production is estimated at almost \$160 Million USD annually under farmer practices (*ibid*). Non-crop plant species are also noted to play an important natural host role for the pest (Kahuthia-Gathu *et al.*, 2009; Furlong, Wright and Dosdall, 2013). Native to Europe, the DBM has spread rapidly around the world to nearly every continent (Zalucki and Furlong, 2011; Zalucki *et al.*, 2012). While the southeastern United States and the rim of the Pacific Coast are the only core territories in the United States, migration facilitates seasonal spread throughout the entire country (Zalucki and Furlong, 2011; Zalucki *et al.*, 2012).

The average rate of egg production by females is estimated to be 12.9 eggs per female per day (Marchioro and Foerster, 2014), the vast majority of which are laid on leaf surfaces (Harcourt *et al.* 1986). After an incubation period of 5-6 days, first instar larvae begin feeding on leaves and florets. Emergence to adulthood is between 17-20.3 days (Niu *et al.*, 2013; Marchioro and Foerster, 2014), with the development time from larva to pupa being about 6 days and from pupa to adult about 10 days.

4.2.2 Bt Resistance and the DBM Case

Bt produces a wide variety of toxins, many of which have been utilized as effective pesticides. “Bt crops” are those agricultural species that have been genetically engineered to produce a *Cry* toxin and are lethal to most Lepidopteran pest species (Tabashnik, Brévault and

Carrière, 2013). *Cry* toxins are ingested and activated in the insect midgut, where they bind perforate lethal holes in the gut lining (Tabashnik, 1994). Mechanisms of resistance are genetically diverse but many involve disruptions in the ability of *Cry* toxins to bind in the midgut (Heckel *et al.*, 2007). Refuges were modeled decades ago to be a possible method of resistance management (Tabashnik, 1994; Gould, 1998), and their effectiveness has been affirmed with empirical evidence (e.g., Tabashnik, 2008).

DBM is notorious for evolving resistance to many insecticides and is known to carry Bt resistance alleles due to overuse of Bt insecticidal spraying (Heckel *et al.*, 2007). Broccoli, a host plant of DBM, has been engineered to carry a Bt gene and is available for non-commercial research purposes. This was found to be a robust study system for Harvey-Samuel *et al.* (2015) to investigate the potential use of GM-DBM for both pest control and insect resistance management. The authors were interested in the release ratio of GM to wildtype (non-GM) insects necessary to control the population size, which varies between different genetic pest management strategies and insect species. They were also interested in the novel question of how effective these GM insect releases would be at mitigating resistance to Bt crops.

To investigate potential effects on resistance management, Harvey-Samuel *et al.* (2015) tested four treatment groups in their caged field trials: 1) Bt broccoli only, 2) low release ratio of RIDL GM-DBM to wild-type males, 3) high release ratio of RIDL GM-DBM, and 4) low release ratio plus Bt broccoli (hereafter ‘combined treatment’). All groups began with a founder population estimated to have a low resistance frequency. Harvey-Samuel *et al.* found that the combined treatment resulted in a lower level of resistance alleles in the population than Bt broccoli alone. The lowest level of resistance was found in the founder population and low release ratio (no selection pressure). Notably, while the high release ratio of GM-DBM

performed similarly to the combined treatment for the population suppression study, the authors did not include this treatment in data presented for the proportion of resistant genotypes in the population. This is notable because although the low release ratio did not result in a lower resistance level than the founding population, a high release ratio possibly could have lowered the resistance level. This has resistance management implications in that low release ratios are enough to maintain the status quo in refuge, but a high release ratio might actually decrease the resistance level in refuge. Compared to the high ratio release, Harvey-Samuel *et al.* (2015) state that the combined treatment is likely the more ‘economical’ approach to Bt resistance management due to GM insect production costs.

Much of the modeling work in the (economically) optimal control of Bt crops has focused on investigating non-Bt crop refuge requirements to slow resistance (Laxminarayan and Simpson, 2002; Livingston, Carlson and Fackler, 2004). This also generally involves consideration of insecticide as a non-Bt pest control alternative (e.g., Livingston, Carlson and Fackler (2004)), and within one model has been extended to include insecticides, refuges, and SIT releases (Tabashnik *et al.*, 2010). Notably, models for some species indicate that resistance can be avoided for more than 20 years, even with no refuge requirement, when SIT releases are high in Bt zones (Tabashnik *et al.*, 2010). Biological models have also been extended to examine Bt resistance management through GM repressible female-specific lethal insect releases (Alphey *et al.*, 2007; Alphey, Bonsall and Alphey, 2009), but have not included an economic component. This article extends a two-locus biological model to bridge the disciplinary gap and provide analysis of economic outcomes from each of these biological and policy instruments.

4.3 Economic Conceptual Framework

4.3.1 Bt and GM-DBM as Damage Abating Inputs

The economic conceptual model takes the perspective of a farmer interested in maximizing profit from the production of a Bt crop. In the most basic form, a farmer maximizes profits by choosing an optimal bundle of inputs (Z) when input prices (v) and output prices (p) are set competitively by the market:

$$\max_{\{Z\}} p * Y(Z) - v * Z$$

We characterize the yield function $Y(Z)$, following the economic damage abatement framework of Lichtenberg and Zilberman (1986). This framework emphasizes the difference between yield *increasing* inputs such as fertilizer, irrigation, labor, and seed volume (or inherent germ quality) and inputs that simply prevent that maximum potential yield from being eroded by damaging agents such as pests and weeds. The latter inputs are termed “damage abating” and are only useful to the farmer *in the presence of a pest population*. The Bt trait, along with pesticides and herbicides, would fall in this category. We also take an additional step (relative to Lichtenberg and Zilberman (1986)) of more fully integrating the insect genetic and population dynamics, framing to acknowledge that damage abating inputs are dependent on both insect presence and susceptibility to achieve their function.

Normalizing the maximum potential yield to 1, this previous work motivates the yield specification:

$$Y = g(Z) * [1 - D(J_1)]$$

$$\text{with } J_1 = h(J_0, BT(S_i), GMI)$$

$$\text{and } S_i \equiv 1 - R_i$$

Where Y is yield, Z is a vector of yield increasing inputs, and J_1 is the current pest population governed by the “kill function” $h(\cdot)$. Within the kill function, J_0 is the initial pest population, BT is the effective Bt crop area which is dependent on insect susceptibility, and GMI is the release of GM insects (moths). Y is increasing in Z , decreasing in J , and weakly increasing in BT . S_i is the percentage of the insect population susceptible to Bt, alternatively defined as the percentage who are not resistant ($1 - R_i$). Yield is thus decreasing in R_i and increasing in S_i . Released GM insects are fully susceptible to Bt and thus, over time, can increase the susceptibility level S_i while also reducing overall populations. This general form of the damage abatement function is mathematically equivalent to a revenue loss damage abatement function, albeit in empirical work it is generally restricted to a yield function (e.g., Mutuc, Rejesus and Yorobe (2011), Cobourn *et al.* (2011) among many)⁹. The key biological parameters governing the economic equations are levels of susceptibility S_i to the damage abatement input(s), and the initial pest population J_0 during the decision making period to invest in inputs Z , BT , and GMI . The key biological equations driving the economic components of the model are the population dynamics of the insect J_1 and the damage function $D(\cdot)$ for crop yield.

This dynamic calls into question under which conditions Bt crops and GM insect inputs are technical substitutes or complements. In economic terms, inputs that are technical substitutes perform the same role in a production system and the increase of one will decrease the other

⁹ One could go further, seeking to separate the effects of insect damage on price and quantity (e.g., Babcock, Lichtenberg and Zilberman (1992). To do so we could specify different damage functions (with the same kill functions) to model agronomic and market discount schedules inherent to a particular farmer’s anticipated situation. We could also frame pest damage through a profit-based function allowing optimal supply and input adjustments to be executed by a rational, profit-maximizing farmer in response to the presence of a pest, rather than just the loss from maximum potential yield (Chambers, Karagiannis and Tzouvelekas, 2010). Additionally, refuge considerations may evolve into an important part of this story, though for the initial model we opt to ignore this component. So, at this stage we begin with a parsimonious yield-based damage abatement approach to build our model, and leave additional layers of complexity to future research.

input's marginal effect on yield (i.e. a decrease in the input's 'marginal product'). With technical complements, an increase in one input will increase the marginal product of the other. Bt and GM-DBM have substitutive effects by both playing a role in reducing overall DBM damage. However, they can be complementary through several routes. A first is that GM-DBM reduce resistance alleles and thereby enhance the marginal product of Bt. Another route is Bt-induced mortality could have complementary effects with reproductivity reductions facilitated by GM-DBM in the underlying population dynamics. The net complementarity or substitutability is likely to vary at different levels of initial DBM densities and Bt resistance, as well as the economic time horizon being considered (addressed in next section), and therefore requires specification of a biological model to characterize further.

Fully contextualizing to our present problem, we split yield between the Bt crop and the (non-Bt) conventional crop planted acres as a function of Bt refuge (q) on the interval [0,1]. Narrowing to unsprayed refugia, conventional crops are fully vulnerable to pest attack. Per-insect damage to crops is incurred through the parameter δ . The juvenile pest population J and susceptibility S_i are both functions of the refuge area q and weekly releases of GM-DBM males r . When only GM males are released and all female progeny die, J is decreasing in r and weakly increasing in q . We will relax this assumption to allow for the RIDL system's incomplete female juvenile mortality (Jin *et al.*, 2013), which may actually increase the juvenile population. Susceptibility, S_i , is weakly increasing in both q and r . We arrive at the maximization problem:

$$\max_{\{q,r\}} (1 - q) * [1 - \delta * J(q, r) * (1 - S(q, r))] + q * [1 - \delta * J(q, r)] - (BtPrm) * (1 - q) - m * r$$

This leads to the following first order conditions, which seek a configuration of inputs which make the marginal product of each input equal to its marginal cost:

$$\frac{\partial y}{\partial q}: (1 - q) * J * \frac{\partial S}{\partial q} - \frac{\partial J}{\partial q} * [(1 - q) * (1 - S) + q] - J * S + (BtPrm) = 0$$

$$\frac{\partial y}{\partial r}: (1 - q) * J * \frac{\partial S}{\partial r} - \frac{\partial J}{\partial r} * [(1 - q) * (1 - S) + q] - m = 0$$

Both terms $\frac{\partial y}{\partial q}$ and $\frac{\partial y}{\partial r}$ are increasing in the ability of refuge or releases to increase susceptible populations which are killed on Bt area, and decreasing as more refuge or releases lead to higher overall juvenile populations. Marginal yield impact of refuge is also decreasing with total susceptible populations.

One potential route using simulation to examine the extent to which Bt and GM moth releases are substitutes or complements is to examine the second derivative of the first order conditions. Since refuge is the inverse of Bt planting, for technical complementarity we are interested in whether $\frac{\partial}{\partial r} \left(\frac{\partial y}{\partial q} \right)$ is negative, or whether an *increase* in the release rate *decreases* the marginal yield impact of more refuge. Stated differently, we want to know whether an *increase* in the release rate *increases* the marginal yield impact of Bt planted area. Differentiating the first order condition $\frac{\partial y}{\partial q}$, we arrive at the expression:

$$\frac{\partial^2 y}{\partial q \partial r}: -S * \frac{\partial J}{\partial r} + \frac{\partial J}{\partial q} * (1 - q) * \frac{\partial S}{\partial r} + (1 - q) * \frac{\partial J}{\partial r} * \frac{\partial S}{\partial q} - J * \frac{\partial S}{\partial r} +$$

$$(1 - q) * J * \frac{\partial^2 S}{\partial q \partial r} - [(1 - q) * (1 - S) + q] * \frac{\partial^2 J}{\partial q \partial r} = 0$$

This expression is admittedly difficult to evaluate at first glance and, even in this simplified framework, depends heavily on the functional form of $J(q,r)$ and $S(q,r)$. The first two terms are likely positive if the GM-DBM system is working ‘well’. With full GM female lethality, $\frac{\partial J}{\partial r} < 0$, though in the presence of some surviving GM females this could flip. We will explore this in simulations. The terms $\frac{\partial J}{\partial q}, \frac{\partial S}{\partial r}$ are ≥ 0 . The third and fourth term are likely negative as $\frac{\partial J}{\partial r} < 0$ (with full female lethality), $\frac{\partial S}{\partial q} > 0$, and $\frac{\partial S}{\partial r} > 0$. The fifth and six terms are ambiguous, depending on the sign of $\frac{\partial^2 S}{\partial q \partial r}$ and $\frac{\partial^2 J}{\partial q \partial r}$. Further, we are interested in how release rates change the long-term, time discounted or ‘net present value’ of refuge requirements throughout a 20+ year time horizon. Therefore, this expression is not immediately able to be solved analytically and we move to simulations to parameterize and more explicitly examine these relationships.

4.3.2 Analyzing through a Net-Present-Value Framework

The simple model in the previous section is framed in static terms to illustrate the possible substitutability and complementarity between Bt and GM-DBM. However, these relationships are fundamentally dynamic, and require computational modeling to analyze further, as well as an economic framework for weighing benefits and costs over time. In this context, we assume farmers seek to maximize net present value (NPV) of the crop less input costs, specified as follows:

$$NPV = \int_{t=0}^T [((1-q) * [1 - \delta * J_t(J_0, q, r) * (1 - S_t(S_0, q, r))] + q * [1 - \delta * J_t(J_0, q, r)]) - BtPr * (1 - q) - m * r_t] e^{-\rho t} dt$$

where $\rho \geq 0$ is the economic discount rate, t indexes time, and T is the time horizon. Note that juvenile pest population size J_t and Bt susceptibility S_t are now changing over time. These dynamics are specified by a system of differential equations described below and are governed by refuge policy q and GM-DBM releases r which are based on initial or current-period wildtype adult male populations M_{wt} ¹⁰. This NPV criterion is effectively a weighted average value of yields on refuge and non-refuge crop over time, less the costs of Bt and GM-DBM releases. The discount rate (when positive) operates to place progressively less relative value on average yields farther in the future.

4.4 The Model

The objective of our biological model is to study how release levels of transgenic, female-killing DBM (GM-DBM) will control Bt resistance and the overall damaging population. The change in resistance genotypes and the overall pest population size are the main biological variables impacting NPV. Analyzing the sensitivity of these variables to percentage of refuge being planted in the crop system is important for analyzing the claims by Harvey-Samuel *et al.* (2015) from a biological perspective. To build our biological model, we start from the continuous time model of (Robert *et al.*, 2013) which tracks two loci, one for the female killing gene and – in our use of the model – a second locus for the Bt resistance gene. Two bi-allelic loci in a diploid organism yields nine possible genotypes. Robert *et al.* (2013) model three sets of equations for juveniles, males, and females, for each of the nine genotypes i . This provides a total of twenty seven equations governing the system. This complexity, though posing challenges for analyzing and interpreting results, is necessary for the research objectives here, because only

¹⁰ Modeled as static ratios throughout the present analysis, a point we discuss at the end of the article.

juveniles damage crops and the GM-DBM releases are one genotype and (almost all) adult males.

Juveniles:

$$\frac{d}{dt}J_i = B_i(t) - J_i \left(\alpha \sum_g J_g \right)^{\beta-1} - \mu_J J_i - v J_i$$

The change in juveniles of genotype I is given by the amount of births of that genotype (B_i) minus the density-dependent deaths determined by coefficients β and α , minus the density independent deaths of juveniles of genotype I ($\mu_J J_i$), minus the number of juveniles that are leaving the juvenile class to become adults ($v J_i$).

Juvenile Births:

$$B_i(t) = W_i \sum_m F_m(t) \lambda \sum_n \Pr(i|m, n) \frac{M_n(t)}{\sum_g M_g(t)}$$

The amount of births of genotype I (B_i) can further be expanded to reflect the fitness of different genotypes (W_i), multiplied by the sum of females with genotype m (F_m), multiplied by the average number of eggs laid per female (λ). This is in turn multiplied by the sum of the probabilities of having an offspring of genotype I , given a female parent of genotype m and a male parent of genotype n , $\Pr(i|m, n)$, multiplied by the proportion of males that have genotype n (M_n) from the total male population.

Adult Females:

$$\frac{d}{dt} F_i = 0.5v\gamma_i J_i - \mu_f F_i + U_i^F$$

The rate of change of adult females of genotype I is given by the proportion of viable females (γ_i) from half of the number of juveniles that are leaving the juvenile class to become adults ($0.5vJ_i$), minus the density independent deaths of female adults of genotype I ($\mu_f F_i$), plus the amount of transgenic adult females being incidentally released into the system at a constant rate (U_i^F). If the RIDL system works perfectly and all GM females die before adulthood, then U_i^F is zero. The female killing gene affects female viability, which is given in Table 4.1 by γ_i , and in the model is acting on the females moving from the juvenile to the adult stage. This is appropriate for our model as well since the RIDL OX4319L line females reared off of tetracycline die during larval stages with only 9% surviving to pupal stage, and 1% surviving to adult stage (Jin, Walker, Fu, Harvey-Samuel, Dafa'Alla, *et al.*, 2013). Since 1% of female GM-DBM survive to adulthood we allow for some ‘leakiness’ in the unintended releases of GM-DBM females. This enters through two parameters: The first, as incidental releases of transgenic females due to incomplete mortality in the rearing facility (U_i^F), and the second as incomplete mortality in the field γ_i . If the female killing system works perfectly and all GM females die before adulthood, then U_i^F is zero and γ_i is zero for genotypes with the lethal allele.

Adult Males:

$$\frac{d}{dt} M_i = 0.5vJ_i - \mu_M M_i + U_i^M$$

The rate of change of adult males of genotype I is given by half of the number of juveniles that are leaving the juvenile class to become adults ($0.5vJ_i$), minus the density independent deaths of male adults of genotype I ($\mu_M M_i$), plus the amount of transgenic adult males being released into the system (U_i^M).

4.4.1 Adaptations of the biological model for female-lethal transgenic diamondback moth in Bt crops

To adapt the model from Robert *et al.* (2013) for our purposes, we add a function for the survivability of insects with genotype I , given a proportion of Bt planted versus refuge. To do so, we modified the juvenile equation to be given by the proportion of births of that genotype (B_i) that survive on Bt (θ_i).

$$\frac{d}{dt} J_i = B_i(t) \theta_i - J_i \left(\alpha \sum_g J_g \right)^{\beta-1} - \mu_J J_i - v J_i$$

At the locus for the female lethal gene, individuals can have either the female lethal allele K , or the non-lethal, wild-type allele k . At the locus for the Bt resistance gene, individuals can have the resistance allele s , or the susceptible, wild-type allele S . This leads to the nine genotypes as shown in Table 4.1.

The inclusion of fitness in the birth equation is intuitive since biological ‘fitness’ is the genetic contribution of an individual to the next generation, relative to the population. The fitness of an individual with genotype $KkSs$ is one minus the fitness cost of carrying the female lethal transgene, multiplied by one minus the fitness cost of carrying the resistance allele. The dominance of the fitness costs for each locus are given by h , where $h=1$ is dominant and $h=0$ is recessive. Viability of wild-types γ_i is normalized to 1 and transgenic genotypes survive at the

leakiness (L) rate, taken from empirical estimates of this specific RIDL system (Jin, Walker, Fu, Harvey-Samuel, Dafa'Alla, *et al.*, 2013). On Bt, Bt resistant moths (genotype ss) will have the relative survival of 1. Bt susceptible moths (SS) will have the relative survival of 1 minus the per capita mortality rate on Bt (D), multiplied by the proportion of Bt planted in the field (Bt). Heterozygous moths (Ss) will survive depending on the dominance of survivability on Bt (h_0). The Bt resistance gene in the pest is acting immediately after birth, before these individuals have a chance to add to density dependent effects. The resistance gene affects survival of individuals of genotype I , as given in Table 4.1:

Table 4.1: Possible juvenile genotypes resulting from female killing releases with corresponding fitness values (W_i), female viability coefficients (γ_i) and juvenile survival in Bt fields (θ)

i	Genotype	W_i	γ_i	θ
1	KKSS	(1- c_L)	L	1- D^*Bt
2	KKSs	(1- c_L)*(1- h_{RCR})	L	1- $h_0^*D^*Bt$
3	KKss	(1- c_L)*(1- c_R)	L	1
4	KkSS	(1- $h_L c_L$)	L	1- D^*Bt
5	KkSs	(1- $h_L c_L$)*(1- h_{RCR})	L	1- $h_0^*D^*Bt$
6	Kkss	(1- $h_L c_L$)*(1- c_R)	L	1
7	kkSS	1	1	1- D^*Bt
8	kkSs	(1- h_{RCR})	1	1- $h_0^*D^*Bt$
9	kkss	(1- c_R)	1	1

Note: $c_{L,R}$ = homozygous fitness cost of RIDL lethal gene (c_L) or Bt resistance (c_R);
 $h_{L,R}$ =dominance of fitness costs of RIDL lethal gene (h_L) or Bt resistance (h_R) in heterozygotes.
 h_0 =dominance of lethality of Bt in heterozygotes. L = ‘leakiness’ survival of transgenic RIDL individuals

4.4.2 Assumptions of the model

The main assumptions of the model are the nature and timing of fitness effects, and deaths from female killing or Bt mortality. In this initial treatment, we assume a *static* management strategy to mirror the field trial done by Harvey-Samuel *et al.* (2015). The release ratio of transgenic males carrying the lethal gene is constant, but the absolute number of transgenic males released thus decreases (or increases) with the wildtype male population. We also assume that in the absence of the female killing transgene the sex ratio would be 1:1.

Another assumption is a single locus conferring resistance to Bt. In reality, the mechanism of resistance is likely to be through changes in multiple steps along the toxicity pathway, and therefore comprise more than the single locus (Heckel *et al.*, 2007). Not only would this be significantly more complex to model, but the mechanisms for Bt resistance would

also likely differ on a population basis. Thus, it is expedient to simplify to one resistance gene for the purpose of the model.

Another assumption is that deaths from Bt occur immediately after birth, before the juvenile stage. This is a small deviation from reality since in this case the Bt toxin is being expressed within the crop and needs to be ingested in order to have pesticidal activity. Bt toxicity occurs within a couple of hours to days of ingestion, while the larva are still very young. At this age they are very small and eat much less than in late larval instars. So, the larvae die as early instars and likely do not have as much of an effect on density dependence. Thus, in our mathematical framework the most accurate place to evaluate the function for deaths from Bt is at the beginning of the juvenile stage before density dependence and other factors.

In addition, we assume random mating and do not account for migration. Our deterministic, continuous time model does not explicitly allow for extinction. Further, we only model diamondback moth as a single pest system without spatially explicit natural refuge, as exclusion of these complexities is judged necessary to keep the model tractable.

4.4.3 Further parameters

The fitness cost associated with the female lethal gene (0.523) was estimated using survival to adulthood relative to the wild type from Harvey-Samuel *et al.* (2014). The dominance of the fitness cost associated with the female lethal transgene was calculated with results reported in the same paper by using the relative fitnesses of KK homozygotes and Kk heterozygotes: $KK = (1 - s) = 0.477$; $Kk = (1 - h * s) = 0.736$. Solving for s is 0.523 and the dominance, h, is thus 0.505 (Harvey-Samuel *et al.* 2014). The high fitness cost (0.417) associated with Bt resistance was estimated using data from Groeters *et al.* (1993) and the much lower cost (0.035) is estimated from more recent data in Yi *et al.* (2015). Tang *et al.* (1997) also report extremely

low, and perhaps zero, fitness cost from Bt resistance, leading us to place more credence in lower fitness costs but still investigate across a wide range to inform policy decisions in diverse contexts. The dominance of mortality on Bt (h_θ) as reported in Yi *et al.* (2015) is 0, meaning that for θ , the resistance allele is recessive and heterozygous individuals for the resistance allele (Ss) will have the same phenotype (Bt lethality) as homozygous susceptible individuals (SS). The mortality of susceptible homozygotes and heterozygotes in Yi *et al.* was 100%. The strength of density dependence was drawn from parameterizations in Robert *et al.* (2013) in the absence of data in the literature specific to DBM.

For analysis, the refuge planting percentage is varied to measure the sensitivity of the system. This is important in the analysis of the claims made by Harvey-Samuel *et al.* (2015) that GM-DBM releases may decrease or eliminate need for refuge. The weekly release ratio of transgenic individuals to wild-type males was specifically tested at 3:1 and 40:1 in Harvey-Samuel *et al* (2015) and we include this range in broader model tests.

To model the potential complementarity or substitutability of Bt and GM-DBM, we loop through a broad sensitivity analysis of many levels of both inputs over a 20-year time horizon. We analyze refuge policy in 5% increments over the full range [0, 5%, ..., 95%, 100%]. Harvey-Samuel *et al.* (2015) outline release rates varying from “low”, at 3-4 times the current wild-type male population per week, up to “prohibitively expensive” (yet likely more effective) rates of 40 times the male population. We analyze releases from very low rates of 0.5:1 up to 40:1 times the current male population. Further, the initial level of Bt resistance alleles is of paramount importance in the resulting input trade-offs. We model initial levels of resistance alleles along a very wide range, from 0.1% (i.e. 1 of every 10,000 individuals are functionally resistant, assuming resistance is recessive) to fixation at 100%. Economic parameters are derived from

cost outlays of broccoli input markets in the Eastern United States (Atallah and Gomez, 2013), published premiums for Bt seed in other major crops (Finger *et al.*, 2011), and operational costs of SIT production systems for lepidopteran pests (Alphey, Alphey and Bonsall, 2011). We note that use of a linear damage function may in fact provide conservative estimates of economic damage from pests, as partially damaged plants may be discarded entirely. An estimated 10.66 acre experimental area is inferred through simple algebraic manipulation of the analytical population model equilibrium, assumed initial infestation levels from literature examples, and published planting rates.

Table 4.2: Biological Model Parameters

Parameter	Description	Default value	Citation
μ_J	Density-independent juvenile mortality rate	0.0029 day ⁻¹	Marchioro and Foerster (2014)
μ_M	Adult male mortality rate	0.0192 day ⁻¹	Marchioro and Foerster (2014)
μ_F	Adult female mortality rate	0.0370 day ⁻¹	Marchioro and Foerster (2014)
λ	Average rate of larval production by females	12.9 day ⁻¹	Marchioro and Foerster (2014)
v	Rate of emergence to adulthood	0.0493 day ⁻¹ 0.0588 day ⁻¹	Marchioro and Foerster (2014) (Niu <i>et al.</i> , 2013)
α	Density dependence parameter	2×10^{-4}	Robert <i>et al.</i> (2013)
β	Strength of density dependence	3.4	Robert <i>et al.</i> (2013)
c_L	Fitness cost associated with female lethal gene	0.523	Harvey-Samuel <i>et al.</i> (2014)
h_L	Dominance of fitness cost associated with female lethal gene	0.505	Harvey-Samuel <i>et al.</i> (2014)
c_R	Fitness cost associated with Bt resistance	0.035 0.417	Yi <i>et al.</i> (2015) Groeters et al (1994)
h_R	Dominance of Bt resistance allele (off Bt)	0	Yi <i>et al.</i> (2015)
W_i	Fitness of genotype i	i	See Table 4.1
γ_i	Female viability coefficient of genotype i	$\gamma_i = 1 i=7,8,9$ $\gamma_i = L = 0.01 i=1-6$	Jin <i>et al.</i> (2013)
θ_i	Juvenile survival in Bt fields of genotype i	i	See Table 4.1
h_0	Dominance of Bt resistance allele (on Bt)	0	Yi <i>et al.</i> (2015)
M	Mortality on Bt	1.00	Yi <i>et al.</i> (2015)
Bt	Percent of field planted to Bt crop [alternatively, refuge $q = 1 - Bt$]	[0 – 100%]	
r	Weekly release ratio of transgenic individuals to wild-type males	0 – 40:1	Harvey-Samuel <i>et al.</i> (2015)

Table 4.3: Economic parameters and inferred values

Parameter ^a	Value	Source
Discount factor ρ	0.04	Assumption of model
Larvae per 20 plants	2	Bhagat, Yadu and Sharma (2018) [cabbage, unsprayed]
Plants per acre	12,000	Atallah and Gomez (2013) [Cornell written, NC broccoli extension doc, pg16 Tb.16 and pg 20]
Harvested ‘boxes’ per acre	440	Atallah and Gomez (2013)
Price per box	\$12 USD	Atallah and Gomez (2013)
Conventional (non-Bt) seedling cost per acre	\$277 USD	Cornell (2016)
Bt seed % premium	98%	Finger <i>et al.</i> (2011), based on worldwide mean estimated Bt cotton premium
Cost per RIDL insect released	\$10k per 1M (\$0.01/each)	Alphey, Alphey and Bonsall (2011) [based on Codling Moth SIT case as only Lepidopteran example]
Linear % Yield Damage per insect (δ) ^a	0.007%	1/(Model Equilibrium Juv. Pop.) [assumption of model]
Revenue per acre ^a	\$5,280 USD	(Price_per_box)*(Boxes_per_acre)
Acreage in simulation ^a	10.66	$\frac{(\text{Model Equilibrium Juv. Pop})}{\left(\frac{\text{plants}}{\text{acre}}\right) * \left(\frac{\text{larvae}}{20 \text{plants}}\right)}$
Total Revenue in simulated acreage ^a	\$56,285 USD	(revenue_per_acre)*(acres)

^aComputed from other parameters

4.4.4 Mechanics of the model

The model is written in MATLAB, version R2019a and utilizes the differential equation solver ode23s. To improve model functionality and reduce numerical approximation error, we derive and incorporate the analytical 27x27 Jacobian matrix for the system solver. The high dimensionality inherent in the model, while limiting, is justified for a number of reasons. First, the biological question is one that considers two independent loci in a diploid organism and a GM-DBM release of a sex- and age-specific single genotype. Damage is also limited to juvenile insects. Therefore, the specificity in age, sex, and genetic structure does not permit the reduction in equations governing the system. Second, one may argue that our continuous time model presents more complexity than a discrete time model. However, we believe this model structure will likely give a better representation of nature because the DBM has overlapping generations and therefore may be inconsistent with a discrete time framework (Koshihara, 1986; Wührer and Hassan, 1993). The structure of our model is thus derived heavily from published research which addresses a comparable sex, age, and genetic structure in a continuous time, deterministic model (Robert *et al.*, 2013).

4.5 Results: Biological Model

We first test the model and then examine genotype and population changes under various release regimes. Releases of transgenic individuals (GM-DBM) of genotype KKSS, in combination with Bt planting intensity, have dramatic effects on overall pestiferous juvenile frequencies and resistance development. The release regimes encompass several strategies which involve either a constant release ratio to current period wild type males (i.e. 3:1), which is therefore declining in frequency, vs. a constant release number (i.e. 10,000 individuals) based on initial period populations, in which the ratio to current period wild types is increasing. We

further expand to an analogous strategy of releasing wild-type Bt-susceptible males (WT-DBM) of genotype kkSS at a constant number as a comparator.

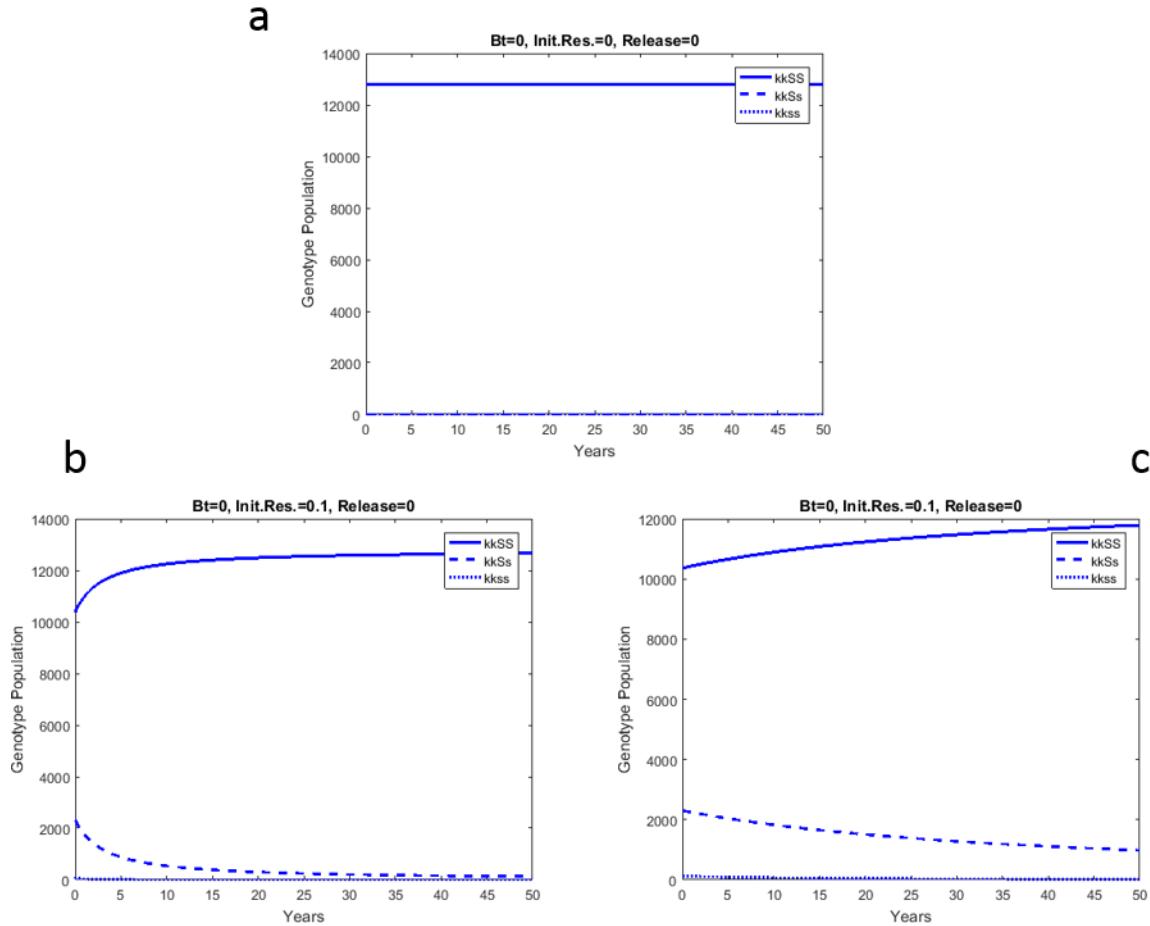
Bt planting intensity is examined at 80% Bt (20% refuge) or 0% Bt (100% ‘refuge’) to isolate release impacts. Here, the “leakiness” parameter for GM females surviving to adulthood is set equal to 0.01 as reported in Jin *et al.* (2013) and the “leakiness” parameter for wildtype DBM is set equal to 1 because there is no sex-specific lethality associated with the wild-type alleles. Since these assumptions, such as illustrative initial resistance alleles frequencies, may prove inaccurate or not be varied enough to identify interesting phenomena, we vary additional parameters in the next section in analysis of NPV.

4.5.1 No Releases on Bt and non-Bt crops

Testing the mechanics of the basic model, we confirm the equilibrium juvenile population of 12,792 individuals holds for even a 50-year period in the absence of Bt planting, Bt resistance alleles, or GM releases (Figure 4.1, top). Over a long time horizon, the fitness cost of carrying resistance alleles will also lead to their decline from the population in the absence of selection pressure, and a higher fitness cost will expedite this decline.

Figure 4.1: Basic Model Mechanics – Juvenile Genotype Populations

Note: (a; top) At equilibrium, juvenile population with no Bt planting ($Bt=0$), Bt resistance alleles ($Init.Res.=0$), or GM releases ($Release=0$); (b & c; bottom) Natural loss of Bt resistance alleles via fitness costs, with no Bt planting or GM releases, at (b) Bt fitness cost = 0.417; (c) Bt fitness cost = 0.035. The dotted line indicates resistant genotypes.

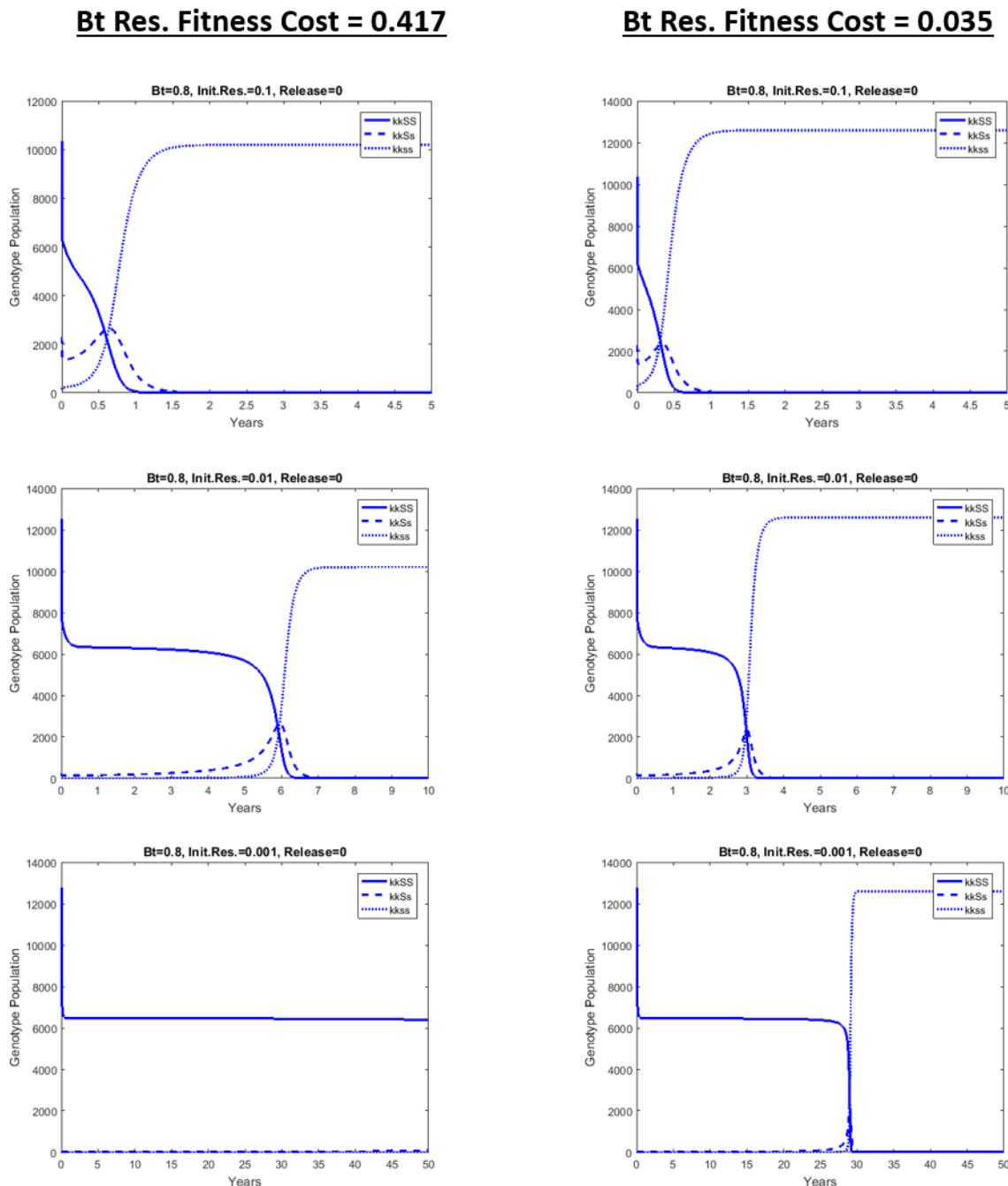


Bt resistance management is predominantly through refuge policies and our model confirms this importance in delaying the spread of resistance alleles. In Figure 4.2 we examine refuge policy when Bt fitness costs are high and low. A full derivation of fitness costs is available in Appendix H. When fitness costs are high and at a 20% refuge mandate and a relatively high resistance allele frequency of 10% (with 1% functionally resistant individuals), there is near fixation of resistance within two years. As allele frequency declines to 1% (0.1%

functionally resistant individuals), a 20% refuge delays resistance by about 7 years. A low frequency of resistance alleles of 0.1% delays resistance fixation beyond even a 50-year horizon. However, even with a low 0.1% initial allele frequency, reducing refuge size quickly expedites fixation of resistance. While reducing refuge to 10% still delays widespread resistance over 20 years, a 5% or 1% refuge leads to near fixation of resistance alleles within about 11 and 3 years, respectively (not shown). As Bt fitness costs decrease, the time before resistance is able to reach fixation is reduced by about half. Given the likely variation in fitness costs associated with Bt resistance mutations over time and population (Sayyed and Wright, 2001), we further explore the implications of fitness costs below to examine how this factor may influence the broader outcomes of GM-DBM releases.

Figure 4.2: Bt resistance under Bt resistance fitness costs (columns) and initial resistance levels (rows)

Note: The dotted line indicates resistant genotypes.

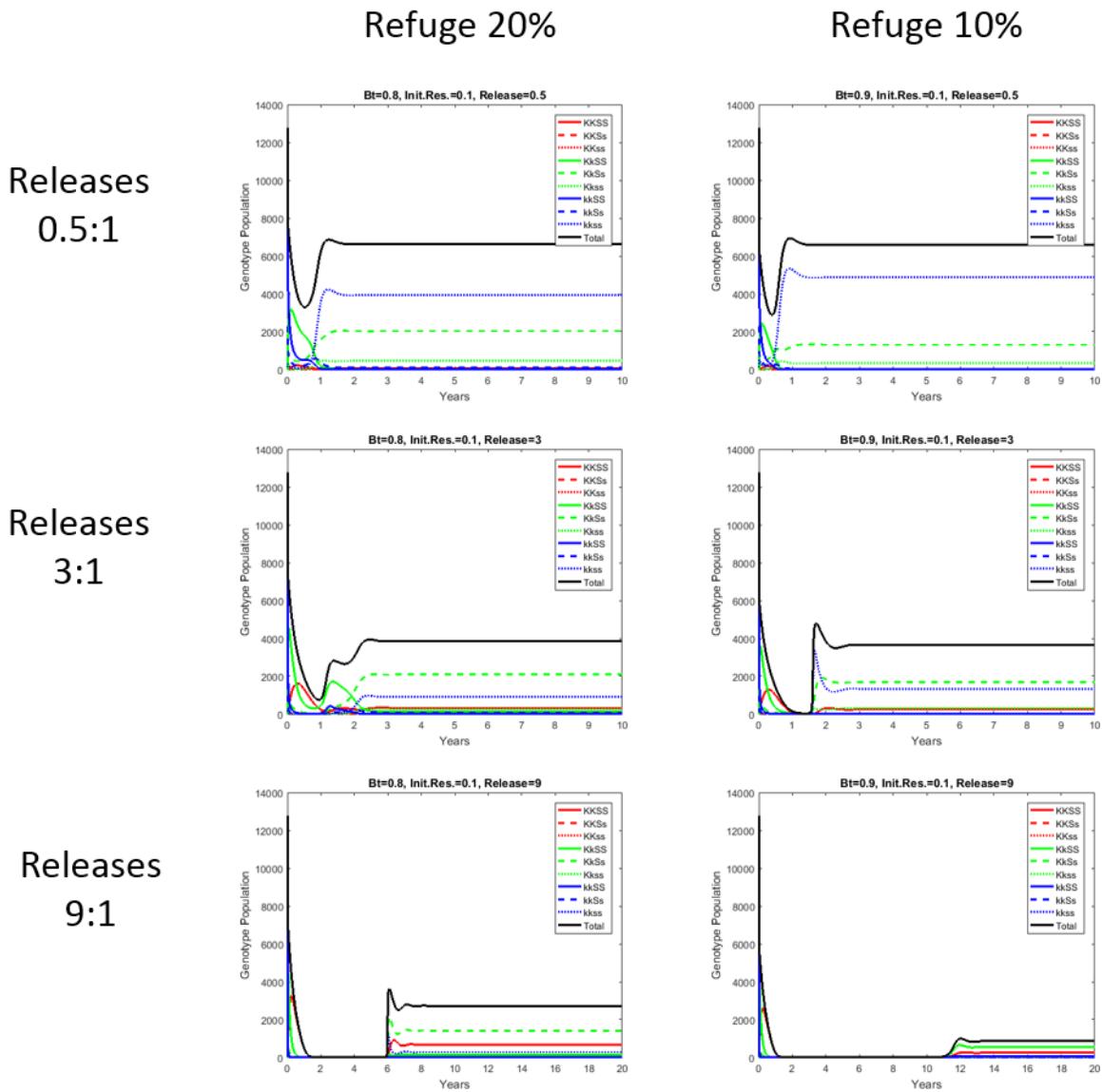


4.5.2 Low vs. High Release Ratios of GM-DBM

Releasing GM-DBM individuals into the wild population reduces the amount of resistance alleles in the population and decreases the wild population. In Figure 4.3 we build from the seemingly more likely case where Bt fitness costs are low and resistance is able to reach fixation more quickly. The equilibrium population level is always lower when Bt planting is combined with GM-DBM releases, though high Bt levels are required for releases to crash the population. At a very low 0.5:1 release level (lower than the 3:1 recommended by Harvey-Samuel *et al.* (2015)), resistance does not reach fixation but functionally resistant individuals comprise over 2/3 of the population after about a 1-2 year stabilization period. At a release ratio of 3:1, resistance is maintained at about ¼ of the juvenile population from two years onward. In both the cases of a classic 9:1 and 40:1 ratio (not shown) there is an initial abrupt decline in population accompanied by an eventual rebounding to a new, lower equilibrium population. At a classic 9:1 ratio, about 10% of the rebounded population is still resistant to Bt.

Figure 4.3: Juvenile population size, by genotype, under various release ratio intensities

Note: Bt fitness cost = 0.035, initial resistance alleles (Init. Res.) = 0.1. GM-DBM release ratios are a function of current time period wild-type male populations. Colors differentiated KK, Kk, and kk genotypes groups. Dark black lines represent total juvenile DBM population. Dotted lines represent resistant genotype populations. *Left column:* GM-DBM releases on Bt crops (20% refuge), *Right column:* releases on 10% refuge, *Top row:* Very low release ratios of GM-DBM to wild-type males (0.5:1), *Middle Row:* Low release ratios of GM-DBM (3:1), *Bottom Row:* Higher release ratios of GM-DBM (9:1).

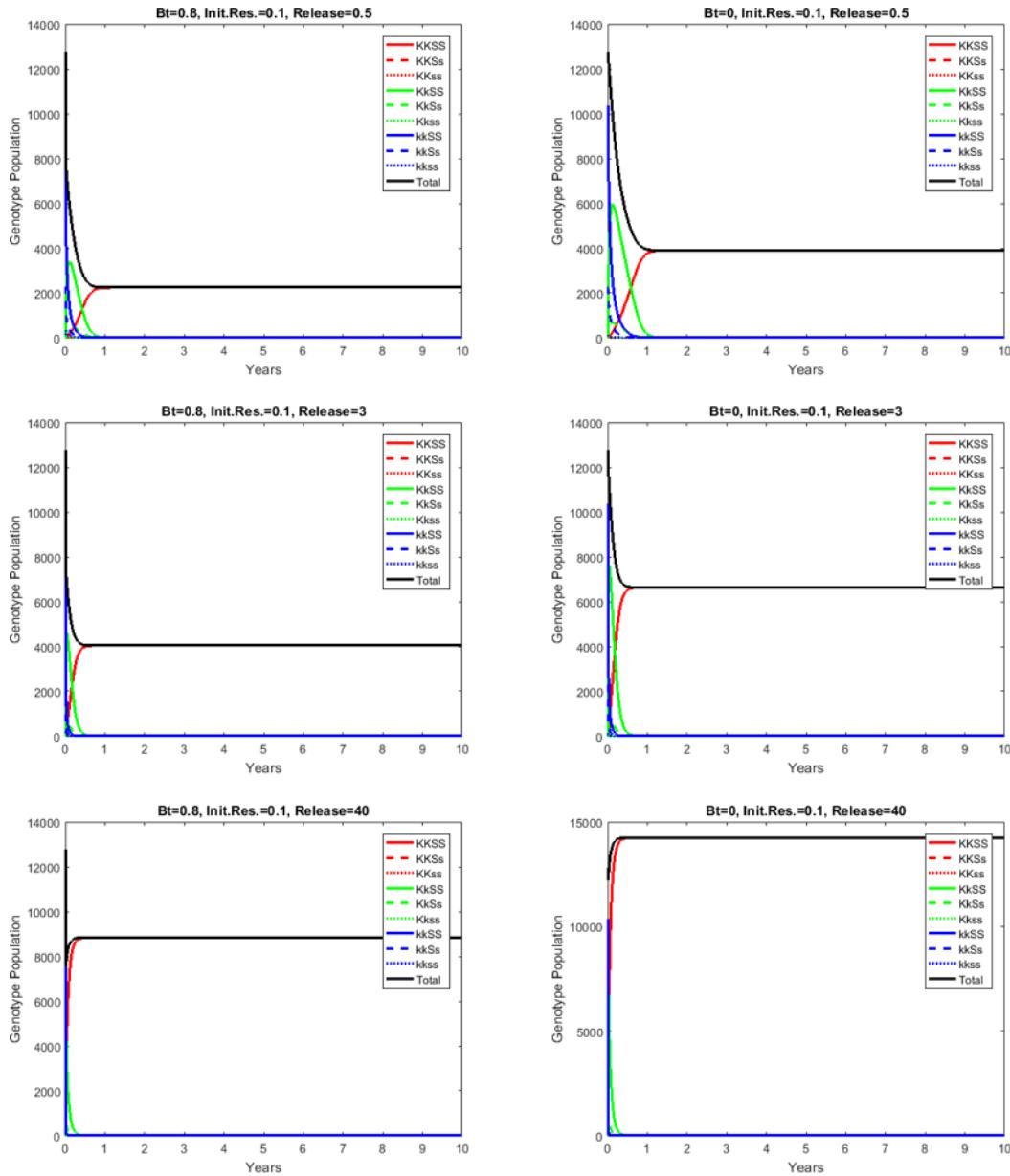


Higher fitness costs for Bt resistance result in lower equilibrium population levels, lower resistance frequencies, and enhance the population control (and susceptibility introgression) ability of GM-DBM releases (full results in Appendix Figure A.6). At low 3:1 releases, resistance is almost entirely controlled with 20% refuge and partially controlled at 10% refuge. Releases at 9:1 and 40:1 (omitted) result in more extended periods of very low populations before rebounding to a low, almost entirely homozygous susceptible population. Notably, with aggressive dual measures of 9:1 or 40:1 release ratios coupled with high Bt planting at 90%, the impact of increased Bt resistance fitness costs is largely negated, with little to no change in overall population dynamics.

Under a constant release *number* (Figure 4.4), where releases are based on the initial ($t=0$) wild-type male population, the wild type juveniles are quickly replaced by susceptible GM juveniles. These juveniles are produced due to the GM male moths, as well as the 1% ‘leaky’ female GM moths which do not die as larvae and go on to mate with GM and wild-type males. The new equilibrium population is therefore increasing as the release number increases and the wildtype population crashes and is replaced by GM moths.

Figure 4.4. Juvenile population size under various constant release frequency

Note: The dotted line indicates resistant genotypes. The dark black line indicates total juvenile population. Release amount based on initial wild-type male population (18,514), Bt fitness cost = 0.035). *Left column:* GM-DBM releases on Bt crops, *Right column:* GM-DBM releases on non-Bt crops. *Top row:* Very low release ratios of GM-DBM to t=0 wild-type male population (1:1), *Middle Row:* Low release ratios of GM-DBM (3:1), *Bottom Row:* Very high release ratios of GM-DBM (40:1).

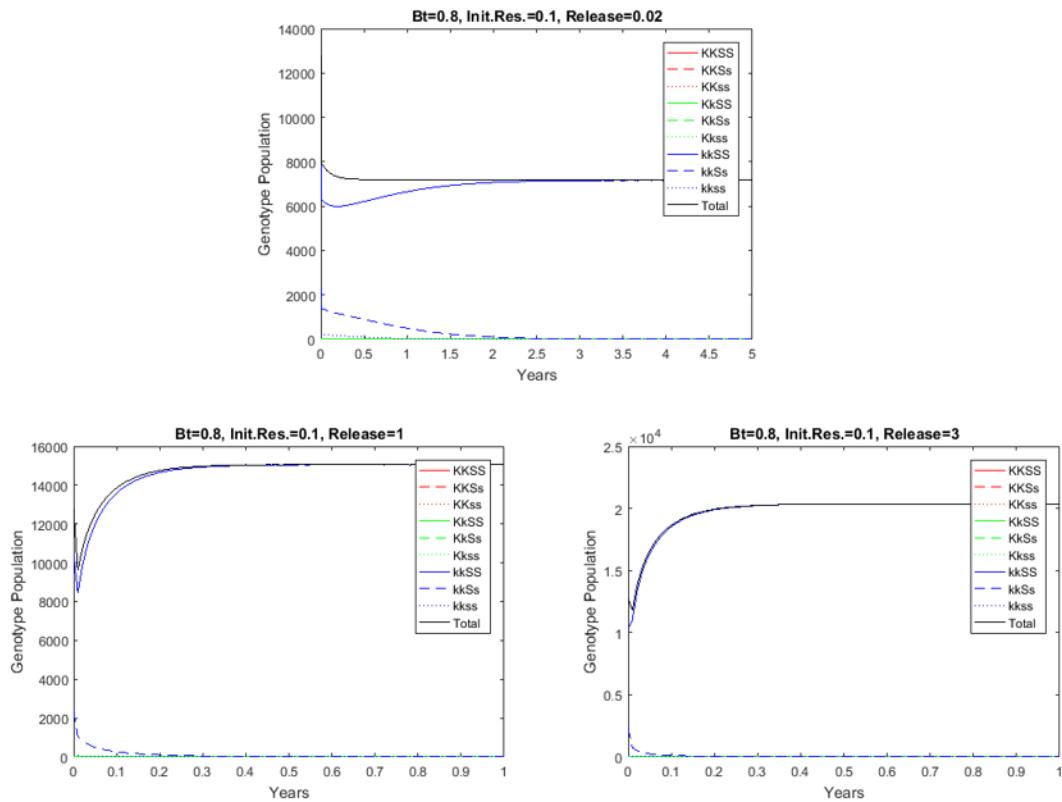


4.5.3 Low vs. High Release Ratios of susceptible, wild-type DBM

For completeness, we also test a strategy of simple releases of homozygous susceptible wild-type males (kkSS) (Figure 4.5). Such a strategy would almost certainly be impractical due to grower concerns, since it would involve the release of insects that would *increase* damage in the short-run to sustain Bt effectiveness for longer. However, this strategy merits exploration in the simulation analysis to elucidate key differentiating characteristics with GM releases. When initial resistance frequency is 0.1, releasing homozygous susceptible wild-types at a constant frequency does control resistance, even at extremely low release frequencies, but also results in higher stabilized juvenile populations due to higher fitness than GM counterparts. While Bt crops are protected, this would be highly detrimental for any proximate non-Bt producers. We constrain the results to one year, as the population stabilizes within the first six months. Interestingly, a much lower release rate of wild-type males on the order of 2% of the initial population appears to control resistance while stabilizing the overall population (with Bt mortality) at about 2/3 the initial equilibrium population (shown to five years). At a 1% release rate, however, we fail to control resistance (omitted).

Figure 4.5. Juvenile population dynamics with wild-type susceptible male releases with 20% Bt refuge

Note: The dotted line indicates resistant genotypes. The dark black line indicates total juvenile populations. *top*: extremely low release rate (0.02:1) of wild-type susceptible males (5-year scale); *bottom*: ‘low’ release rates (1:1) & (3:1) of wild-type susceptible males (1-year scale). As wild-types only confer a susceptibility introgression, only Bt-planting scenarios are shown.



4.5.4 Noteworthy Biological Model Results

Under these assumptions, the most biologically effective method tested for controlling Bt resistance and overall population levels is a high constant release *ratio* of GM-DBM paired with very low refuge. The low-level releases at a 3:1 ratio are not sufficient to reduce populations to near-zero levels, though resistance is suppressed. Releases do not provide long-term population control on their own or in combination with 20% refuge (80% Bt planting) area. When high releases are combined with lower refuge (greater Bt) area, this can much more effectively drive the population closer to zero via increased Bt control of survivors from incomplete GM-DBM

female mortality, or ‘leakiness’. Eliminating juvenile populations, rather than replacing them with susceptible genotypes, could be more desirable for non-Bt areas. A constant release frequency is less desirable given the GM-DBM system leakiness, as the imperfect female-specific lethality results in higher levels of surviving (susceptible) progeny which would damage non-Bt crops. Similarly, releases of wild-type homozygous susceptibles are not desirable, as they can dramatically increase the background juvenile population.

It should be noted that the model assumes no migration – which is admittedly unlikely in the context of DBM populations (Zalucki et al. 2011). Therefore, a population which is suppressed locally could be a temporary outcome if releases are ultimately terminated. Further, high fitness costs for Bt resistance are desirable to help delay resistance fixation and maintain a lower equilibrium population, though evidence suggests fitness costs in DBM may be particularly low (Yi *et al.*, 2015). However, it is important to note the impact of resistance fitness costs is largely negated when high release ratios are coupled with very high Bt planted area. Density dependence parameters are taken from similarly structured models in the literature (Robert *et al.*, 2013) and are difficult to verify within the diamondback moth literature given lack of data available. We explore the impact of varying each density dependence parameter on the population genetic system in Appendix Figure A.7.

4.6 Interfacing with economic modeling

The claims made by Harvey-Samuel *et al.* (2015) are inherently interdisciplinary and we thus need to fully integrate a bio-economic model. Empirical results obtained in Harvey-Samuel *et al.* (2015) are validated by our model under certain parameter conditions. Particularly important in the model framework are prevalence and fitness costs associated with Bt resistance,

parameters which may vary over time and space in real-world environments. As initial prevalence of Bt resistance increases and the fitness costs of resistance decrease, optimal refuge size at ‘low’ and mid-level release rates changes significantly. The optimality of eliminating refuge also changes in meaningful ways. Our model results are also largely consistent with simulation results and empirical findings by Tabashnik *et al.* (2010), in which high SIT releases allowed for lower refuge requirements in Bt cotton. The significance of our *static* decision framework should be underscored, as this does not allow readjustment of refuge sizes over time as conditions change.

The key variables in the biological model which are pivotal to the economic output are insect juvenile population size, resistance allele frequency, and Bt resistance allele fitness costs. Parameters which policymakers and developers can control are refuge requirements (assumed as net refuge *with compliance*), release rate of GM-DBM, and, potentially, the efficiency of female lethality (leakiness) of the GM-DBM strain.

4.7 Results: Economic Model

4.7.1 Changes in Marginal Product of Bt with GM-DBM releases

Insecticidal traits of Bt crops are only able to contribute towards increased yields in the presence of susceptible insects. Even without GM-DBM releases, this marginal yield effect or ‘marginal product’ of Bt is reduced over time as resistance builds. In Figure 4.6, we begin by examining the equilibrium partial derivative of yield with respect to the proportion planted to Bt.¹¹

¹¹ This is computed by taking a finite difference approximation at the corresponding refuge level and capturing the end-of-period estimate. We use a step interval of 1e-3 with a relative ODE error tolerance of 1e-6 and absolute error tolerance of 1e-8.

While refuge and release strategies vary in length of time to equilibrium, at the modeled initial resistance allele frequencies the deterministic nature of model results in equilibrium fixation of resistance at both 20% and 10% refuge-only policies and thus a Bt marginal product of 0. As GM-DBM releases begin, the Bt marginal product is quite high through maintenance of susceptibility and ‘preservation’ of background juvenile populations. However, as GM-DBM releases increase, the coincident reduction in juvenile population decreases the equilibrium marginal product. At about at an 8:1 ratio breakpoint with a 20% refuge policy and 4:1 ratio with a 10% refuge policy, the juvenile populations and Bt marginal product are reduced to nearly zero. However, for the first few years, Bt would have a relatively high marginal product without GM-DBM releases since the susceptible population is high (for population dynamics reference, see Figure 4.2).

We extend results in Figure 4.7 to show marginal impacts of Bt on net revenue in equilibrium. The trend is largely analogous to marginal product results in Figure 4.6. However, given the premium paid for Bt seed, we note the negative Bt marginal impact on net revenue when resistance rises to fixation. This appears both under the no-release scenario and when the population is driven to (near) zero under heavy release ratios.

Figure 4.6. Equilibrium Marginal Product of Bt under increasing GM-DBM releases

Note: Initial Resistance alleles of 1%; Releases as a ratio of male wild-type adult population; *Left*: Bt area at 80% (20% refuge); *Right*: Bt area at 90% (10% refuge).

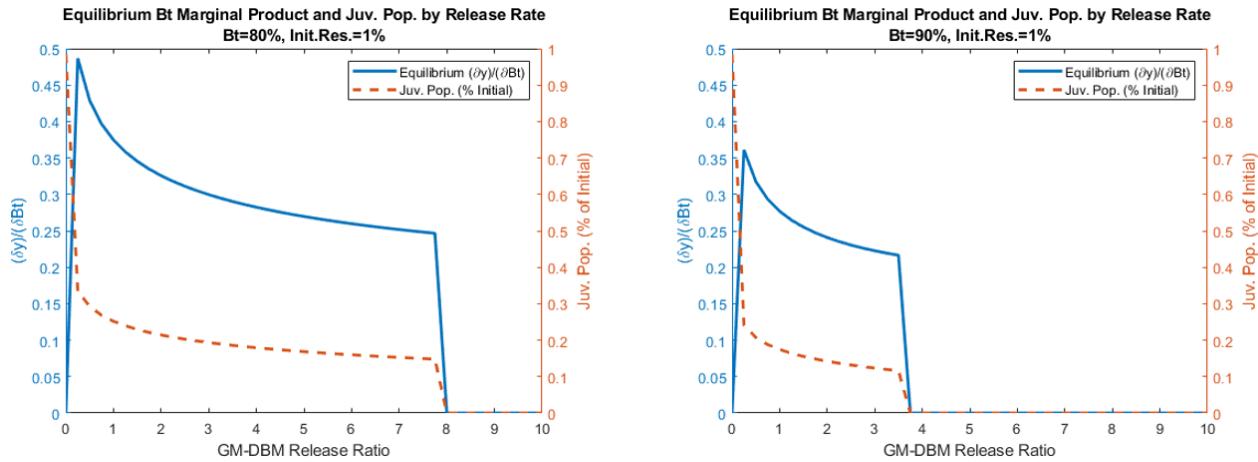
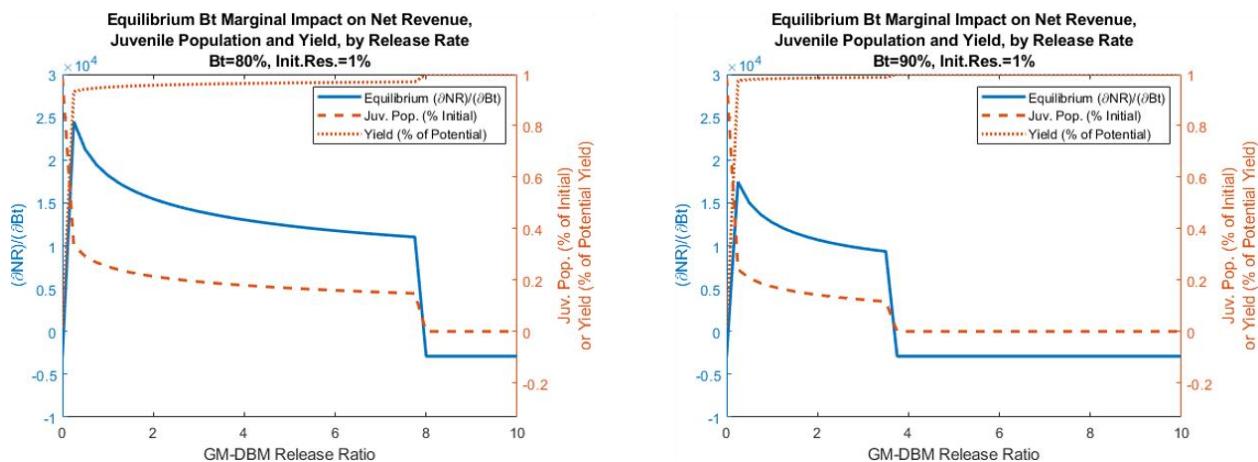


Figure 4.7. Equilibrium Marginal Impact of Bt on Net Revenue under increasing GM-DBM releases

Note: Initial Resistance alleles of 1%; Releases as a ratio of male wild-type adult population; *Left*: Bt area at 80% (20% refuge); *Right*: Bt area at 90% (10% refuge). Marginal impact of Bt on primary y-axis; Juvenile population and yield on secondary y-axis.



4.7.2 NPV Simulation Results

We bridge to full time-discounted returns via NPV heat maps, allowing a clear comparison of cumulative returns under varied refuge regimes and GM moth releases. The major uncertain parameters of significant policy concern are the fitness cost associated with Bt resistance, the ‘leakiness’ of the GM system (surviving percentage of emerging transgenic females), and the initial Bt resistance allele frequency in the population. As expected, a major factor driving the results appears to be the selection pressure of Bt planting intensity interacting with the initial resistance frequency. Optimal strategies are dramatically different as this initial resistance frequency changes, making this parameter a key component of uncertainty in the model. We begin with low Bt resistance fitness costs and examine the implications of increased fitness costs in the following section.

Figure 4.8 illustrates that in the absence of GM-DBM releases when initial resistance frequency is 0.1% and 1%, optimal static refuge is about 15% (85% Bt) and 60% (40% Bt), respectively. Incorporation of very modest GM-DBM releases on the order of 0.5:1 allows for a drop in optimal refuge size to about 5 and 10%, respectively. At much higher initial resistance levels of 5-90%, optimal refuge without GM-DBM releases is between 80-100%. However, at 5% resistance alleles, optimal refuge is reduced to about 30% with very modest release ratios of 0.5:1 and drops further to 10% at a 4:1 release rate. By 10% initial resistance alleles, the resistance pressure necessitates about a 10:1 release rate to allow for a similar 10% refuge level. This underscores the importance of acting quickly to contain an outbreak of resistance alleles.

The rebound of the optimal static refuge/release policy path is visible at each initial resistance level and begins to bend at increasingly higher release rates. Stated differently, Bt and GM-DBM releases begin as *complementary* inputs and this complementarity continues for

longer in environments with more resistance. However, it is rational for producers to reduce their investment in premium Bt seed if high releases are planned in the area and populations are likely to be driven from a stable and susceptible level to effectively crashing the population.

We next compare the discounted stream of net revenues over fitness costs for Bt resistance. Increased fitness costs provide a natural impediment to the selection pressure for resistance and thus allow for higher optimal Bt planted area. The model illustrates in Figure 4.9 that this countervailing force is most relevant when a) GM-DBM releases are low, and b) initial resistance alleles are high. This is sensible, as the both of these conditions make managing resistance more difficult. At higher release rates of about 10:1 and greater there is little to no impact of higher fitness costs, as releases simply overwhelm the system.

Figure 4.8: Net Revenue NPV heat plots for static management policy, over refuge, release rates, and initial Bt resistance

Note: Bt resistance fitness cost = 0.035; leakiness of GM system (transgenic female survivorship) = 1%; RIDL fitness cost = 0.523.

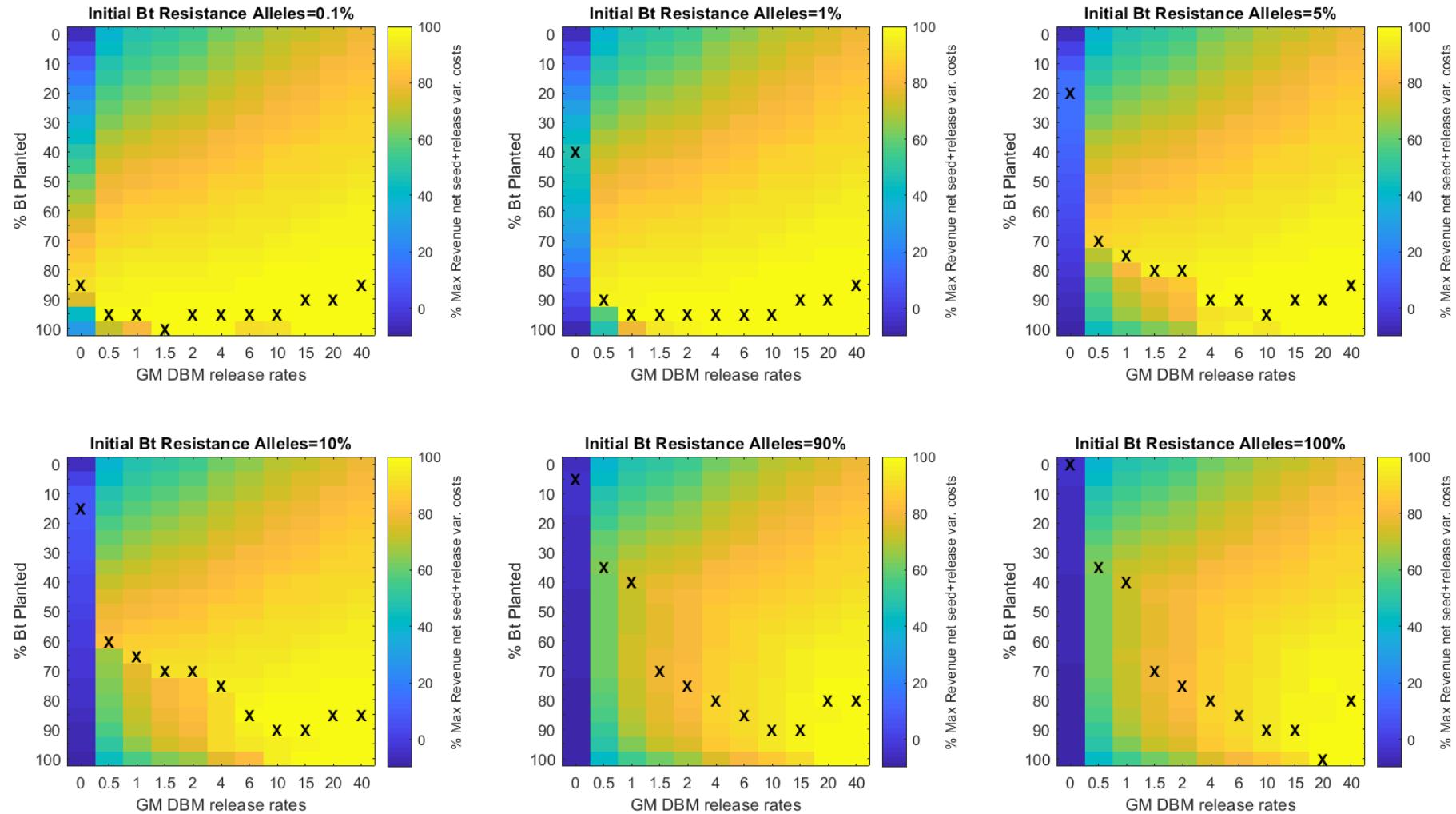
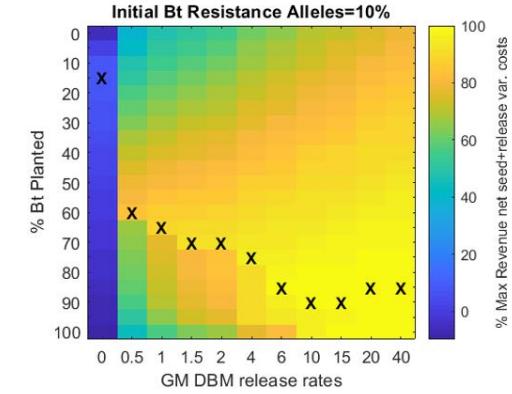
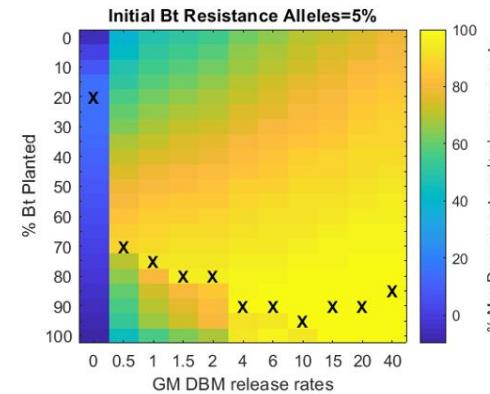
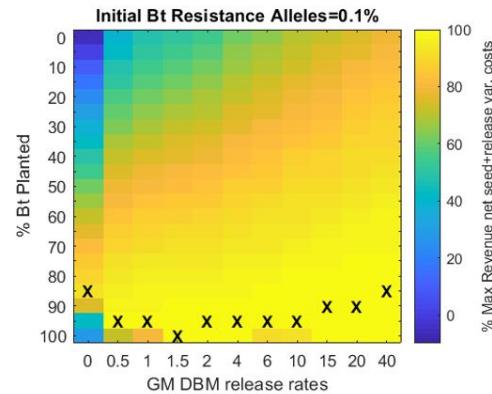


Figure 4.9: Comparing NPV Net Revenue over fitness costs of Bt resistance

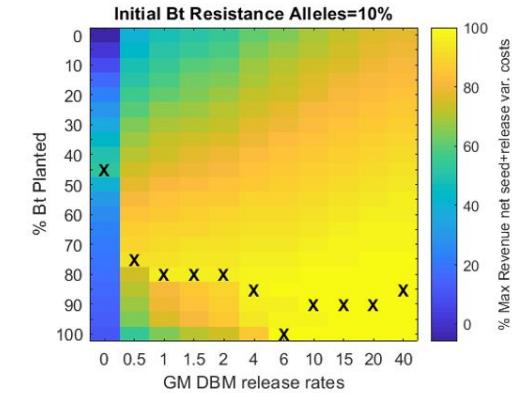
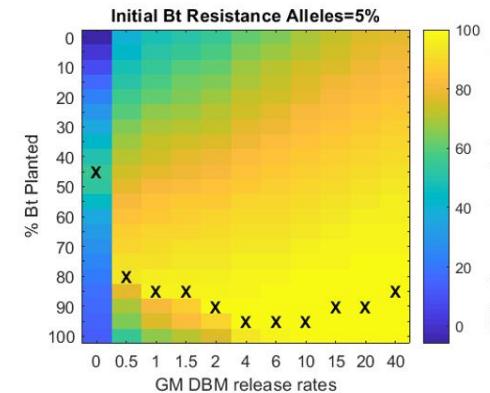
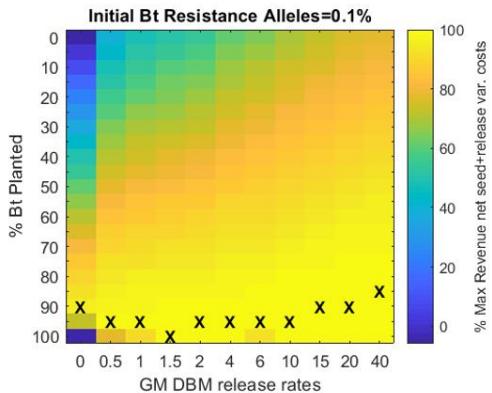
Note: Bt resistance fitness costs assumed static and taken from empirical estimates: 0.035 (Yi *et al.*, 2015) and 0.417 (Groeters *et al.*, 1994). Increased fitness costs for Bt resistance allow for higher proportions of Bt planted area (i.e. lower refuge), though this impact is most pronounced at lower GM-DM release levels. Leakiness of GM system (transgenic female survivorship) = 1%; RIDL fitness cost = 0.523.

Bt resistance fitness cost

0.035



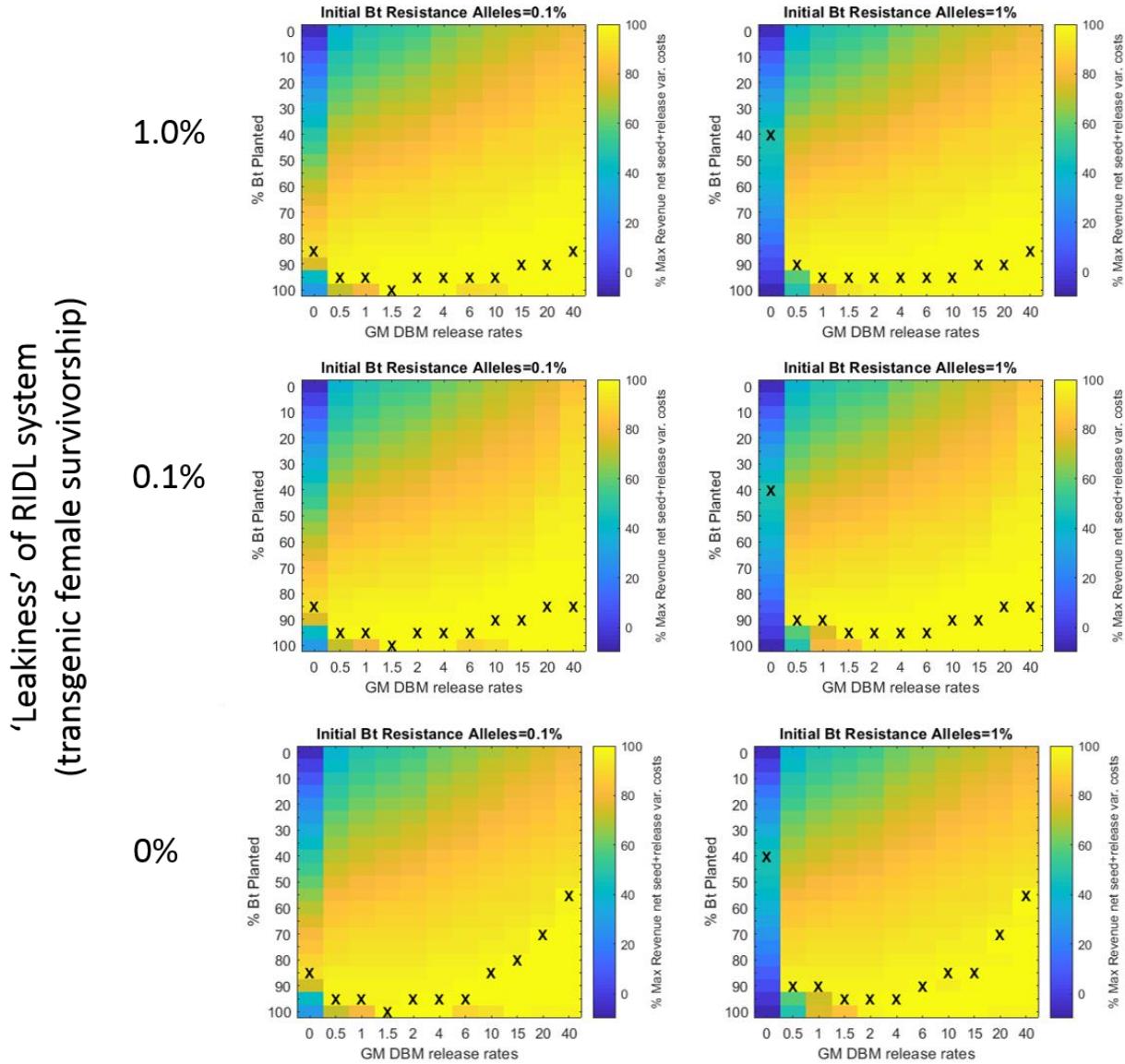
0.417



We extend our analysis to implications of lab-based improvements to the RIDL GM-DBM system in which the leakiness, or female survivorship, is reduced or eliminated. Reducing system leakiness impacts the system through two primary pathways, a) reduced juvenile populations overall, and b) reduced ‘need’ for Bt planted area to control the (susceptible) progeny of the transgenic survivors. Survival of transgenic females has become particularly controversial in RIDL transgenic mosquito release programs (Evans *et al.*, 2019), though to our knowledge we are the first to examine this factor in the context of resistance management efficiency. Interestingly, at lower release levels the system ‘leaks’ a relatively low number of survivors, and thus this factor appears to have very low qualitative impact on optimal Bt planting area. At high release rates, however, many progeny are created by a large number of surviving transgenic females. This subsequently requires more Bt planted area for effective control, and counteracts the substitutive properties of Bt and release inputs. Therefore, when leakiness is completely removed, the inputs are highly substitutive and it can be optimal to drastically reduce Bt usage.

Figure 4.10: Comparing NPV Net Revenues over leakiness of the RIDL GM-DBM system

Note: Reducing leakiness of the RIDL system provides more efficient population control and thus reduces the Bt planted area required to kill survivors. This effect is most prominent at higher release rates. RIDL fitness cost 0.523; Bt fitness cost 0.035.



4.8 Limitations of the model

Several further limitations of the model must be acknowledged. First, the model may best represent an environment with low seasonal population impacts. An environment such as New York would particularly require much more consideration of overwintering impacts on generation length, which we have not incorporated (Alphey, Bonsall and Alphey, 2009). Secondly, returns in this system are assumed to accrue continuously due to the continuously modeled nature of the population genetic system and transgenic insect releases. Revenues are more likely to be accrued discretely at the end of a growing season as the results of cumulative damage to plants (which could be more or less damaging at different growing stages), and thus our framing is likely conservative. Third, we assume a no-spray alternative to reduce the complexity of introducing additional substances for which resistance could be generated. No-spray refuge is a very common resistance management strategy to promote preservation of susceptibility alleles, and thus may be practical for this crop/pest example. Fourth, we assume the crop is only damaged by one species of insect, while *Brassica* crops are typically infested by several species (Orzolek *et al.*, 2012). Thus the model may not capture the residual value of Bt to control other species (which may or may not be as likely to develop resistance), as well as interspecies competition and predation.

Another important consideration is the static nature of Bt planting rates and GM-DBM release ratios. While release ratios are static, the absolute number released adjusts with the contemporaneous wild-type male population and provides more realism. However, adjusting Bt planting rates could add more nuance to the model and allow for an initial complementary input effect on juvenile population reductions and then a subsequent lower investment in premium Bt seed when the returns are lower. However, in practice, EPA-mandated Bt refuge policies are

largely static over time for consistency. Further, on the economics side, we assume equal output prices for Bt and non-Bt broccoli and no discounts for output grown in fields with GM-DBM presence, which may be optimistic given research on consumer preferences for ‘non-GMO’ products (e.g. Costa-Font, Gil and Traill (2008), McFadden and Lusk (2018)) and GM insect presence (Baltzegar *et al.*, 2018; Brown, Jones and Mumford, 2019; Jones *et al.*, 2019; Chapter 3 of this dissertation).

4.9 Discussion and conclusion

We have introduced a deterministic, continuous time model that combines a complex age and sex-specific biological model of transgenic insect releases into a transgenic crop system. We detail the population genetics of the system under key biological parameters of uncertainty. We then layer this biological model into an economic system of time-discounted returns of the crop system over long-term horizons to examine the trade-offs and dynamics of static policy rules for refuge requirements and transgenic insect release programs. Our primary results indicate dynamic conditions of input complementarity and substitutability, which are driven by the value of a) preserving susceptibility of Bt, and b) reducing juvenile populations. ‘Low’ releases of GM-DBM effectively expand optimal Bt planted area and increase overall economic returns in the system. However, depending on the initial resistance conditions in the population, ‘higher’ GM-DBM release rates may overwhelm the relative input contribution for population control and reduce optimal Bt planted area. Thus the validity of claims that releasing Bt-susceptible transgenic insects can ‘save’ Bt as an input or remove refuge requirements should be considered within the broader question of what input combination is economically efficient.

Biological factors both within and (largely) outside of control of technology developers impact the dynamics of these trade-offs. More recent estimates of Bt resistance fitness costs are much lower than earlier estimates and this factor is out of developer control and will vary in the field. The system is most sensitive to lower Bt fitness costs when GM-DBM releases are low, and this effect dissipates as higher ratios of transgenic insect releases overwhelm the fitness costs when reintroducing susceptibility. This will be an important factor to monitor as field tests progress, especially if lower release rates are ultimately targeted. Other factors such as RIDL GM-DBM ‘leakiness’ may be more within developer control and have the potential for dramatic impacts on the economic efficiency dynamics of the crop system at higher release rates. Continued attention to lab-based improvements in the female lethal system to ensure complete lethality in the transgenic insect strain may therefore be merited.

In practice, transgenic insect release decisions may possibly be made at the farm-level depending on the natural dispersion of the insect species, but broader historical trends suggest large, more efficient area-wide release programs (Brown, Jones and Mumford, 2019). Releases of any transgenic insects are inherently controversial and will likely face hurdles at the consumer, producer, policy maker, and regulator levels (NOFA-NY, 2017; Zhang, 2017; Baltzgar *et al.*, 2018). Larger release areas are increasingly more likely to incorporate farmers who both support and oppose area-wide releases, and there will likely be complex bargaining within farmer groups or associations to handle the mechanics of potential releases. Attention to impacts on proximate farmers who grow non-Bt host crops of diamondback moth and who may be in GM-DBM release environments will almost certainly be important in the political economy of these bargains. More advanced spatially explicit models with release diffusion, natural migration, and differentiated grower types will be necessary to illustrate these precise impacts.

Ultimately, the development of novel agricultural biotechnologies will continue to necessitate interdisciplinary lenses to dissect impacts within highly complex natural and social systems. The minimization of ‘unintended consequences’ from releases can thus be expanded beyond ecological concerns to impacting the relative marginal valuation of other production inputs. More research is needed to refine the input biological and economic parameters in this system and evaluate spatially explicit and migratory effects. Attention should also focus on developing a more advanced mathematical modeling approach to handle optimization under a highly multi-dimensional system (Cai, 2019).

Chapter 5: Do farmers with less education realize higher yield gains from GM maize in developing countries? Evidence from the Philippines

(with Roderick Rejesus and Jose M. Yorobe, Jr.)

5.1 Introduction

The impacts of genetically modified (GM) crop production in developing countries has attracted considerable attention from researchers and continues to fuel biotechnology policy debates worldwide (Qaim, 2009). Particularly important in this debate is how new crop varieties can contribute to global food security and raise small farmer yields and incomes. This debate is not new. During the Green Revolution, the ability of high yielding variety (HYV) crops to benefit the poor was hotly contested, with concerns about skewed technology diffusion (Feder and O'Mara, 1981), including access to complimentary physical inputs, credit constraints, and risk aversion (e.g. Smale, Heisey and Leath (1995), among many). Complex learning processes to fully capture HYV yield potential and rents may also lead to differential outcomes based on farmer characteristics (Foster and Rosenzweig, 1995; Alene and Manyong, 2007). The poorest and least educated farmers thus may have less impetus to adopt innovative crop varieties and, if adopting, could accrue disproportionately lower benefits from the technology.

However, the nature of the seed technology in question is of paramount importance when evaluating potential benefit streams that accrue to farmers with different levels of human capital. Genetic engineering advances have led to ‘bundled’ HYV seeds with both high quality germplasm and inherent insecticidal properties from genes coding for *Bacillus thurengiensis* (Bt) toxin expression. These Bt genes can have a particularly large impact on yields under the right conditions. While yield effects can be more muted in developed country settings with high pest

management ability (Shi, Chavas and Lauer, 2013), small developing country farmers – largely in tropical zones with high pest pressure – may reap particularly large benefits when insecticide use is low or sporadic (Qaim and Zilberman, 2003). Thus, the farmers who potentially stand to gain the most from a technology such as Bt seed are those with low or imprecise input use and limited knowledge or education. The primary beneficiaries of the new technology therefore may stand in direct contrast to those documented with many previous input innovations in agriculture.

Previous studies have examined yield, price, and market impacts GM maize adoption in South Africa (Gouse *et al.*, 2005, 2006), Argentina (Trigo and Cap, 2006), as well as the Philippines (Yorobe and Quicoy, 2006; Mutuc, Rejesus and Yorobe, 2011; Mutuc *et al.*, 2012; Sanglestsawai, Rejesus and Yorobe, 2014). However, the link between GM maize in developing country contexts and the role of education and human capital in exploiting potential production benefits has not been tested econometrically. This paper will address this question directly in the context of GM traits and maize yields of Filipino farmers. To address our empirical question, we utilize IFPRI panel data from 2007 and 2011 collected from yellow maize farmers in the provinces of Isabela and South Cotabato in the Philippines, with the panel structure allowing for more precise estimation of GM maize effects.

5.2 Background

5.2.1 Bt traits and Filipino maize production

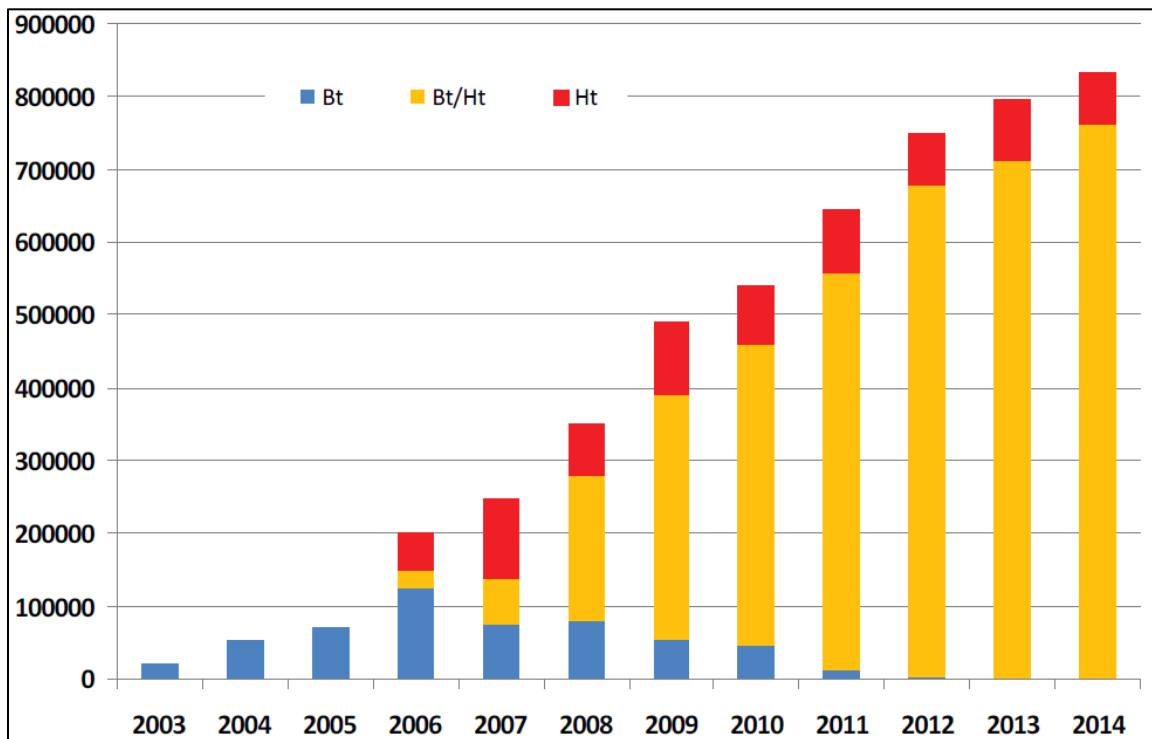
The Philippines is a tropical, lower-middle income country of 103M people with a gross national income per capita of \$3,580 USD (Bank, 2015). About one third of total employment is in agriculture and arable land per capita is estimated at 0.8 hectares (*ibid*). After rice, maize is the second largest crop in the Philippines and yellow maize is the most extensive type grown (PSA, 2015). In most regions there are at least two maize production seasons per year: one in the

wet season and one in the dry season. In Mindanao, the largest southern island, the major wet season growing period runs from April to September. In Isabela, the largest district of the northern island Luzon, there are two major growing seasons from mid-April to September and mid-November to March. The vast majority of the yellow maize grown in Mindanao and Isabela is sold to the feed market (Gerpacio *et al.*, 2004). While insecticide use is low, agricultural pest pressure is particularly high in these tropical latitudes and Asian maize borer infestations of 40-60% can lead to over 25% yield loss (Logroño, 1998). Farmers estimate much higher losses ranging from 30% to almost complete failure (Mutuc *et al.*, 2012).

Among developing countries, the Philippines has experienced particularly fast growth in GM maize adoption and acreage. By 2014, over 415,000 farmers had adopted GM maize, representing 31% of total maize acres and 63% of yellow maize acres (Aldemite, Villena and James, 2015; PSA, 2015). Figure 5.1 illustrates this growth of the single trait for Bt, single trait herbicide tolerance (HT), and a ‘stacked’ combination of Bt/HT traits, from national approval in 2002 until 2014. Introduced in 2006, Bt/HT stacked traits have gradually replaced single trait Bt varieties, while single trait HT maize production has remained relatively stable in absolute terms. It is important to note that in our data set, farmers are only planting single Bt trait and Bt/HT ‘stacked’ traits, so Bt is always a part of the seed by GM maize adopters.

Figure 5.1: GM maize Area (ha) by Variety in the Philippines, 2003-2014

Note: Bt=Bt insecticidal toxin gene; Ht=Roundup-Ready herbicide tolerance



Source: ISAAA 2014; Aldemite, Villena and James (2015)

In the Philippines, the vast majority of GM maize includes a Bt trait coding for the production of an insecticidal toxin. The Bt trait dramatically simplifies insect management, decreasing (but not fully removing) the need for complex and potentially dangerous insecticide application (Qaim and Zilberman, 2003). Poor, inexperienced, and uneducated farmers may be particularly vulnerable to insecticide misuse or poisoning, and adoption of Bt cotton has led to reductions in farmer poisoning in China (Hossain *et al.*, 2004) and South Africa (Bennett, Morse and Ismael, 2003). The intrinsic nature of the pesticidal properties of Bt maize may therefore reduce the burden of training and learning in a way which is distinct from past ‘modern’ inputs and HYV seed technologies. Importantly, the Bt trait in maize has been incorporated exclusively into hybrid varieties for both commercial and agronomic (hybrid vigor) reasons. A farmer facing

traditional (i.e. non-'improved') vs. Bt and stacked varieties would therefore face many of the same complexities of managing a hybrid maize production system, with potentially differing input responses.

5.2.2 Human Capital and Agricultural Productivity

Studies both inside and outside the context of agriculture have examined the role of knowledge in the adoption and benefits of new technologies. Extensive reviews have found that, especially in modernizing production environments with new inputs, human capital and education are important in leveraging potential improved input benefits and shifting the production frontier outward (Lockheed, Jamison and Lau, 1980). However, most previous studies examining the role of knowledge and education in agricultural productivity have centered on total productive efficiency, rather than the role in enhancing (or reducing) the marginal product of a physical input (see: Reimers and Klasen (2013) and references therein). The productive boost has been primarily attributed to the 'worker effect' and the 'allocative effect'. In these mechanisms, the 'worker effect' refers to more efficiency in (given) resource utilization and the 'allocative effect' refers to farmers being more adept at processing information about how to acquire and properly exploit an optimal sub-set of physical resources (Welch, 1970; Reimers and Klasen, 2013).

In the case of the complex processes behind production pest control, both are likely important. In short, production pest control is quite difficult. Effective pest control requires applying the right type of control (i.e. product) at the right time, in the right quantity. The diverse market for pesticides and the importance of optimal application timing, considering pest biology and environmental factors such as precipitation, make this crucial part of the production process

truly challenging. Formal education provides literacy and comfort with arithmetic and may enhance abilities to select proper products, filter recommendations from merchants and/or extension agents, and properly meter dosing. This may contribute to findings by Qaim (2003) that more educated farmers use less pesticide in cotton fields. Qaim claims these producers likely use products more selectively due to greater familiarity with available products and appropriate application schedules. Informal education can similarly improve practical knowledge of pest biology and infestation cycles, anticipating weather patterns, and familiarity with pest risk on one's own land. In a more recent study, both formal education and farming experience were shown to be important in objective measurements of farmer production 'pest knowledge' among Kenyan farmers (Abtew *et al.*, 2016). While extension training may contribute as a form of practical semi-formal education, Abtew *et al.* (2016) (perhaps somewhat surprisingly) did not find this to be a significant predictor of pest knowledge.

Previous authors have taken these arguments to posit that higher education levels may facilitate a greater increase in agricultural productivity in richer countries, where newer and likely more complex technologies are more present to disrupt traditional equilibria (Schultz, 1975). In describing new technologies, the terms 'traditional' and 'simple' tend to be grouped, whereas the concepts of 'new' and 'complicated' are lumped together (e.g. Reimers and Klasen (2013)). In the case of fertilizer-responsive hybrids, irrigation, and agricultural machinery this grouping of newness and complexity may apply. In contrast, biotechnology presents a different genre of potentially 'new' yet 'simpler' technologies where hybrids have already been adopted. The specific pesticidal genes inserted in Bt crops allow for continual expression of toxins, helping to (in part) automatically control some of the most challenging production pests. Significant reductions in pest spraying with Bt planting are widely documented in the developing

and developed country literature, as part of simplification of the pest control process (Kirsten and Gouse, 2003; Qaim, 2003; Barwale *et al.*, 2004; Gouse *et al.*, 2005, 2006).

The *ceterus paribus* removal, rather than addition, of complexity from these seed products challenges the notion that more educated or knowledgeable farmers are disproportionately more able to increase agricultural productivity with new technology. If more educated farmers are already outperforming their less educated counterparts in *status quo* pest control, biotechnological trait introductions may help ‘level the playing field’ by absorbing (i.e. substituting for) the previously documented resource allocation advantage.

5.3 Estimation Strategy

Our objective is to measure the impact of human capital and pest knowledge on yield gains from planting GM maize. We use years of formal education and maize farming experience as plausible and tested proxies for pest knowledge (Abtew *et al.*, 2016). Moock (1981) investigates an analogous factor input elasticity problem, interacting education, extension, and experience variables with physical input levels (e.g. fertilizer). Incorporating education and experience in a yield function, we begin with a simple Cobb-Douglas (CD) framework for estimation. In this system, outlined in equation 1, the yield (Y) of an individual i in time t is a function of j inputs X in per-hectare application values. The error term is broken into two components, an individual specific time invariant component c_i and a time varying random component u_{it} .

$$Y_{it} = \prod_{j=1}^J (X_{ijt}^{\beta_{jt}}) e^{c_i + u_{it}} \quad (1)$$

Non-agricultural input factors are routinely incorporated into yield functions and may or may not impact the elasticities (β_{jt}) of agricultural input factors. An exposition allowing the interaction between input factor elasticity and education is obtained in equation (2). For household i in time t , the elasticity of yield with respect to each input X_j would be $(\beta_{jt} + \delta_{jt} Educ_{it})$. Experience and extension contact can be similarly incorporated as an interaction term to examine both the role of informal and formal education. Time-varying non-agricultural input factors which may also impact yield are included in a vector \mathbf{Z} , including extension training, land quality, land size for scale effects (Barrett, Bellemare and Hou, 2010), and a subjective pest pressure coefficient for expected maize borer infestation level.

$$Y_{it} = \prod_{j=1}^J (X_{ijt}^{\beta_{jt} + \delta_{jt} Educ_{it}}) e^{\alpha + \gamma \mathbf{Z}_{it}} e^{c_i + u_{it}} \quad (2)$$

To investigate the effect on GM maize yields, an easily estimable regression structure is constructed by including a dummy for GM variety with the appropriate interaction terms and taking logs of yield and other physical inputs in equation (3).

$$\ln(Y_{it}) = \alpha + \varphi GM_{it} + \boldsymbol{\delta} Educ_i GM_{it} + \sum_{j=1}^J (\beta_{jt} \ln(X_{ijt})) + \gamma \mathbf{Z}_{it} + c_i + u_{it} \quad (3)$$

5.4 Identification Strategy

An ideal strategy to identify impacts of GM maize variety yield effects may generally be thought of as a randomized control trial (RCT) in which participants were randomly assigned an opportunity to plant seeds (Bulte *et al.*, 2014). However, the roll out of GM maize in the Philippines was already underway at the first panel wave in 2007 and a significant number of

producers had already adopted. The timing of survey waves and the very rapid uptake of GM varieties make this strategy extremely difficult in our context. Further, a ‘double-blind’ seed varietal experiment (such as Bulte *et al.* (2014)) could be misleading, as production input application will almost surely vary in response to farmers knowing the Bt or HT trait is present. Given the data at hand, we employ several strategies to control for endogeneity concerns with observational data.

Households may be heterogeneous in their ability and incentive to access and adopt GM seed, as well as in their access to information and extension education. These factors may be time invariant or time-varying in nature. Farmers may have heterogeneity unobserved by the econometrician in their information about the benefits of GM seed which could vary greatly over time, given the 250% expansion in production acres accompanied by likely increasing and heterogeneous learning between waves.

Therefore, we attempt to control for potential time-varying endogenous effects via a Control Function (CF) approach (Wooldridge, 2010), using the (time varying) distance to seed source and seed price as first-stage exogenous regressors to predict GM seed adoption via a reduced form Probit model. These instruments have been used in previous analyses with the first cross section of this data set to control for potential endogeneity of adoption (e.g. Yorobe and Smale, 2012; Sangestaswai, Rejesus and Yorobe, 2014). Seed price is a reasonable IV as price clearly influences adoption, yet competitive markets prevent any individual farmer from influencing it. Distance to seed source is also a reasonable IV, as this likely correlates with adoption but not production. Seed suppliers in the Philippines, particularly Monsanto, often offer delivery to the farm which may be particularly attractive for remote producers. This likely results in findings of past studies have shown more distant farmers are more likely to adopt GM

seed. A CF approach is required instead of a traditional IV approach, as the coefficients of interest are for an interaction between an endogenous variable and human capital proxies. In the CF approach, the generalized residuals from the first stage probit regression are included as a covariate in the second stage estimation. Significance of the residual in the yield regression model provides a test of and an appropriate controls for correlation between GM seed adoption and time-varying shocks.

5.5 Data

Data come from two waves of yellow maize producer surveys conducted by IFPRI. All farmers grew fewer than 5 hectares of maize on their main plot. Surveys were conducted for the 2006/2007 growing season and again for the 2010/2011 growing season. The two surveys provide a panel of 266 producers¹² in the South Cotabato province of the southern island Mindanao and in Isabela province on the northern island of Luzon. These zones represent the vast majority of the country's maize growing regions and hot-zones of early GM maize adoption, given extensive targeted private industry marketing. Within these provinces, seventeen major maize-producing villages were selected and yellow maize farmers were randomly sampled from a list, with farmer frequencies determined from a village fixed sampling fraction. We correct for potentially non-random attrition between survey waves using standard inverse probability weights (IPW) (Wooldridge, 2010). The procedure involves first using a probit to estimate whether observable factors from the first survey influenced inclusion in the second round, then obtaining these predicted probabilities. The IPW of an individual is thus $IPW = 1/Pr_{iWave2}$.

¹² Sample size varies at times due to occasional missing data for regression controls

To focus on the highest quality data, only estimates from a farmer's main maize plot (vs. including secondary plots) are reported.

We also include a term for subjective pest pressure. While insect pheromone trap counts are the gold standard in these measurements, the IFPRI data do not include these advanced and very expensive entomological data complements. However, producers were asked "Do you expect lower maize borer infestation this season?" We incorporate this subjective pest pressure insight as a binary measurement to control for environmental factors, taking the value of 1 if "lower" and 0 otherwise. The relative nature of this variable thus provides an imprecise, yet potentially useful component to control for infestation levels.

5.6 Results

5.6.1 Descriptive Results

Descriptive results from the two waves are displayed in Table 5.1. *Prima facie* evidence suggests that while yields were increasing overall between waves, average and median yields with GM seed are somewhat higher than hybrid seed. Plot size is generally small, with an average of about 1.3 hectares and a median of one hectare. The sample is predominantly male and about 78% in each year accessed credit markets in the last season. Notably, while over two-thirds of farmers expected lower maize borer infestation in the 2007 wave, this dropped to only 17% in 2011.

Table 5.1: Summary Statistics of Farmer Sample

Variable	2007		2011	
	mean	median	mean	median
Yield (main plot, kg/ha)	4,274	4,183	5,728	5,400
Hybrid seed planters (%)	0.45	-	0.10	-
GM seed planters (%)	0.55	-	0.90	-
Bt-only planters (%)	0.548	-	0.09	-
Bt/HT ‘stacked’ planters (%)	0.004	-	0.82	-
Insecticide applied (kg/ha)	0.39	-	0.13	-
Insecticide Use (%)	0.36	-	0.07	-
Herbicide applied (kg/ha)	1.11	1.00	2.83	2.00
Seed Vol. (kg/ha)	18.71	18.00	18.44	18.00
Fertilizer applied (50 kg bags/ha)	8.34	7.00	7.98	6.00
Labor (man-days/ha)	29.49	26.00	21.07	14.40
Seed Price (Php/kg)	255.71	255.56	413.96	444.44
Uses Irrigation (1-y,0-n)	0.06	-	0.08	-
Maize plot size (Main plot, ha)	1.04	1.00	1.06	1.00
Owner of Land (1-y, 0-n)	0.04	-	0.05	-
Years Farming Maize (#)	17.79	16.00	21.07	19.00
Household Size (#)	4.61	4.00	4.89	5.00
Borrowed Funds in last season (1-y,0-n)	0.78	1.00	0.77	1.00
Family Off-farm Income (pesos/yr)	3,269	-	4,642	1,500
Farmer Off-farm Income (pesos/yr)	834	-	2,140	-
Farmer Age in Years (#)	43.10	42.00	45.37	44.00
Sex of Farmer (1-male, 0-female)	0.90	1.00	0.90	1.00
Years of Education (#)	7.20	6.00	7.20	6.00
Received Extension Information (1-y,0-n)	0.44	-	0.29	-
Received Any Pest Training (1-y,0-n)	0.37	-	0.49	-
Expecting ‘Lower’ Maize Borer Infestation (1-y,0-n)	0.72	1.00	0.17	-
Distance to Seed Source (km)	6.58	2.00	6.69	4.00

Cross tabulations of mean yields by education and maize farming experience levels

(Table 5.2) provide initial evidence of heterogeneity in yield gains. Across both waves, farmers planting GM varieties have 38.3% higher yields, increasing from an average 4.0 t/ha to 5.4 t/ha. However, this yield advantage peaks at 74.7% among farmers with incomplete primary education (<6 years schooling), declining to 21.9% among those with post-primary studies (>6

years schooling). Similarly, the yield advantage declines from 49.6% for farmers with less than 10 years of maize farming experience to 27.6% for those with greater than 25 years of experience. Interestingly, the absolute yield trend appears to be somewhat increasing with education in hybrid producers but slightly decreasing in GM maize producers. The correlation coefficient between continuous years of education and main plot yield is -0.0002 ($p=0.997$). Separating by seed type, this coefficient is 0.2020 ($p=0.031$) for hybrid planters, and -0.0518 ($p=0.335$) for GM planters. The correlation coefficient between continuous years of farming experience and main plot yield is 0.0477 ($p=0.306$), splitting into 0.0648 ($p=0.494$) for hybrid and -0.0010 ($p=0.985$) for GM planters. However, given the potential presence of confounding factors we do not further interpret this unconditional relationship here. We instead focus on relative percentage yield gains in the following econometric analysis.

Table 5.2: Cross Tabulations of Yield (kg/ha) by Maize Type Planted and Education/Experience

Education Level	Hybrid	GM maize	Mean % Diff.	p-value
No primary (<6 years)	3,376 n=25	5,898 n=59	74.7%	<0.001
Primary (=6 years)	3,796 n=37	5,476 n=145	44.2%	<0.001
Post-Primary (>6 years)	4,388 n=52	5,349 n=144	21.9%	0.007
Total	3,974 n=114	5,494 n=348	38.3%	<0.001
Maize Farming Experience	Hybrid	GM maize	Mean % Diff.	p-value
<10 Years	4,089 n=24	6,117 n=49	49.6%	<0.001
10-25 Years	3,860 n=73	5,355 n=212	38.7%	<0.001
>25 Years	4,300 n=17	5,485 n=87	27.6%	0.057
Total	3,974 n=114	5,494 n=348	38.3%	<0.001

Note: p-values from two-sided mean difference t-tests of Hybrid and GM maize yield rows

5.6.2 Econometric Results

Fixed Effects Model with Control Function

Fixed Effects (FE) model results are presented to account for time-invariant unobservables. Under FE specifications, the first stage residual is highly significant, adding confidence to endogeneity of GM maize selection and justification for use of the control function. GM maize retains a positive, significant coefficient in each specification, with an average yield effect of 40.4% (95% CI: 12.4 – 68.4%; column 1). However, this average masks

significant heterogeneity. Education and Experience are interacted with GM planting in (2), then included in a full model (3) with additional pest extension training and plot size interactions. Formal education and farming experience are shown to be significantly negatively correlated with GM seed yield effects, adding credence to predictions of substitutability of knowledge inputs and intrinsic pesticidal properties in the seed. Each year of formal education and experience reduces the yield effect by about 6.7 and 1.6 percentage points, respectively. Extension pest training does not appear to be a significant factor influencing yield effect heterogeneity, though the sign is negative as expected. The size of farmers' maize plot, which has served as a primary point for heterogeneity analysis in GM yields in developing countries (e.g. Gouse, Kirsten and Jenkins, 2003; Gouse, Pray and Schimmelpfennig, 2004), is also insignificant. The positive coefficient may partially reflect that pest monitoring becomes increasingly difficult with land area.

To examine potential non-linearities in the effects of education and experience, we also group these terms into logical categorical levels in based on examination of variable kernel densities (available upon request), reporting estimates in column (4). The disparity in yield gains from GM maize is not statistically significant between those with incomplete and complete primary education (stopping at 6 years of education). However, there is a statistically significant 56.3% reduction in GM yield effects between farmers with post-primary (at least some secondary) education and those with incomplete primary. This seems to run contrary to findings by Asadullah and Rahman (2009), which suggest basic education is more important for agricultural productivity than higher education. Additionally, we find that, compared to farmers with less than 10 years of experience, those with 10-25 and greater than 25 years realize a 41.3% and 53.4% lower yield effect, respectively, from planting GM seed.

Per hectare labor hours and seed volume planted are also significant positive drivers of maize yields. In addition, we find further evidence for the inverse farm size-productivity theory, with yields decreasing with main plot size (controlling for a crude yet informative designation for ‘flat’ plots).

Table 5.3: FE-CF Model of Yield Effects

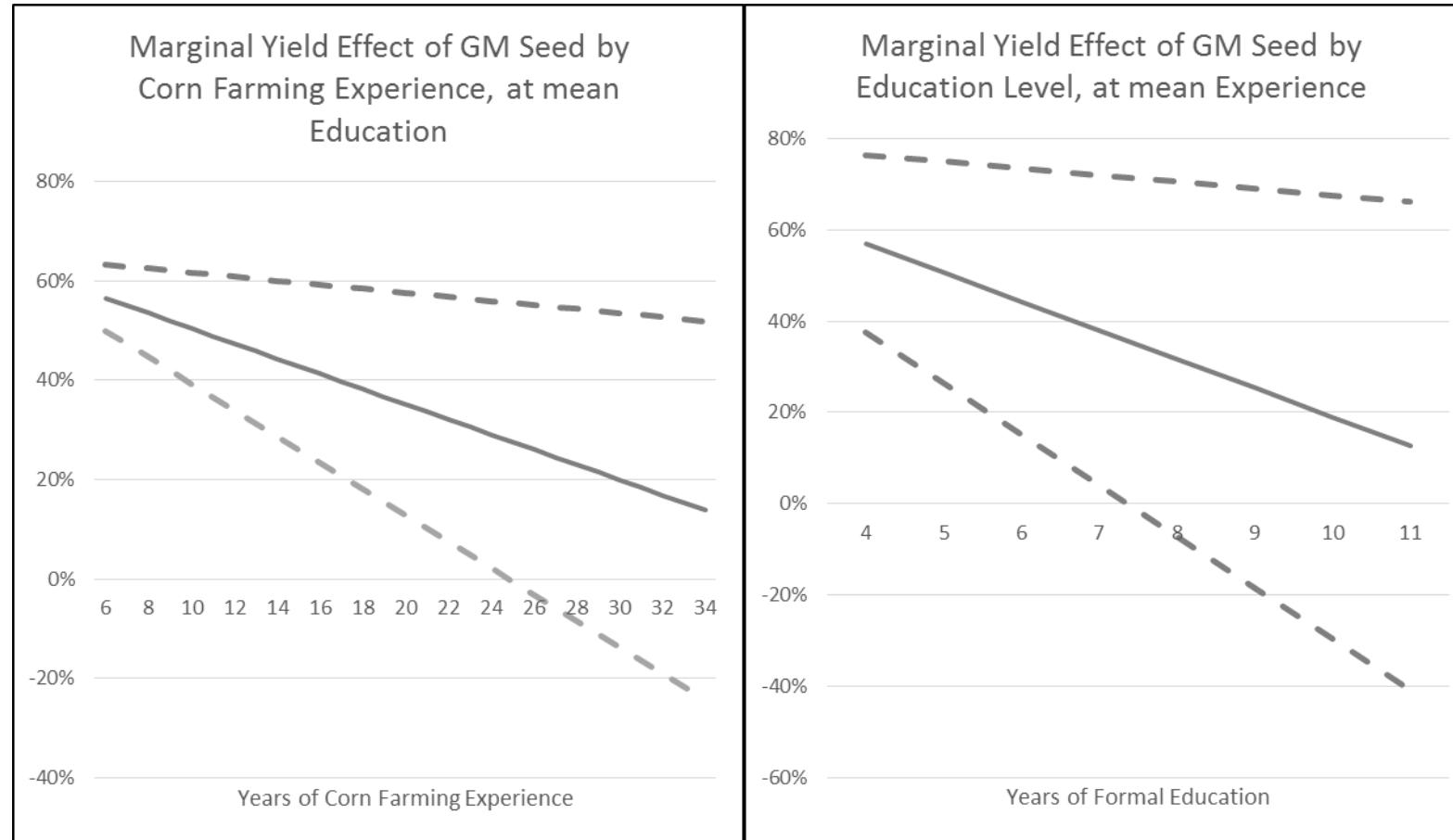
VARIABLES	(1) Log Yield	(2) Log Yield	(3) Log Yield	(4) Log Yield
Residual, first-stage	-0.217** (0.095)	-0.196** (0.097)	-0.204** (0.102)	-0.220** (0.104)
GM Seed (vs. Hybrid)	0.404*** (0.136)	1.113*** (0.244)	1.141*** (0.258)	1.125*** (0.267)
GM x Years of Educ. (linear)		-0.063** (0.025)	-0.067*** (0.025)	
GM x Complete Prim. Education (vs. Incomplete Prim.)				-0.290 (0.201)
GM x Post-Primary Education (vs. Incomplete Prim.)				-0.563*** (0.187)
GM x Years of Farming Exper. (linear)		-0.015*** (0.006)	-0.016*** (0.006)	
GM x 10-25 Yrs. Farm Exper. (vs. <10 Years Exper.)				-0.413*** (0.144)
GM x 10-25 Yrs. Farm Exper. (vs. <10 Years Exper.)				-0.534*** (0.172)
GM x Insecticide			0.014 (0.025)	0.016 (0.024)
GM x Pest Training (=1)			-0.028 (0.132)	-0.082 (0.131)
GM x Plot Size (ha)			0.085 (0.069)	0.119 (0.074)
Log Seed (kg/ha)	0.301*** (0.092)	0.269*** (0.092)	0.291*** (0.094)	0.290*** (0.093)
Log Fert. (kg/ha)	-0.019 (0.047)	-0.003 (0.046)	-0.003 (0.048)	0.008 (0.048)
Log Labor (days/ha)	0.152*** (0.041)	0.168*** (0.040)	0.164*** (0.042)	0.152*** (0.041)
Log Insecticide (kg/ha)	0.012 (0.015)	0.015 (0.015)	0.004 (0.018)	0.005 (0.018)
Log Herbicide (kg/ha)	-0.009 (0.011)	-0.008 (0.010)	-0.010 (0.010)	-0.011 (0.010)
(Lower) Maize Borer	0.035	0.013	-0.028	-0.020
Expectation (=1)	(0.086)	(0.081)	(0.091)	(0.091)
Year 2007 (=1)	-0.327*** (0.094)	-0.376*** (0.093)	-0.346*** (0.096)	-0.320*** (0.098)
Plot Size (ha)	-0.143*** (0.052)	-0.187*** (0.056)	-0.232*** (0.063)	-0.229*** (0.058)
Flat Plot (=1)	0.168** (0.075)	0.146* (0.075)	0.150** (0.076)	0.143* (0.075)
Pest Training (=1)	0.002 (0.070)	-0.006 (0.068)	0.024 (0.122)	0.070 (0.120)
Observations	462	462	462	462
R-squared	0.407	0.435	0.440	0.455

Note: *, **, *** denote significance at the 90, 95, and 99% confidence levels. Standard errors (in parentheses) are clustered at the household level.

Figure 5.2 presents this yield heterogeneity graphically, with the 95% confidence band for education and experience interaction term estimates (Table 5.3, column 2). The effect is evaluated at the mean base GM seed coefficient and mean education and experience, constrained to the education and experience range with sufficient data points. At the mean education level of 7.2 years (primary completion occurs at 6 years), the model estimates a mean yield effect of 58% for farmers with only 6 years of experience, declining to about 30% for farmers with 25 years of experience. At the mean experience level (21 years), we estimate a mean yield effect of 59% for those with only 4 years of formal education. At 10 years of education, or completion of secondary school, the yield effect declines towards 20%.

Figure 5.2: Education and Experience Effects on Yield Gains from GM maize

Note: 95% CI bands represent confidence intervals of Table 2, column 2 GM Seed interaction terms with experience and education, respectively.



5.6 Robustness Check: Damage Abatement Framework

The damage abatement specification has received increased support as an estimation framework for inputs which ‘abate’ damage from insects, rather than contribute to an increase in potential yield (Lichtenberg and Zilberman, 1986). We therefore estimate a first-differenced (FD) non-linear least squares model within a logistic specification for a damage abatement framework¹³.

The specification is structured as follows:

$$\begin{aligned} \Delta \ln Y_i = & \Delta \ln X_{1i} \beta + \Delta Z_i \gamma + \Delta resGMhat_i \zeta \\ & - (\ln(1 + \exp(-X_{2i_{t=1}} \varphi - GM_{i_{t=1}} \lambda - (GM_{i_{t=1}} * K_{i_{t=1}}) \xi)) \\ & - \ln(1 + \exp(-X_{2i_{t=0}} \varphi - GM_{i_{t=0}} \lambda - (GM_{i_{t=0}} * K_{i_{t=0}}) \xi))) \end{aligned}$$

where X_1 is a vector of potential-yield increasing inputs, $resGMhat$ is the control function residual from the first-stage estimate, X_2 is a vector of insecticide and herbicide use, and K is a vector of variables impacting the marginal yield effect of GM seed. The parameters of interest are λ and ξ . Starting values of the nonlinear model are drawn from linear model estimates.

Results are qualitatively consistent with CF-FE linear yield models, with education and maize farming experience reducing the yield effect of GM maize by about 5.5% and 1.2% per year, respectively. We note a decline in the base coefficient for GM maize (column 1) to a more

¹³ We also note that other functional forms for damage abatement specification were attempted (e.g. Guan, exponential), but they did not converge.

conservative 36.1% yield increase. This nearly mirrors the mean difference increase of 38% in descriptive statistics (Table 5.2).

Table 5.4 Nonlinear Least Squares Logistic Damage Abatement Models

	(1) FD Log Yield	(2) FD Log Yield	(3) FD Log Yield
Residual, first-stage	-0.196** (0.091)	-0.174* (0.092)	-0.188* (0.099)
Log Seed Vol. (kg/ha)	0.304*** (0.090)	0.274*** (0.091)	0.298*** (0.090)
Log Fert. (kg/ha)	-0.009 (0.046)	0.003 (0.044)	0.007 (0.046)
Log Labor (days/ha)	0.162*** (0.043)	0.176*** (0.041)	0.170*** (0.043)
(Lower) Borer Expectation	0.001 (0.091)	-0.017 (0.084)	-0.080 (0.088)
Main Plot Size	-0.124** (0.055)	-0.167* (0.060)	-0.180* (0.103)
Flat Plot (=1)	0.144* (0.075)	0.124* (0.074)	0.132* (0.0792)
Insecticide (kg/ha)	-0.024 (0.057)	-0.011 (0.055)	-0.103 (0.075)
Herbicide (ka/ha)	-0.022** (0.010)	-0.021** (0.010)	-0.024** (0.010)
GM seed (=1)	0.355*** (0.127)	1.023*** (0.241)	0.905*** (0.238)
GM seed x Education (years)		-0.058** (0.025)	-0.060** (0.025)
GM seed x Experience (years)		-0.015*** (0.006)	-0.016*** (0.005)
GM seed x Plot Size			0.103 (0.065)
GM seed x Pest Training			-0.017 (0.068)
GM seed x Insecticide			0.119 (0.107)
<i>N</i>	231	231	231
<i>Adj. R-sq</i>	0.220	0.254	0.268

Note: *, **, *** denote significance at the 90, 95, and 99% confidence levels.

5.7 Discussion and Conclusions

We began with the basic hypothesis that the simplifying intrinsic insecticidal properties of GM varieties, particularly Bt traits, may disproportionately benefit farmers with lower levels of education who may have greater challenges with the complexities of traditional pest management. Using tested proxies from the literature for pest knowledge, our analysis from a panel data set of Filipino maize farmers indicates that GM maize provides a greater yield boost for farmers with both lower formal education and practical maize farming experience. Neither pest training from extension staff nor plot size have a statistically significant interactive effect on GM yield advantages. The interactive effect of a year of formal schooling is about 3 times greater (per schooling year) than a year of maize farming experience. To the best of our knowledge, this is the first econometric evidence to support a link between GM Bt maize yield gains and human capital in developing countries.

This evidence suggests that GM varieties, and perhaps particularly Bt maize, may have particular promise in increasing yields in regions with lower human capital and pest knowledge. Developing countries with struggling rural education sectors, especially those in equatorial regions with severe pest pressure, may particularly benefit. As more countries throughout Asia and Africa consider the legalization and promotion of GM varieties, this evidence could provide an important dimension to consider in policy debates. This analysis has only compared hybrid non-GM varieties to their GM counterparts. If GM maize is only deployed via hybrid varieties, there may be competing effects of increasing complexity through hybrid varieties and decreasing complexity with GM traits. This may be fertile ground for more research in regions where traditional, hybrid, and GM varieties are simultaneously grown.

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APPENDICES

Appendix A: Supplementary Figures and Tables

Figure A.1: Best-Worst Scaling Question Example

Note: Question shown from Block 1, Item Subset 1. Set construction satisfied a Balanced Incomplete Block Design for 10 total items and were generated through SAS macro %mktbibd. Final full design contained 15 sets of 4 items each, optimally blocked into 3 groups of 5 sets per respondent.

Of the following options, which one do you feel is the most important and which one do you feel is the least important question to answer before deciding whether gene drive insects should be used to control pest damage to crops?

You may only select ONE 'most important' and ONE 'least important' question per section. (If you are on a mobile phone, you may want to turn your device horizontally if you have Autorotate turned on).

	Most Important	Least Important
If we remove an agricultural pest from an area, will another pest just take its place and cause similar crop damage?	<input type="radio"/>	<input type="radio"/>
Could the added genes in a gene drive insect spread to other species by accident?	<input type="radio"/>	<input type="radio"/>
If we remove an agricultural pest completely from an area, what could happen in the environment?	<input type="radio"/>	<input type="radio"/>
Who will regulate gene drives for agricultural pests - for example, approving field trials or environmental releases?	<input type="radio"/>	<input type="radio"/>

Figure A.2 Choice scenario examples: Fresh Blueberries & Orange Juice

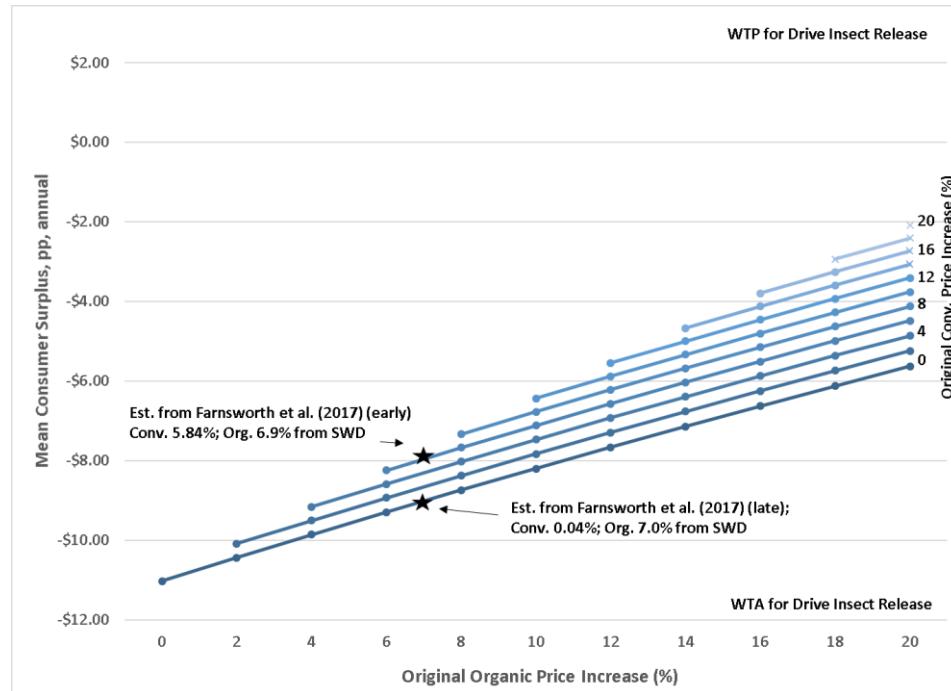
	<u>Option A</u>	<u>Option B</u>	<u>Option C</u>
			
Pest Control	Conventional insecticides applied every five days when fruit is ripe		
Plant Type	The plant is <u>not</u> genetically modified	The plant is <u>not</u> genetically modified	
Gene Drive Insects	Gene drive insects <u>were</u> present in the area to control pest damage	Gene drive insects <u>were</u> present in the area to control pest damage	I would not purchase either one of these products
Price	\$1.06/pint	\$2.12/pint	

	<u>Option A</u>	<u>Option B</u>	<u>Option C</u>
			
Insecticide Use	Conventional insecticides applied in the field 1-2 times per year		
Plant Type	The plant and fruit are <u>not</u> genetically modified	The plant and fruit are <u>not</u> genetically modified	
Gene Drive Insects	No gene drive insects were present in the growing area	Gene drive insects <u>were</u> present in the area to control pest damage	I would not purchase either one of these products
Price	\$4.07/half-gallon	\$5.21/half-gallon	

Figure A.3: Mean consumer surplus from uncontrolled drive insect releases that reduce pesticides and prices, across a range of original pest-induced price increases for conventional and organic goods

Higher original price impacts from pests lead to greater price reductions and thus higher surplus from drive insect releases. Original organic price impacts may exceed conventional prices. HB MXL model, corr. random coefficients, price as log-normal random. Cross-hair markers denote estimates containing zero in 90% CIs. Blueberry empirical points proxied by CA raspberry estimates from Farnsworth et al. (2017). OJ empirical point proxied by FL orange field box prices from Moss et al. (2014).

Fresh Blueberries



Orange Juice

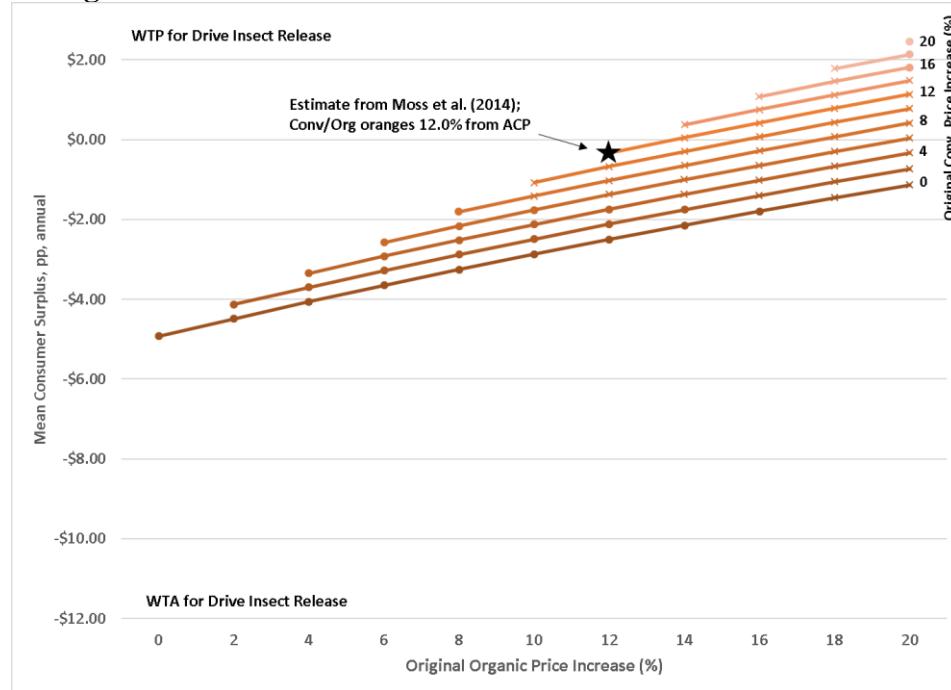
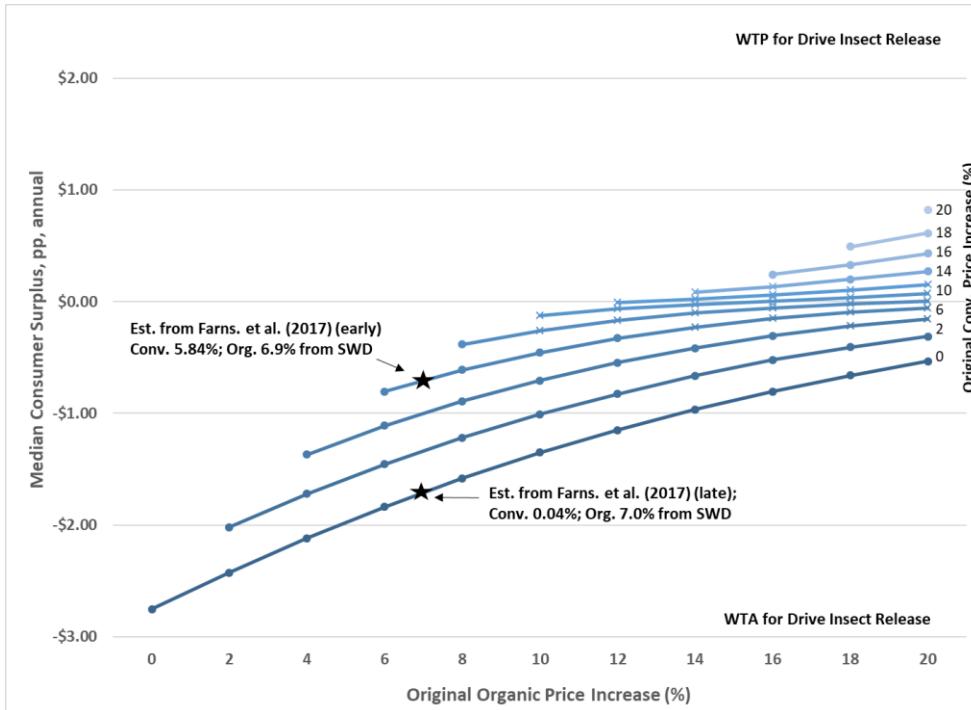


Figure A.4: Median consumer surplus from uncontrolled drive insect releases that reduce pesticides and prices, across range of original pest-induced price increases for conventional and organic goods

Higher original price impacts from pests lead to greater price reductions and thus higher surplus from drive insect releases. Original organic price impacts may exceed conventional prices. HB MXL model, corr. random coefficients, price as log-normal random. Cross-hair markers denote estimates containing zero in 90% CIs. Blueberry empirical points proxied by CA raspberry estimates from Farnsworth et al. (2017). OJ empirical point proxied by FL orange field box prices from Moss et al. (2014).

Fresh Blueberries



Orange Juice

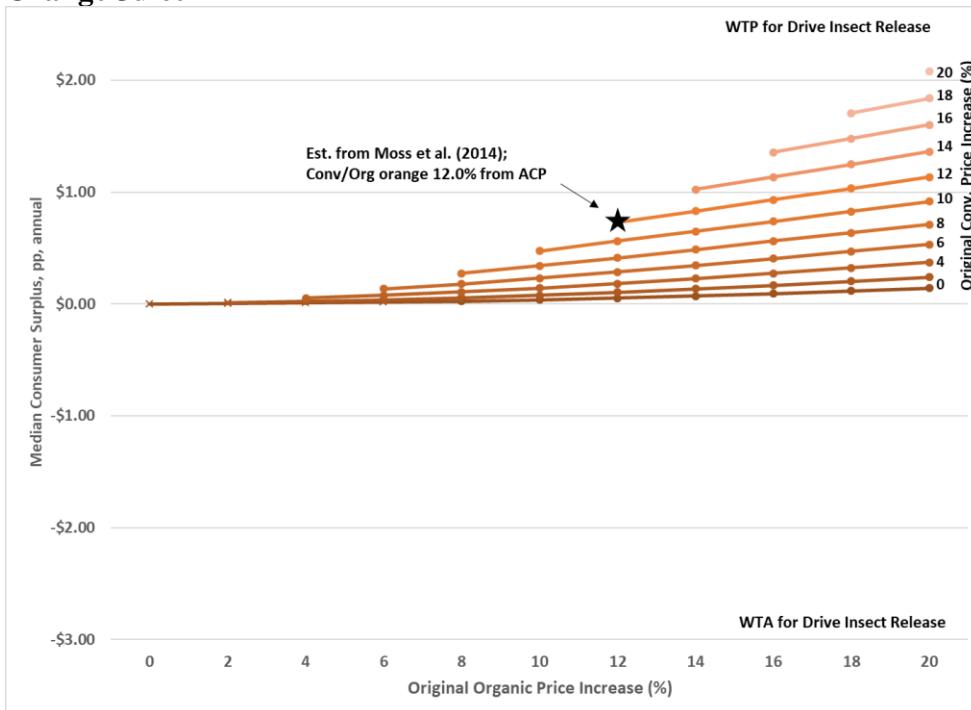
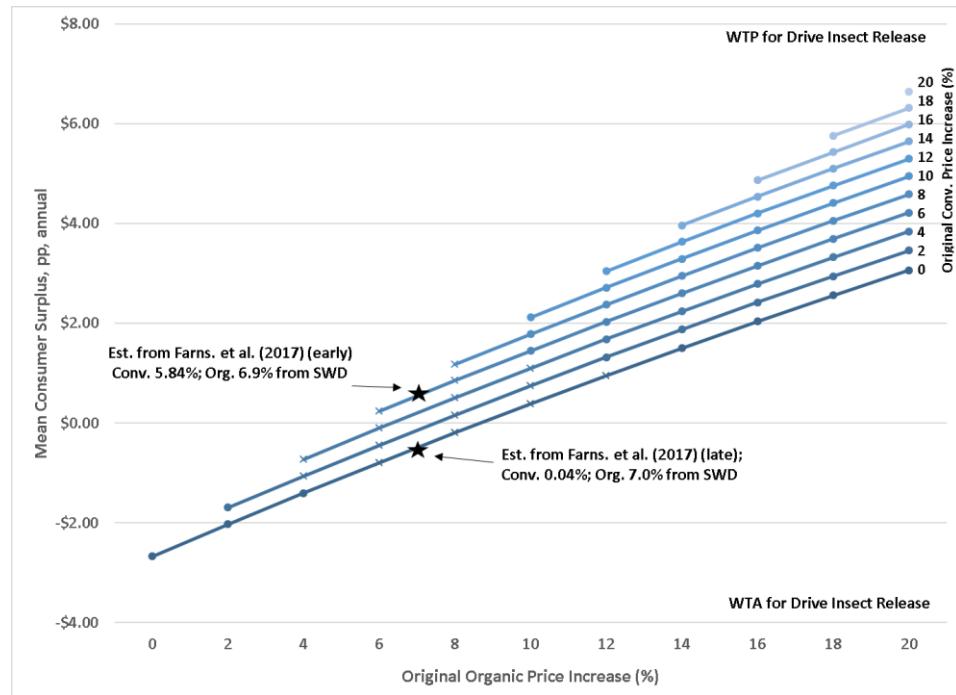


Figure A.5: HB MXL, with correlated random coefficients and price modeled as fixed/non-random, mean consumer surplus from uncontrolled drive insect releases

Higher original price impacts from invasive pests lead to greater reduction in prices and thus greater welfare benefit from drive insect releases. Cross-hair markers denote estimates containing zero in 90% CIs. Blueberry empirical estimates are proxied by California raspberry estimates from Farnsworth et al. (2017). Orange juice empirical estimates are proxied by Florida orange field box prices from Moss et al. (2014).

Fresh Blueberries



Orange Juice

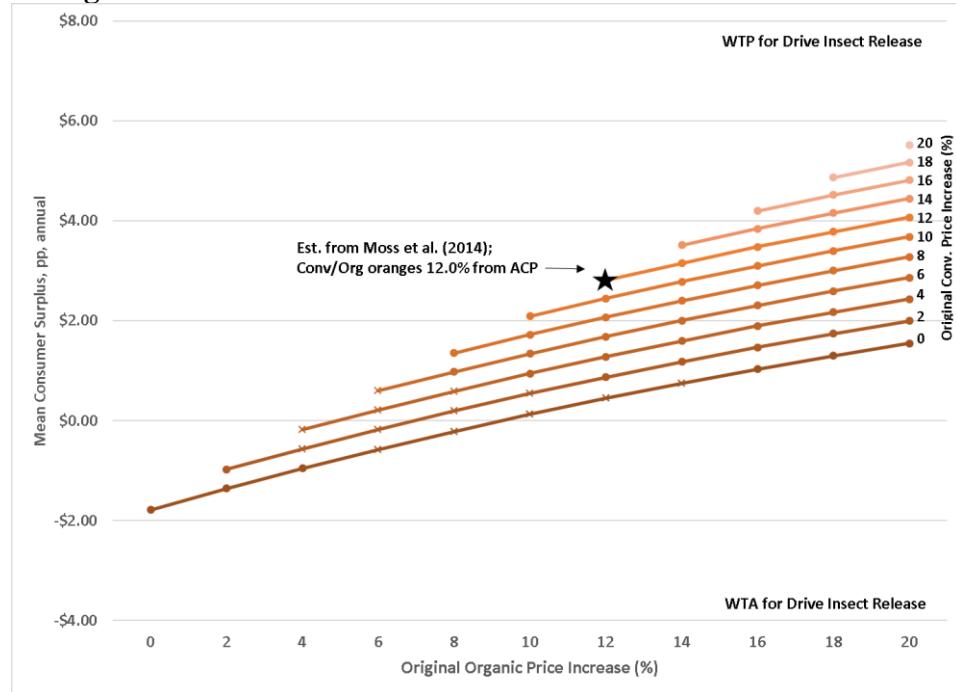


Figure A.6: Juvenile population size under various constant release ratio scenarios (High Bt fitness cost = 0.417)

Note: *left*: GM-DBM releases on non-Bt crops, *middle*: GM-DBM releases on Bt crops (20% refuge), *right*: releases on 10% refuge, *top*: Very low release ratios of GM-DBM to wild-type males (0.5:1), *middle*: Low release ratios of GM-DBM (3:1), *bottom*: High release ratios of GM-DBM (40:1).

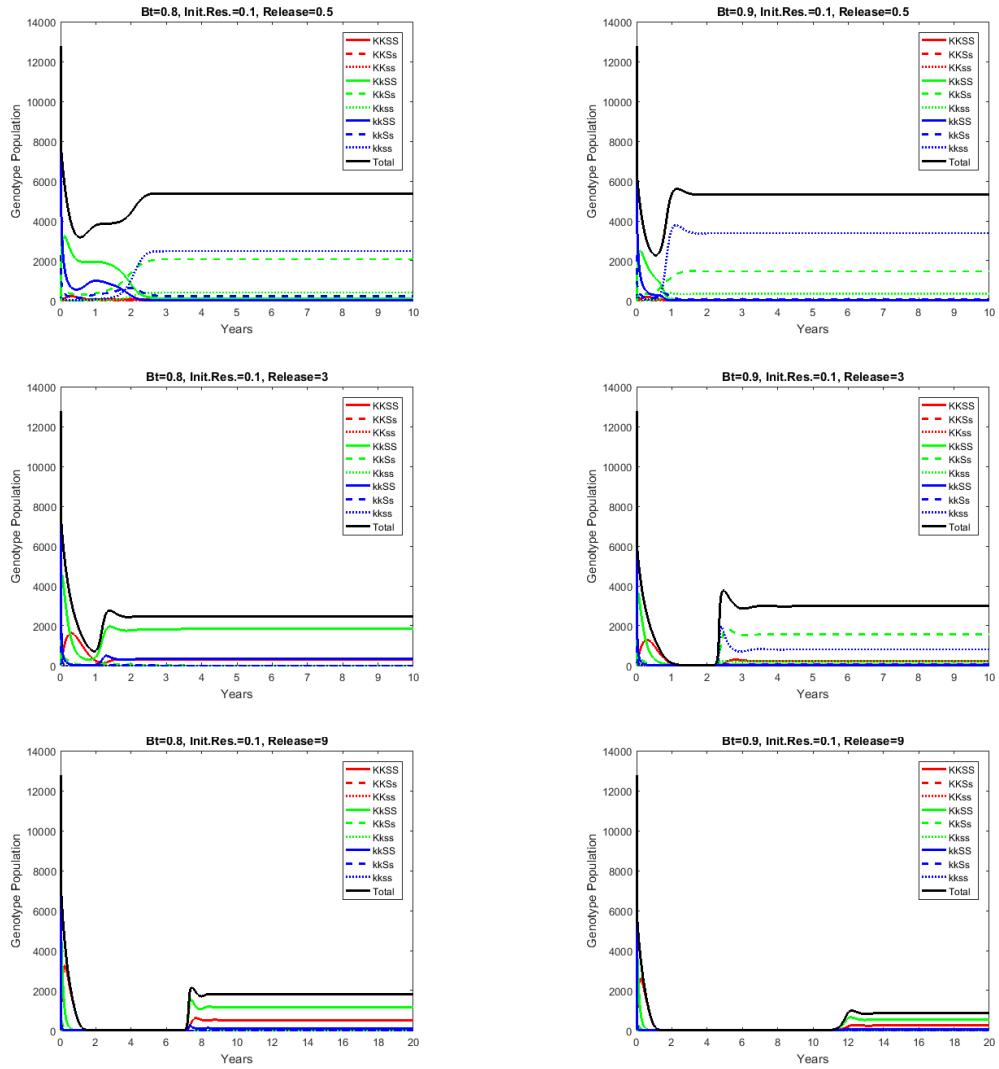


Figure A.7: Population genetics when varying density dependence parameter β

Note: Percent of the initial juvenile population remaining at $t=50$ under varying β parameterizations for density dependence. When the β parameter changes, the (starting) equilibrium populations change, so we include a normalized percent change in the juvenile population from $t=0$ to $t=50$. This is meant to emulate explorations in (Robert *et al.*, 2013) framing shifts as ‘relative’ population changes. Mathematically, a lower β value will result in a lower terminal population, as β controls the pull of a perturbed system towards an initial equilibrium. A value of 2 cancels out the term, as the exponent is constructed as $(J)^{[\beta-1]}$. We follow Robert *et al.* by setting the β parameter at 3.4.

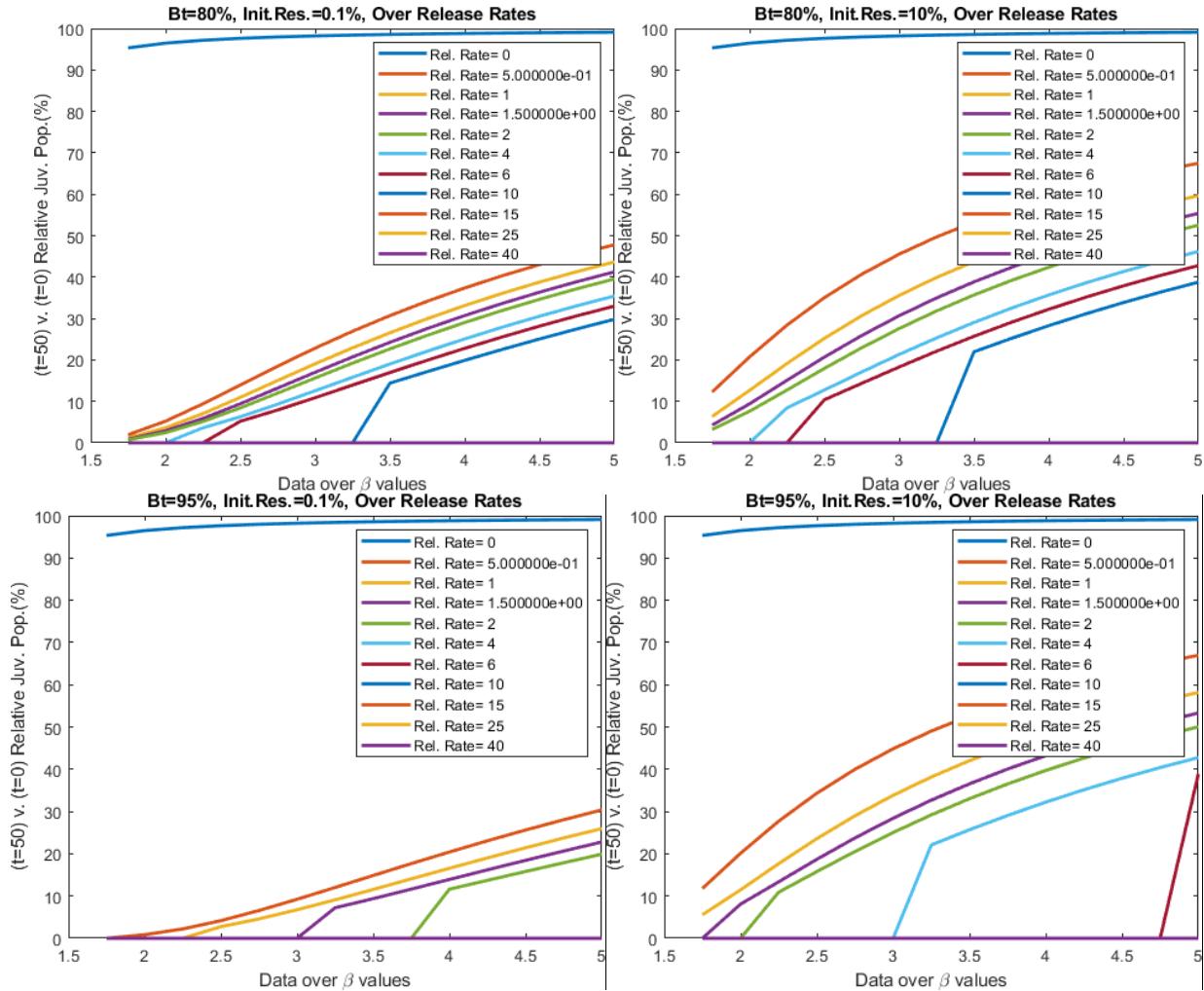


Table A.1 Agricultural Gene Drive Survey, Sample Characteristics

N=1,018 completes	% Qualified Completes	% After Weighting to Sample Frame
Age Categories		
- 18-29	12.48	21.07
- 30-44	24.95	24.92
- 45-59	28.39	26.01
- 60+	34.18	28.00
Sex		
- Male	52.26	48.24
- Female	47.74	51.76
Education		
- <High School	7.07	11.08
- High School	25.25	28.93
- Some College	29.08	28.55
- Bachelor	21.02	17.77
- Masters	13.75	10.78
- PhD	3.83	2.89
Household Income		
- < 25,000	11.00	15.06
- 25k to <50,000	18.37	19.82
- 50k to <75,000	15.80	17.31
- >75k	47.45	47.81
Race/Ethnicity		
- White, Non-Hisp	72.89	64.03
- Black, Non-Hisp	7.47	11.79
- Other, Non-Hisp	4.91	6.96
- Hispanic	12.38	15.92
- 2+ Races, Non-H	2.36	1.30

Note: Sample weights provided by GfK and constructed according to procedure outlined in Methods.

Table A.2: Raw Data from General Likert responses

<u>Item Response %, fully disaggregated</u>								
% Resp.	Replacement				Suppression			
	Controls for Spread		No controls		Controls for Spread		No controls	
	Non-native	Native	Non-native	Native	Non-native	Native	Non-native	Native
Str. Opp.	6.59	9.16	12.71	17.38	6.22	9.83	13.20	21.30
Oppose	9.32	12.97	21.17	24.39	8.05	14.97	20.37	24.86
Neither Support or Oppose	22.20	25.54	23.40	27.11	21.19	27.80	29.11	27.38
Support	32.40	33.66	23.58	19.32	34.88	31.22	21.42	16.66
Str. Supp.	25.00	13.79	13.45	6.53	25.70	12.02	11.47	5.38
Don't Know	4.49	4.87	5.69	5.26	3.95	4.17	4.43	4.42
n=	1,016	1,017	1,017	1,016	1,017	1,017	1,017	1,016
<u>Item Response %, with 3-category aggregation [Fig 1a data]</u>								
% Resp.	Replacement				Suppression			
	Controls for Spread		No controls		Controls for Spread		No controls	
	Non-native	Native	Non-native	Native	Non-native	Native	Non-native	Native
Oppose	15.91	22.13	33.88	41.77	14.27	24.79	33.57	46.16
Neither	26.69	30.42	29.09	32.37	25.14	31.97	33.54	31.80
Support	57.40	47.45	37.03	25.86	60.59	43.23	32.89	22.04
n=	1,016	1,017	1,017	1,016	1,017	1,017	1,017	1,016

Note: Percentage estimates with survey weights; Aggregation groups: ['Strongly Oppose' + 'Oppose'], ['Neither Support or Oppose' + 'Don't Know'], and ['Agree' + 'Strongly Agree'].

Table A.3: Regression Analysis of General Gene Drive Likert Responses, Three-level Likert Aggregation, PPO Ordered Logit Model

Partial Proportional Odds Ordered Logit for Drive Attributes: Three-Level Aggregated Likert Model

VARIABLES	Base Attributes		+ 2-way Interactions		Average Marginal Effects (AME) Predicting Outcomes [Model 1: 3-level base attributes]		
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(3c)
	Support or Neither v. Oppose	Support v. Neither or Oppose	Support or Neither v. Oppose	Support v. Neither or Oppose	AME Support	AME Neither	AME Oppose
No Controls for Spread	-0.980** (0.0505)	-	-1.023** (0.0752)	-0.889** (0.0667)	-0.221** (0.0104)	0.0304** (0.00496)	0.190** (0.00996)
Native Species	-0.512** (0.0435)	-	-0.447** (0.0572)	-	-0.115** (0.00962)	0.0159** (0.00286)	0.0994** (0.00848)
Suppression	-0.0825* (0.0321)	-	0.0844† (0.0466)	-	-0.0186* (0.00722)	0.00256* (0.00109)	0.0160* (0.00622)
Suppression x No Controls			-0.0665 (0.0599)	-0.191** (0.0660)			
Suppression x Native Species			-0.205** (0.0512)	-			
Native Species x No Controls			0.117* (0.0532)	0.00725 (0.0593)			
Constant	1.744** (0.0698)	0.388** (0.0676)	1.689** (0.0808)	0.321** (0.0702)			
Observations	8,133		8,133				
Wald Chi-sq	467.41		473.29				
(Prob > Chi-sq)	(<0.0001)		(<0.0001)				
Pseudo R-sq	0.0393		0.0401				

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, † p<0.1; Distinct coefficients in columns 1a & 1b or 2a & 2b indicate failure of the proportional odds (or parallel trend) hypothesis via a Wald test at the 0.05 significance levels. Evaluated via *gologit2* command in Stata.

Likert responses stacked by respondent; standard errors clustered at respondent level

Wald test - all 2-way interactions: p<0.0001, 3-way interaction (not included): p=0.0658.

Table A.4: Regression Analysis of General Gene Drive Likert Responses, Five-level Likert Aggregation, PPO Ordered Logit Model

Five-level Likert Scale

VARIABLES	Base Attributes				+ 2-way Interactions			
	(1a) SS,S,N, or O v. SO	(1b) SS,S, or N v. O or SO	(1c) SS, or S v. N,O, or SO	(1d) SS v. S,N,O, or SO	(2a) SS,S,N, or O v. SO	(2b) SS,S, or N v. O or SO	(2c) SS, or S v. N,O, or SO	(2d) SS v. S,N,O, or SO
No Controls for Spread	-0.808** (0.0785)	-0.991** (0.0578)	-0.975** (0.0526)	-0.862** (0.0758)	-0.770** (0.0919)	-0.953** (0.0733)	-0.936** (0.0646)	-0.819** (0.0801)
Native Species	-0.458** (0.0613)	-0.479** (0.0488)	-0.541** (0.0465)	-0.822** (0.0748)	-0.389** (0.0771)	-0.410** (0.0638)	-0.469** (0.0567)	-0.747** (0.0774)
Suppression	-	-	-	-	0.0592 (0.0436)	-	-	-
Suppression x No Controls	0.0906** (0.0306)				-0.118* (0.0523)	-	-	-
Suppression x Native Species					-0.181** (0.0459)	-	-	-
Native Species x No Controls					0.0379 (0.0493)	-	-	-
Constant	2.747** (0.123)	1.736** (0.0800)	0.404** (0.0657)	-1.039** (0.0699)	2.685** (0.126)	1.673** (0.0849)	0.338** (0.0693)	-1.107** (0.0717)
Observations	8,133				8,133			
Wald Chi-sq	527.30				545.03			
(Prob > Chi-sq)	(p<0.0001)				(p<0.0001)			
Pseudo R-sq	0.0308				0.0311			

Note: SS: Strongly Support, S: Support, N: Neither (or Don't Know), O: Oppose, SO: Strongly Oppose; Robust standard errors in parentheses; *** p<0.01, ** p<0.05, † p<0.1; Distinct coefficients in columns a,b,c or d indicate failure of the proportional odds (or parallel trend) hypothesis via a Wald test at the 0.05 significance levels. Evaluated via *gologit2* command in Stata. Likert responses stacked by respondent; standard errors clustered at respondent level. Wald test - all 2-way interactions: p=0.0001, 3-way interaction (not included): p=0.0762.

Table A.5: Demographic and Consumption Correlates with number of FAQs selected

VARIABLES	(1) OLS - base	(2) OLS – full	(3) Tobit - base	(4) Tobit - full
female	0.560** (0.142)	0.427** (0.149)	0.745** (0.184)	0.568** (0.193)
age	0.00245 (0.00426)	0.00294 (0.00435)	0.00343 (0.00535)	0.00413 (0.00548)
white	-0.569** (0.158)	-0.565** (0.158)	-0.824** (0.205)	-0.810** (0.206)
Income	0.0241 (0.0185)	0.0146 (0.0184)	0.0290 (0.0236)	0.0165 (0.0238)
Some college	0.438* (0.182)	0.344† (0.182)	0.565* (0.235)	0.441† (0.235)
(v. no college)				
Bachelor's	0.662** (0.210)	0.525* (0.211)	0.834** (0.267)	0.651* (0.267)
Degree (v. no college)				
Graduate	0.520* (0.223)	0.315 (0.228)	0.637* (0.287)	0.370 (0.293)
Degree (v. no college)				
Religiosity Scale	0.0175 (0.0203)	0.0170 (0.0202)	0.0198 (0.0262)	0.0200 (0.0262)
HH buys blueberries		0.269† (0.155)		0.362† (0.201)
HH buys O.J.		0.0620 (0.155)		0.0902 (0.199)
Primary Shopper		0.362* (0.176)		0.481* (0.229)
Buys 'local' foods		0.245† (0.147)		0.279 (0.185)
Buys 'USDA-organic' foods		0.399† (0.208)		0.572* (0.262)
Buys 'non-GMO' foods		0.268 (0.197)		0.290 (0.251)
Constant	2.364** (0.356)	1.884** (0.377)	2.229** (0.449)	1.591** (0.477)
Observations	1,013	1,001	1,013	1,001
(Pseudo) R-squared	0.055	0.090	0.014	0.024

Note: Standard errors in parentheses; significance denoted ** p<0.01, * p<0.05, † p<0.1.

Observation disparities between parsimonious and full specifications due to item non-response.

Table A.6: Tests for combining Suppression and Replacement in sub-group analysis

P-values for Adjusted Wald Tests for No Difference between Suppression v. Replacement Likert response, by Application Item and Sub-group (justifying combination in Figure 2).

Searching for non-GMO foods

	Controls, Non-Native	Controls, Native	No controls, non-native	No controls, native
Support	0.431	0.373	0.169	0.600
Oppose	0.654	0.679	0.961	0.546

Not searching for non-GMO foods

	Controls, Non-Native	Controls, Native	No controls, non-native	No controls, native
Support	0.257	0.128	0.187	0.070
Oppose	0.413	0.183	0.851	0.076

Table A.7: Ranking Most Important Gene Drive Questions

Question Abbreviation in this Text	Full Question Wording in Survey	% Time Selected		Best-Worst Scores†	Paired WLS Coeff. (st. err.)
		'Most Imp.'	'Least Imp.'		
Human Health Effects	Could gene drive agricultural pests impact human health?	56%	8%	0.9054	1.04*** ^a (0.0738)
Environmental Consequences of Pest Removal	If we remove an agricultural pest completely from an area, what could happen in the environment?	44%	11%	0.6579	0.881*** ^b (0.0746)
Secondary Pest Potential	If we remove an agricultural pest from an area, will another pest just take its place and cause similar crop damage?	26%	19%	0.1487	0.376*** ^c (0.0772)
Horizontal Gene Transfer Potential	Could the added genes in a gene drive insect spread to other species by accident?	25%	22%	0.0625	0.353*** ^c (0.0752)
Who Regulates Trials/Releases	Who will regulate gene drives for agricultural pests - for example, approving field trials or environmental releases?	26%	22%	0.0421	0.277*** ^{c,d} (0.0772)
Will the Drive Work Technically	Will the gene drive work? For example, will wild insects mate with gene drive insects and, if they mate, how efficiently will the gene drive continue to be inherited by the next generations?	19%	28%	-0.0508	0.169* ^d (0.0805)
Cost Effectiveness	Are gene drive agricultural pests cost effective - are the expected benefits greater than expected costs of development, regulation, release, and monitoring?	19%	24%	-0.1883	0 ^e [reference]

Ability to Reverse Genetic Changes	Could genetic changes caused by a gene drive be reversed?	15%	36%	-0.5208	-0.253**f (0.0781)
Food Taste/Appearance Change	Could a gene drive agricultural pest change the taste or appearance of food?	10%	40%	-0.4968	-0.320**f (0.0741)
Speed of Drive Spread	How quickly might gene drive insects spread after they are released?	10%	38%	-0.5600	-0.332**f (0.0768)
Constant					3.840** (0.0301)
Obs.					90
R-sq.					0.891

Note: †Best-Worst score = [% Time Selected ‘Most’ Important] – [% Time Selected ‘Least’ Important]. Computed at individual level and averaged across sample; includes survey weights. Weighted least squares model observations are $10*(10-1)=90$ best-worst pair possibilities. Letters in WLS rankings denote statistically equivalent items (Flynn et al., 2007¹⁷).

** p<0.01, * p<0.05, † p<0.1

Table A.8: Trust in Institutions to conduct research on gene drive agricultural pests

Note: Percentages calculated using survey weights. Response to this question was ‘requested’, not ‘forced’, so all 1,018 respondents did not answer every question. Presentation order randomized to avoid order effects. Question wording: “Different institutions may be involved in researching gene drives to control agricultural insect pests. In this section, please indicate how trustworthy you feel each type of institution would be **conducting research on gene drive insects to control agricultural pests.**” [emphasis in survey]

	U.S. University	U.S. Dept. Agriculture	Foreign University	U.S. Dept. of Defense	Small Private Company	Large Private Company
Not at all trustworthy	4.12%	4.88%	7.24%	15.07%	9.93%	17.92%
Somewhat not trustworthy	4.40%	9.87%	17.02%	17.75%	22.20%	28.08%
Neutral	29.36%	22.71%	41.65%	38.80%	43.63%	37.69%
Somewhat trustworthy	42.66%	42.04%	28.11%	21.90%	22.44%	14.83%
Very trustworthy	19.46%	20.50%	5.98%	6.47%	1.80%	1.48%
N	1,011	1,014	1,012	1,009	1,009	1,013

Table A.9: OLS Robustness Check for 3- and 5-level Gene Drive Attitude Likert Questions

VARIABLES	(1) 3-level	(2) 3-level	(3) 3-level	(4) 5-level	(5) 5-level	(6) 5-level
<i>Drive Attributes</i>						
No Controls for Spread (v. controls)	-0.423** (0.0216)	-0.425** (0.0217)	-0.429** (0.0219)	-0.604** (0.0298)	-0.607** (0.0299)	-0.612** (0.0302)
Native Species (v. non-native)	-0.216** (0.0186)	-0.220** (0.0185)	-0.220** (0.0187)	-0.358** (0.0270)	-0.364** (0.0267)	-0.366** (0.0270)
Suppression (v. replacement)	-0.0353** (0.0136)	-0.0355** (0.0136)	-0.0368** (0.0138)	-0.0575** (0.0197)	-0.0587** (0.0197)	-0.0625** (0.0199)
<i>Demographic Variables</i>						
Female		-0.0651† (0.0366)	-0.0769* (0.0379)		-0.108† (0.0562)	-0.120* (0.0570)
Age		0.000916 (0.00114)	0.000923 (0.00116)		0.00182 (0.00176)	0.00181 (0.00176)
White		-0.0199 (0.0411)	-0.0274 (0.0416)		-0.0460 (0.0622)	-0.0602 (0.0633)
Income		0.00733 (0.00470)	0.00641 (0.00498)		0.0131† (0.00710)	0.0124 (0.00753)
<i>Post-secondary education</i>						
No college (base level)	-	-	-	-	-	-
Some college		0.0585 (0.0481)	0.0546 (0.0481)		0.118 (0.0736)	0.113 (0.0730)
Undergraduate completed		-0.000110 (0.0568)	-0.00455 (0.0574)		-0.00146 (0.0858)	-0.00356 (0.0866)
Graduate completed		-0.0104 (0.0604)	-0.0107 (0.0614)		0.0220 (0.0916)	0.0306 (0.0929)
Religiosity Scale		0.00536 (0.00523)	0.00605 (0.00522)		0.00626 (0.00810)	0.00731 (0.00800)
Buys Blueberries			0.0862* (0.0408)			0.115† (0.0619)
Buys OJ			0.0791* (0.0386)			0.113† (0.0603)
Primary Shopper			0.0976* (0.0467)			0.144* (0.0721)
Buys 'local' foods			-0.0474 (0.0394)			-0.0817 (0.0596)
Buys 'USDA-organic' foods			-0.0456 (0.0504)			-0.0759 (0.0788)
Seeks out 'non-GMO' foods			-0.172** (0.0543)			-0.306** (0.0844)
Constant	2.455** (0.0247)	2.319** (0.0845)	2.225** (0.0934)	3.649** (0.0377)	3.410** (0.131)	3.291** (0.145)
Observations	8,133	8,093	7,997	8,133	8,093	7,997
Respondents	1,017	1,012	1,000	1,017	1,012	1,000
R-squared	0.083	0.090	0.107	0.085	0.095	0.117

Note: Robust standard errors in parentheses, clustered at respondent level; 3-level: [Strongly Support + Support], [Neither + DK], [Oppose + Strongly Oppose]; 5-level: Strongly Support, Support, [Neither + DK], Oppose, Strongly Oppose; ** p<0.01, * p<0.05, † p<0.1.

Table A.10 Hierarchical Bayes Mixed Logit Coefficients and WTP – Fixed Price Coefficient – Fresh Blueberries

Variables	<u>Coefficients</u>				<u>Willingness-to-Pay</u>	
	Without Interactions		With GD Interactions		Without Interactions	With GD Interactions
	Mean (SD)	Var (SD)	Mean (SD)	Var (SD)	Mean (SD) [95% CI]	Mean (SD) [95% CI]
GM Plant (v. not GM)	-1.067 (0.144)	4.191 (0.655)	-1.070 (0.145)	4.203 (0.657)	-1.171 (0.156) [-1.47, -0.87]	-1.178 (0.156) [-1.50, -0.89]
GD Insects (v. none)	-0.617 (0.102)	2.089 (0.332)	-0.551 (0.148)	2.085 (0.353)	-0.677 (0.111) [-0.91, -0.46]	-0.605 (0.158) [-0.91, -0.29]
Organic (v. Conv. High Spray)	1.834 (0.164)	7.225 (0.983)	1.882 (0.200)	7.323 (1.051)	2.012 (0.178) [1.68, 2.39]	2.072 (0.213) [1.66, 2.50]
Conv. Low Spray (v. Conv. High Spray)	0.693 (0.137)	3.175 (0.554)	0.746 (0.151)	3.197 (0.591)	0.761 (0.15) [0.47, 1.04]	0.821 (0.167) [0.50, 1.15]
Optout	-3.639 (0.224)	9.659 (1.403)	-3.608 (0.231)	9.841 (1.448)	-3.991 (0.204) [-4.39, -3.61]	-3.971 (0.205) [-4.37, -3.56]
Price	-0.912 (0.034)		-0.909 (0.038)			
GD Ins. X Organic			-0.091 (0.165)			-0.101 (0.183) [-0.44, 0.25]
GD Ins. X Conv. Low Spray			-0.116 (0.184)			-0.13 (0.204) [-0.55, 0.26]
Log-Lik	-3075.200		-3074.893			

Table A.11: Hierarchical Bayes Mixed Logit Coefficients and WTP – Fixed Price Coefficient – Orange Juice

Variables	Coefficients				Willingness-to-Pay	
	Without Interactions		With GD Interactions		Without Interactions	With GD Interactions
	Mean (SD)	Var (SD)	Mean (SD)	Var (SD)	Mean (SD) [95% CI]	Mean (SD) [95% CI]
GM Plant (v. not GM)	-1.018 (0.152)	5.153 (0.781)	-1.028 (0.151)	5.142 (0.788)	-0.908 (0.135) [-1.18, -0.65]	-0.913 (0.131) [-1.19, -0.67]
GD Insects (v. none)	-0.713 (0.106)	1.767 (0.315)	-0.556 (0.153)	1.793 (0.324)	-0.637 (0.096) [-0.82, -0.45]	-0.495 (0.137) [-0.75, -0.20]
Organic (v. Conv. High Spray)	1.812 (0.198)	8.842 (1.245)	1.903 (0.216)	8.894 (1.262)	1.617 (0.17) [1.28, 1.95]	1.691 (0.19) [1.30, 2.06]
Conv. Low Spray (v. Conv. High Spray)	1.289 (0.141)	3.42 (0.565)	1.395 (0.157)	3.359 (0.586)	1.151 (0.126) [0.92, 1.41]	1.24 (0.137) [0.97, 1.52]
Optout	-5.641 (0.308)	12.287 (1.622)	-5.589 (0.313)	12.285 (1.699)	-5.032 (0.196) [-5.43, -4.67]	-4.965 (0.194) [-5.38, -4.58]
Price	-1.121 (0.046)		-1.126 (0.047)			
GD Ins. X Organic			-0.175 (0.196)			-0.156 (0.175)
GD Ins. X Conv. Low Spray			-0.245 (0.162)			-0.217 (0.144) [-0.49, 0.05]
Log-Lik	-2851.04		-2849.6			

Table A.12: Classical MSL Logit - Fresh Blueberries - Preference Space Estimates

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Cond. Logit Base Coeff. (s.e.)	Cond. Logit Full Coeff. (s.e.)	MXL Uncorrelated Base Coeff. (s.e.)	MXL Uncorrelated Full Coeff. (s.e.)	MXL Correlated Base Coeff. (s.e.)	MXL Correlated Full Coeff. (s.e.)
Mean						
Price	-0.531*** (0.0245)	-0.521*** (0.0250)	-0.843*** (0.0291)	-0.850*** (0.0319)	-0.883*** (0.034)	-0.897*** (0.036)
Plant GM	-0.377*** (0.0692)	-0.376*** (0.0693)	-0.898*** (0.106)	-0.913*** (0.106)	-1.056*** (0.125)	-1.152*** (0.132)
GD Insects	-0.160*** (0.0492)	0.000229 (0.0700)	-0.467*** (0.0750)	-0.271** (0.116)	-0.612*** (0.094)	-0.568*** (0.137)
Organic (v. High Spray)	0.848*** (0.0833)	0.950*** (0.0972)	1.536*** (0.125)	1.626*** (0.150)	1.809*** (0.172)	1.934*** (0.186)
GD insects x Org.		-0.227*** (0.0831)		-0.369*** (0.143)		-0.132 (0.156)
Low Spray (v. High)	0.200*** (0.0720)	0.320*** (0.0791)	0.527*** (0.0972)	0.654*** (0.119)	0.701*** (0.143)	0.776*** (0.149)
GD insects x Low Spray		-0.257*** (0.0976)		-0.245 (0.168)		-0.092 (0.174)
Opt-out	-1.807*** (0.124)	-1.698*** (0.130)	-3.471*** (0.177)	-3.340*** (0.182)	-3.499*** (0.240)	-3.523*** (0.231)
SD¹						
Plant GM			1.395*** (0.124)	1.455*** (0.127)	1.969*** (0.156)	2.000*** (0.157)
GD Insects			0.870*** (0.124)	1.014*** (0.110)	0.593*** (0.130)	0.390*** (0.097)
Organic			1.769*** (0.138)	1.896*** (0.143)	2.365*** (0.241)	1.128*** (0.249)
Low Spray			-0.886*** (0.146)	1.166*** (0.146)	-0.349*** (0.382)	0.494*** (0.208)
Opt-out			2.553*** (0.155)	2.470*** (0.152)	1.997*** (0.321)	1.729*** (0.252)
Observations	12,339	12,339	12,339	12,339	12,339	12,339
LL	-3898	-3895	-3229	-3220	-3073	-3068

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table A.13: Classical MSL Logit – Fresh Blueberries – WTP Estimates

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Cond. Logit - Base	Cond. Logit – Full	MXL Uncorrelated Base	MXL Uncorrelated Full	MXL Correlated Base	MXL Correlated Full
Plant GM	-0.709*	-0.722*	-1.065*	-1.074*	-1.196*	-1.285*
(v. Non-GM)	[-0.971, -0.447]	[-0.990, -0.454]	[-1.305, -0.826]	[-1.314, -0.835]	[-1.471, -0.921]	[-1.571, -0.999]
GD Insects	-0.302*	0.0004	-0.554*	-0.319*	-0.693*	-0.634*
Present	[-0.488, -0.116]	[-0.263, 0.264]	[-0.724, -0.383]	[-0.582, -0.056]	[-0.900, -0.487]	[-0.922, -0.345]
(v. Absent)						
Organic	1.595*	1.823*	1.822*	1.914*	2.050*	2.157*
(v. High Spray)	[1.250, 1.941]	[1.412, 2.234]	[1.542, 2.102]	[1.575, 2.252]	[1.662, 2.436]	[1.754, 2.560]
Low Spray	0.377*	0.614*	0.625*	0.769*	0.794*	0.865*
(v. High)	[0.108, 0.647]	[0.304, 0.924]	[0.405, 0.846]	[0.492, 1.047]	[0.473, 1.116]	[0.531, 1.198]
GD Insects x		-0.436*		-0.434*		-0.148
Organic		[-0.756, -0.115]		[-0.765, -0.103]		[-0.489, 0.194]
GD insects x		-0.494*		-0.288		-0.103
Low Spray		[-0.874, -0.114]		[-0.682, 0.105]		[-0.486, 0.281]
Opt-out	-3.401*	-3.260*	-4.117*	-3.931*	-3.963*	-3.929*
	[-3.707, -3.094]	[-3.589, -2.931]	[-4.454, -3.779]	[-4.255, -3.607]	[-4.398, -3.528]	[-4.340, -3.518]

Note: 95% confidence intervals constructed by Delta method (Hole 2007)

Table A.14: Classical MSL Logit - Orange Juice – Preference Space Estimates

	(1) Cond. Logit Base Coeff. (s.e.)	(2) Cond. Logit Full Coeff. (s.e.)	(3) MXL Uncorrelated Base Coeff. (s.e.)	(4) MXL Uncorrelated Full Coeff. (s.e.)	(5) MXL Correlated Base Coeff. (s.e.)	(6) MXL Correlated Full Coeff. (s.e.)
Mean						
Price	-0.605*** (0.0313)	-0.607*** (0.0312)	-1.023*** (0.0399)	-1.026*** (0.0401)	-1.078*** (0.044)	-1.086*** (0.045)
Plant GM	-0.336*** (0.0710)	-0.336*** (0.0702)	-0.867*** (0.117)	-0.870*** (0.117)	-0.944*** (0.136)	-1.069*** (0.146)
GD Insects	-0.333*** (0.0547)	-0.252*** (0.0633)	-0.590*** (0.0788)	-0.477*** (0.124)	-0.628*** (0.094)	-0.473*** (0.144)
Organic (v. High Spray)	0.904*** (0.0908)	1.006*** (0.101)	1.555*** (0.133)	1.640*** (0.160)	1.674*** (0.180)	1.811*** (0.210)
GD insects x Org.		-0.204** (0.0905)		-0.170 (0.176)		-0.204 (0.195)
Low Spray (v. High)	0.558*** (0.0680)	0.569*** (0.0895)	0.980*** (0.0893)	1.036*** (0.109)	1.200*** (0.122)	1.345*** (0.143)
GD insects x Low Spray		-0.0515 (0.0898)		-0.151 (0.147)		-0.259 (0.158)
Opt-out	-2.804*** (0.175)	-2.785*** (0.179)	-5.421*** (0.252)	-5.396*** (0.253)	-5.515*** (0.290)	-5.561*** (0.300)
SD¹						
Plant GM			1.774*** (0.133)	1.765*** (0.133)	4.401*** (0.661)	4.735*** (0.743)
GD Insects			0.723*** (0.122)	0.729*** (0.123)	1.431*** (0.285)	1.310*** (0.270)
Organic			1.763*** (0.158)	1.755*** (0.159)	8.045*** (1.073)	8.497*** (1.126)
Low Spray			0.945*** (0.124)	0.940*** (0.124)	2.568*** (0.487)	2.614*** (0.465)
Opt-out			2.722*** (0.183)	2.724*** (0.183)	11.503*** (1.400)	12.025*** (1.480)
Observations	11,016	11,016	11,016	11,016	11,016	11,016
LL	-3668	-3667	-2996	-2995	-2856	-2862

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table A.15: Classical MSL Logit – Orange Juice - WTP Estimates

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Cond. Logit - Base	Cond. Logit – Full	MXL Uncorrelated Base	MXL Uncorrelated Full	MXL Correlated Base	MXL Correlated Full
Plant GM	-0.555*	-0.554*	-0.847*	-0.847*	-0.876*	-0.985*
(v. Non-GM)	[-0.788, -0.322]	[-0.784, -0.324]	[-1.065, -0.630]	[-1.063, -0.631]	[-1.118, -0.634]	[-1.238, -0.732]
GD Insects Present	-0.550*	-0.416*	-0.577*	-0.465*	-0.583*	-0.435*
(v. Absent)	[-0.738, -0.362]	[-0.625, -0.208]	[-0.730, -0.423]	[-0.703, -0.226]	[-0.757, -0.409]	[-0.697, -0.173]
Organic	1.494*	1.659*	1.520*	1.598*	1.553*	1.668*
(v. High Spray)	[1.177, 1.813]	[1.310, 2.008]	[1.283, 1.756]	[1.306, 1.889]	[1.237, 1.869]	[1.301, 2.035]
Low Spray	0.923*	0.937*	0.957*	1.009*	1.113*	1.239*
(v. High Spray)	[0.685, 1.162]	[0.629, 1.245]	[0.792, 1.122]	[0.812, 1.207]	[0.891, 1.335]	[0.984, 1.494]
GD Insects x		-0.336*		-0.165		-0.188
Organic		[-0.629, -0.044]		[-0.501, 0.170]		[-0.540, 0.164]
GD insects x		-0.085		-0.147		-0.238
Low Spray		[-0.376, 0.206]		[-0.427, 0.133]		[-0.522, 0.045]
Opt-out	-4.638*	-4.591*	-5.297*	-5.258*	-5.116*	-5.121*
	[-4.942, -4.334]	[-4.907, -4.276]	[-5.617, -4.977]	[-5.583, -4.932]	[-5.471, -4.761]	[-5.492, -4.749]

Note: 95% confidence intervals constructed by Delta method (Hole 2007)

Appendix B: Agricultural Gene Drive Survey, full informational text and illustration materials

The survey informational text is in quotations (emphasis in text present in fielded survey). Invisible timers recorded time spent on each page.

Introduction with consequentiality statement:

“You will be shown four (4) short pages in the next section. Please read the information carefully. Your responses to questions about this information will inform policy decisions at the US Department of Agriculture.”

Panel 1:

“(Page 1 of 4)”

In this section, we are going to ask your opinion about a new technology being developed. We will first give a bit more detail about the technology and then two examples of how people are proposing to apply it in food production. We will also ask how use of this technology may affect your food purchases.

Insect pests cause significant damage to crops in the United States. Farmers try to control these insects as scientists continue to develop new pest control methods and technologies.

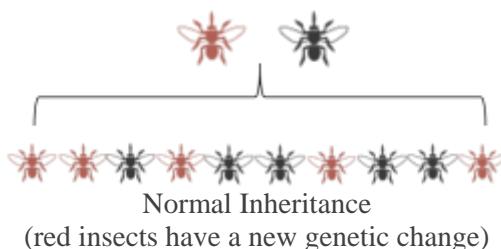
As you may have heard, a new strategy under development is called a ‘gene drive’, using a genetic engineering technology called CRISPR/CAS9 (pronounced “crisp-er”). **With this approach, scientists may be able to modify the genes of insect pests 1) to prevent them from being able to transmit diseases to a crop or 2) to reduce their populations by preventing them from reproducing normally.”**

Panel 2:

“(Page 2 of 4)”

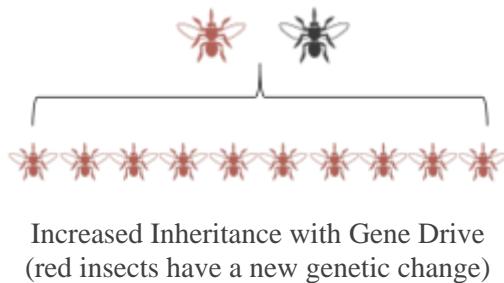
How does a gene drive work?

Imagine you wanted to make a population of insects a different color. Normally, half of an offspring’s genes come from the father and half come from the mother. So if a male with some genetic change mated with a normal female, about half of the offspring would inherit the change in the father’s DNA. **This is illustrated in the figure below.**



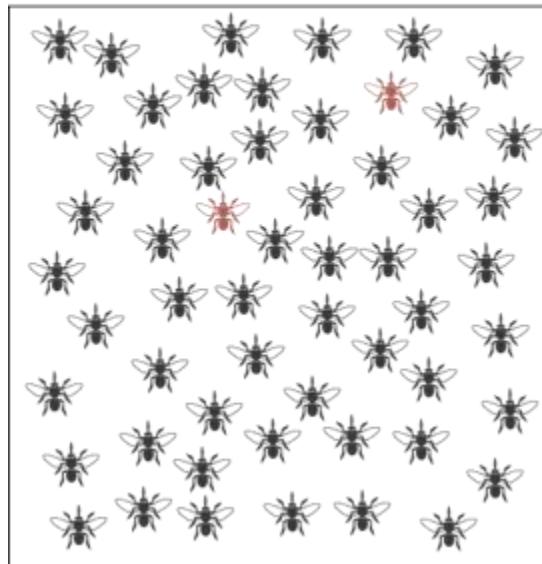
However, with a ‘gene drive’, genetic changes are inherited by almost 100% of the offspring. Their offspring then pass on these genetic changes to the next generation, continuing the process. **This is**

represented in the figure below.

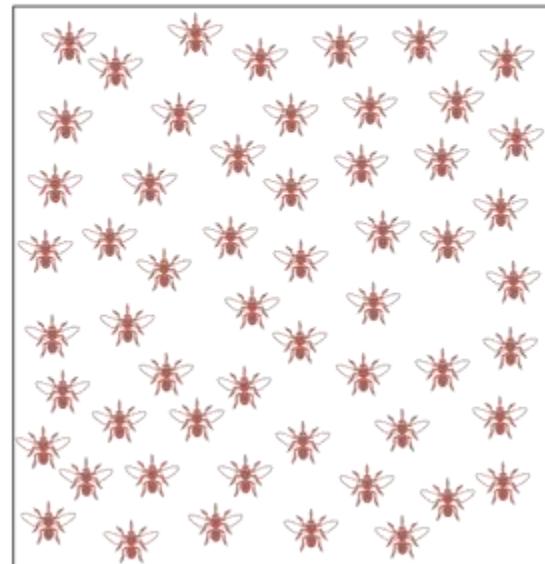


This means, in theory, if you release gene drive insects, over time they could 'drive' the modified genes to the entire population of that insect species (demonstrated below). These changes could potentially spread to wherever that insect occurs in the world.

Release of a small number of gene drive insects (red)...



... could spread over time so the species population all inherits the genetic changes



In agriculture, some scientists have proposed spreading modified genes which could prevent insects from transmitting crop diseases. Other scientists have also proposed spreading genes to disrupt insect reproduction to reduce or eliminate local populations of specific insect pests.

However, gene drives have never been used in the environment, and there could be many reasons why they could fail to spread as intended."

Panel 3:

"(Page 3 of 4)

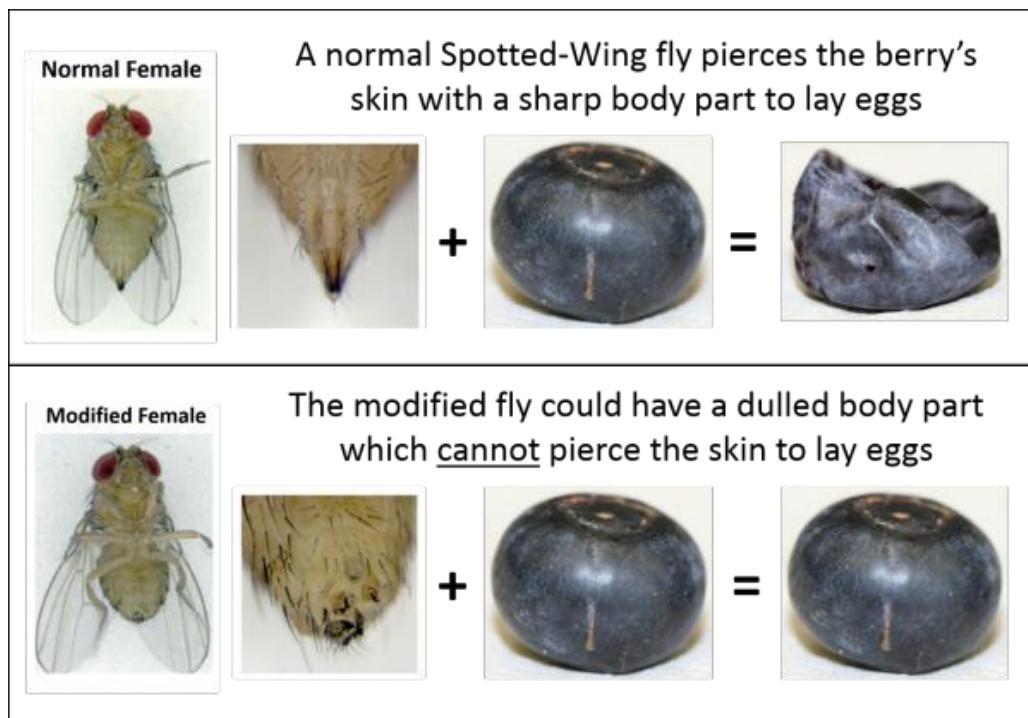
Gene drives could potentially be used to reduce or eliminate an insect population

An example under consideration is an invasive species of fruit fly called ‘Spotted-Wing Drosophila’, which recently arrived from East Asia. This pest causes significant damage to crops, especially soft berries like blueberries, raspberries, and strawberries (see picture below). The fly lays eggs inside the berries, which develop into juvenile insects that eat the fruit. Contaminated shipments cannot be sold as fresh fruit.

To prevent damage from Spotted-Wing, many farmers have increased insecticide applications, spraying up to every 3-5 days and frequently approaching limits enforced by the US Environmental Protection Agency. Organic farmers have fewer insecticide options than non-organic farmers for this pest, meaning they often have higher losses. Many farms have also stopped growing fruit or have gone out of business because they could not afford to control this pest.

Scientists have proposed genetically modifying the insects to make female Spotted-Wing flies not able to lay eggs inside the fruit (see picture below). Males would be modified to pass on genes which cause their female offspring to not be able to lay eggs. The male offspring would survive, mate with normal (wild) females, and continue the process.

This could eventually reduce or locally eliminate this fruit fly. A reduction in flies could mean less damage and a reduced need for insecticide sprays to protect certain fruit crops.



Base photo credits: Berries: Vaughn Walton, Oregon State University; Flies: Li and Scott (2016), NC State University.

Panel 4:

“(Page 4 of 4)

Gene drives could potentially be used to alter a population of insects to not transmit crop diseases

One example is the invasive species Asian Citrus Psyllid (pronounced “si-lid”) which recently arrived from East Asia. This pest spreads a type of bacteria which causes a very damaging disease called “citrus greening” in US citrus groves.

Citrus greening is not harmful to humans and the fruit is still safe for people to consume. However, citrus greening causes trees to slowly die and significantly reduces the amount of fruit produced (see picture below). To slow the spread of the disease, many farmers have increased insecticide spraying up to 11-14 applications per year, frequently approaching limits enforced by the US Environmental Protection Agency. Citrus greening has cost the US citrus industry billions of dollars because infected trees cannot be cured of the disease and increased insecticide spraying has not successfully controlled the insect. Many farms have stopped growing citrus or have gone out of business.



Example of healthy vs. citrus greening fruit and leaves from a healthy vs. citrus greening tree
Photo credit: University of Florida

Scientists have proposed genetically modifying the Asian Citrus Psyllid so it cannot transmit the bacteria that causes citrus greening disease. The insects would continue to live and reproduce in the citrus groves, but they would no longer pass the disease to trees. The gene drive could potentially spread this disease immunity to the entire species around the world.”

Appendix C: Agricultural Gene Drive Survey, full Frequently Asked Questions (FAQ) wording

FAQ introduction text:

“Frequently Asked Questions (FAQs)

During discussions with the public about gene drives in agriculture, people have frequently asked a number of questions. In reading the information on the previous pages, you may have wondered about similar things.

We have included a short series of seven FAQs with a brief explanation for each. **Please mark all questions you would like to learn more about.** You will be shown information on all questions you select. Answers to some questions may be randomly shown whether you select them or not.

- Is a gene drive insect the same as a genetically modified organism (GMO)?
- Would engineered gene drives work in any species?
- Could gene drives be created to affect human populations?
- Has anyone created an actual gene drive?
- What are some possible risks of gene drives?
- Could a genetically modified Spotted-Wing fly or Asian Citrus Psyllid bite humans?
- How long would the gene drive remain in an insect population after it's released into the environment?"

Appearing in separate frames:

FAQ 1:

“Is a gene drive insect the same as a genetically modified organism (GMO)?

Answer:

A gene drive insect is genetically modified (or 'genetically engineered'), but not all genetically modified organisms are gene drives.

The major difference is that a gene drive insect is modified with the intention that the genetic changes pass to all of their offspring and can potentially 'drive' through the population of that insect species.”

FAQ 2 (adapted from Wyss Institute press release):

“Would engineered gene drives work in any species?

Answer:

No, only in species that reproduce sexually, such as insects, animals, and most plants. They would not work in bacteria or viruses, for example. The genetic changes only spread through the population as individuals mate, so it works much faster in species like insects which can reproduce very quickly.”

FAQ 3 (adapted from Wyss Institute press release):

“Could gene drives be created to affect human populations?

Answer:

Not without taking centuries. It takes a very long time to spread a gene drive through a species that takes many years to reach sexual maturity. For example, if a trait was introduced into elephants (which live for a long time, like humans) using a gene drive today, there would only be four times as many elephants with that trait in 100 years than if we hadn't used a gene drive.

No scientist has proposed using a gene drive in human beings or any higher mammal. This is partly because gene drives work best in organisms with fast reproduction cycles and many offspring (like insects). ”

FAQ 4 (adapted from Wyss Institute press release):

“Has anyone created an actual gene drive?

Answer:

Yes, though work is ongoing. Some gene drive insects have been developed in specific laboratory populations by scientists, but have never been released in the wild.”

FAQ 5:

“What are some possible risks of gene drives?

Answer:

The National Academy of Science, Engineering and Medicine has stated that ‘many of the possible harmful effects of gene drives have to do with environmental outcomes’. For example, a gene drive that eliminates a species in a particular environment might have impacts on other species. Some of these impacts might be predictable, but some species serve functions in the environment that we don't yet understand very well. Even in a farmer's field, removing a pest through gene drives may leave room for another pest to fill its place. Or, if a gene drive changes the behavior of an insect pest, there might be impacts that were not predicted.

Though extremely rare, sometimes in nature genes can be transferred between species. With other genetically modified animals this has never been found, but it is not yet known if this is possible with gene drive insects.”

FAQ 6:

“Could a genetically modified Spotted-Wing fly or Asian Citrus Psyllid bite humans?

Answer:

No. Neither the Asian Citrus Psyllid nor the Spotted Wing fruit fly can bite humans or other animals.”

FAQ 7:

“How long would the gene drive remain in an insect population after it's released into the environment?

Answer:

Theoretically, if enough gene drive insects are released and the drive works as intended, the genetic changes could carry on indefinitely and spread throughout the entire population of that species. That said, since gene drives are still under development, it is not known for sure if specific types of gene drive insects will be successful at finding mates or if all of their offspring actually inherit the DNA changes.

Some studies have also shown that insects may be able to adapt and develop a 'resistance' to the gene drive. This process is similar to insects evolving resistance to a pesticide, with some surviving even when they are sprayed. For gene drives, this could mean the gene drive might initially spread, but break down (or stop working) after a certain period. Over time, the insect populations might return to having no genetically modified individuals."

Appendix D: Agricultural Gene Drive Survey, Question format of Support or opposition to organic certification with gene drive insects

Question format

We further investigate the potential effects of gene drive insects on certified organic agriculture, in the context of perceived certification credibility. To understand respondent awareness of certification standards, we first ask respondents to “indicate the extent to which you believe the following statement is true or false: ‘Food that is certified ‘USDA-Organic’ can be produced applying certain types of insecticides”. The statement was accompanied by the USDA-Organic logo for a visual cue. Possible responses were “Definitely True”, “Probably True”, “Probably False”, “Definitely False”, and “I don’t know”; we code a correct response as ‘Definitely True’ or ‘Probably True’. Only 57.3% of respondents affirmed regular certified organic food purchases answered correctly (vs. 51.6% of the remaining population ($p=0.168$, two-tailed mean difference t-test). As the use of gene drive insects is likely to reduce applications of insecticides (synthetic or otherwise), awareness that this reduction is also possible in certified organic production would be key to perceived benefits from drive insect releases.

While all respondents completed the organic section of the survey, we focus only on the results of regular certified organic consumers ($n=228$), as their preferences are the most pertinent for certification policy discussions. Results from all respondents available from the authors upon request.

We survey respondents on two levels of insect proximity with crops, which always appeared sequentially. Each example was accompanied by the USDA-Organic logo for a continued visual cue. In the first level, gene drive insects are simply ‘used in the area to control a damaging insect species’. The second level, however, probes perceptions with much greater insect interaction with crops, with genetically modified insect material ‘getting in or on crops’. Any pest that infests the salable portion of the crop could fall into this category. This is possible, for example, in the context of Spotted-Wing Drosophila, if a wild female is inseminated by a gene drive male and the resulting eggs are deposited in a ripening berry. While there is zero-tolerance for Spotted-Wing presence in any fresh market or whole frozen fruit shipment in the United States, the ability of a stray egg to pass through the inspection process is within the realm of reason.

Responses to each were provided along a 5-point agreement scale, ranging from 1=”Strongly Disagree” to 5=”Strongly Agree”. Tests described in the text are based on coding ‘Strongly Disagree’ or ‘Disagree’ as an aggregate category ‘Disagree’ and ‘Strongly Agree’ and ‘Agree’ as an aggregate ‘Agree’ category. Data and statistical tests are summarized in Supplementary Table 6..

The exact question wording is as follows:

Level 1:

“Currently, for a food product to be certified ‘USDA-Organic’, the United States Department of Agriculture has strict regulations on what types of pesticides may be used and does not allow the use of genetically modified crops.



Suppose a farmer is following all current requirements for certified organic production and 'gene drive' insects are used in the area to control a damaging insect species.

To what extent do you agree or disagree that this farmer's crops should still be allowed to be certified as 'USDA-Organic'?"

Level 2:

"Now, suppose a farmer is still following all requirements for certified 'USDA-Organic' production, and the use of gene drive insects in the area results in some genetically modified insect eggs, immature larva, or adults getting on or in the crops.



To what extent do you agree or disagree that this farmer's crops should still be allowed to be certified as 'USDA-Organic'?"

Appendix E: Agricultural Gene Drive Survey, Ranking Gene Drive Uncertainties to Resolve Before Use Decisions – Question construction

Selection of ‘questions to answer’ before making gene drive release decisions drew from both the NASEM (2016) report recommendations and three focus group discussions, which occurred Feb-April 2017. Where judged necessary, items were combined and paraphrased to facilitate understanding with audiences of diverse educational and experiential backgrounds, with full NASEM report and paraphrased survey questions detailed in Supplementary Table 9. This was particularly necessary with technical themes of insect ‘fitness’, drive ‘conversion rates’, resistance management, and nuanced ecological concerns.

Focus groups lasted 2.5 hours and had 4-10 participants, drawn from a stratified random sample of interested parties recruited from an urban area grocery retailer, a rural area grocery retailer, and an urban farmers’ market. After an introduction to the subject, extensive discussion, and review of paraphrased NASEM-generated questions, participants were asked “What else do you think we should know before we used anything like gene drives for an agricultural pest?” Responses from each group are detailed below, along with thematic clustering used to inform the final 10 item list.

Additional questions requested from FGD 1:

1. What agency could they use to regulate gene drives?
2. How would new genetic animals affect humans?
3. [What are] effects on food production and other species of food?
4. Changes in the food web affecting people?
5. Could a modified insect cause illness in humans?
6. What type of control group would be used to ensure it’s safe for the public?
7. With the gene drive being successful, how would it affect the food chain?
8. How would [gene drives] affect the food that we eat?
9. Could the gene drive insects carry another disease once they can’t carry the targeted disease?

Additional questions requested from FGD 2:

1. How to measure the spread of the gene drive?
2. Will all gene drive [insects] have a marker?
3. Real world experiments – has anyone tried this?
4. Have any reversal drives been developed? [What is the] ability to recall?
5. What controls how far the flies can spread?
6. Do we know the gene drive has no effect on natural selection?
7. Will there be a cost/benefit [advantage] year over year? Increases over time?
8. Who will be paying for this?
9. Will there be a black market for this technology?
10. What is the potential for lawsuits? Like with GMO crops.
11. Will there be any controls so that the technology isn’t developed for just any species?
12. What are the other benefits, if some farmers don’t adopt, but benefit from the technology?
13. Who will say who can or can’t have this technology?
14. Will there be any effects on other species, like bees?
15. Will the private sector get involved in gene drives? With all the public funding cutbacks, may have different interest in the gene drive development.

16. Who would control the price of the technology? (potential situation like Epipen, with price setting power)

Additional questions requested from FGD3:

1. What is the cost? (For the research and applying it)
2. What group of people have final say-so? For-profit entity or not?
3. What effects would it have on humans by taking away the flies?
4. Would it change the taste [of the fruit/food]?
5. How would this be better for us?
6. How does it affect the supply chain?
7. Could [gene drives] start with flies and end up with people?
8. If gene drive [as a concept] is successful, could it help address something like cancers?
9. What happens if the flies are modified and escape the testing facility? How safe would it be in testing?

Synthesized list of additional questions by topic (constructed topic bins, from above FGD-generated questions)

Cost/Market Effects

1. What is the cost? (For the research and applying it) [FGD3]
2. How does it affect the supply chain? [FGD3]
3. Who would control the price of the technology? (potential situation like Epipen, with price setting power) [FGD2; repeated]
4. Will the private sector get involved in gene drives? With all the public funding cutbacks, may have different interest in the gene drive development. [FGD2; repeated]
5. Will there be a black market for this technology? [FGD2]
6. Will there be a cost/benefit [advantage] year over year? Increases over time? [FGD2]
7. Who will be paying for this? [FGD2]
8. What are the other benefits, if some farmers don't adopt, but benefit from the technology? [FGD2]
9. How would this be better for us? [FGD3]

➔ Proposed question generated:

- Are gene drive agricultural pests cost effective - are the expected benefits greater than expected costs of development, regulation, release, and monitoring?

Authority/Regulatory

1. Will the private sector get involved in gene drives? With all the public funding cutbacks, may have different interest in the gene drive development. [FGD2; repeated]
2. Who will say who can or can't have this technology? [FGD2]
3. Will there be any controls so that the technology isn't developed for just any species? [FGD2]
4. What group of people have final say-so? For-profit entity or not? [FGD3]
5. What agency could they use to regulate gene drives? [FGD1]
6. What is the potential for lawsuits? Like with GMO crops. [FGD2]
7. Who would control the price of the technology? (potential situation like Epipen, with price setting power) [FGD2; repeated]

➔ Proposed question generated:

- Who will regulate gene drives for agricultural pests - for example, approving field trials or environmental releases?

Human Effects

1. Could the gene drive insects carry another disease once they can't carry the targeted disease? [FGD1]
2. How would [gene drives] affect the food that we eat? [FGD1; repeated]
3. Changes in the food web affecting people? [FGD1]
4. Could a modified insect cause illness in humans? [FGD1]
5. What type of control group would be used to ensure it's safe for the public? [FGD1]
6. How would new genetic animals affect humans? [FGD1]
7. What effects would it have on humans by taking away the flies? [FGD3; repeated]
8. Could [gene drives] start with flies and end up with people? [FGD3]
9. If gene drive [as a concept] is successful, could it help address something like cancers? [FGD3]

➔ Proposed question generated:

- Could gene drive agricultural pests impact human health?

Technical/Containment

1. How to measure the spread of the gene drive? [FGD2]
2. Will all gene drive [insects] have a marker? [FGD2]
3. Real world experiments – has anyone tried this? [FGD2]
4. Have any reversal drives been developed? [What is the] ability to recall? [FGD2]
5. What controls how far the flies can spread? [FGD2]
6. Do we know the gene drive has no effect on natural selection? [FGD2; repeated]
7. What happens if the flies are modified and escape the testing facility? How safe would it be in testing? [FGD3]

➔ Proposed question generated:

- Could genetic changes caused by a gene drive be reversed?

Environmental/Ecosystem

1. With the gene drive being successful, how would it affect the food chain? [FGD1]
2. Do we know the gene drive has no effect on natural selection? [FGD2; repeated]
3. Will there be any effects on other species, like bees? [FGD2]
4. What effects would it have on humans by taking away the flies? [FGD3; repeated]

➔ Proposed question generated:

- [judged adequately addressed by the NASEM questions condensed to: "If we remove an agricultural pest completely from an area, what could happen in the environment?"]

Crop/Fruit Effects

1. Would it change the taste [of the fruit/food]? [FGD3]
2. How would [gene drives] affect the food that we eat? [FGD1; repeated]
3. [What are] effects on food production and other species of food? [FGD1]

→ Proposed question generated:

- Could a gene drive agricultural pest change the taste or appearance of food?

Summary of Ranking Exercise Item Construction

NASEM (2016) Report phrasing	Condensing and restructuring in fielded survey, with matching from FGDs
1. The evolutionary ‘fitness’ of individual carrying the gene drive – that is, their ability to produce fertile offspring – as compared to individuals not carrying the gene drive. (p.3)	1. Will the gene drive work? For example, will wild insects mate with gene drive insects and, if they mate, how efficiently will the gene drive continue to be inherited by the next generations?
2. The ‘conversion rate’, which describes how the gene drive is passed to subsequent generations when one parent carries the gene drive and the other does not. (p.3)	
3. Could the target species develop mechanisms to neutralize the gene drive (e.g. evolve resistance), and how might that dynamic affect others in the ecological community? (p.4)	
4. ‘Gene flow’, which describes how the gene drive moves between different populations of the target species. (p.3)	2. How quickly might gene drive insects spread after they are released?
5. ‘Horizontal gene transfer’, or the potential for gene drives to move from the target species into entirely different species. (p.4)	3. Could the added genes in a gene drive insect spread to other species by accident?
6. What is the species’ role in its community? (p.4)	
7. Is there a tipping point at which the community may change rapidly from one configuration to another, and could the gene drive lead to such a tipping point? (p.4)	4. If we remove an agricultural pest completely from an area, what could happen in the environment?
8. How might a dramatic change in the population of the target species affect other species with which it has coevolved? (p.4)	
9. Are there other species that would fill a similar ecological niche in the community if the target species were to disappear? (p.4)	5. If we remove this insect, what is the chance another pest will just take its place and cause problems?
NASEM report discussion analogues (loosely addressed)	FGD and pre-test generated questions
the use of gene drives and who will make decisions about them (p.4)	6. Who will regulate gene drives for agricultural pests - for example,

	approving field trials or environmental releases?
the potential benefits and harms of gene drive research for people (p.4)	7. Could gene drive agricultural pests impact human health?
It is particularly imperative to use caution when considering the development of a “reversal drive”—a gene drive designed to mitigate the unintended consequences of another gene drive—as it may be impossible to effectively employ this strategy without off-target effects or to fully redress ecological and environmental effects from the original gene drive. (p.5)	8. Could genetic changes caused by a gene drive be reversed?
the potential benefits and harms of gene drive research for people (p.4)	9. Are gene drive agricultural pests cost effective - are the expected benefits greater than expected costs of development, regulation, release, and monitoring?
[none]	10. Could a gene drive agricultural pest change the taste or appearance of food?

Note: NASEM report items from explicit calls for research advocated in (1)

Appendix F: Agricultural Gene Drives, Focus Group Guide

Focus Group Questions, Consumers/Public (~2.5 hours)

Gene Drives in Agriculture

[Read and complete informed consent forms.]

Hi! My name is X [moderator, social scientist] and I'm a researcher at X. We are conducting a new study about people's opinions on food and new technology in agriculture.

I'll let X [assisting researcher 1, social scientist] and X [assisting researcher 2, entomologist] introduce themselves as well.

Let's just go around the room and introduce ourselves, saying our

- 1) name and
- 2) our favorite food.

Warm up/Introductory questions: (12-15 minutes)

- Ground rules, respect of people's opinions. Open environment to share thoughts.
- "When you go to the grocery store, what are the most important things you consider when choosing which fruits and vegetables to buy? What are the most important things you consider when deciding?"
 - Probe (if necessary):
 - Price
 - Healthy
 - Organic
 - GMOs
 - If stuck here-> 'going to talk more about this today'
 - Hard questions -> people are welcome to talk to X [assisting researcher 2] afterward for more information on GM crops
 - Appearance

Transition Question: (12-15 minutes)

- "We all know our food, especially fruits and vegetables, is coming from farms. We would like to talk about this a little bit. Pests and insects are a big problem for farmers."
 - How do you think farmers are trying to control insects right now?"
 - How do you think pests should be controlled?"

[At this mark, about ~30 min]

Information Presentation on Genetic Engineering Advances in Agriculture (12-15 minutes)

- (X [assisting researcher 2]): New systems are being designed as part of Genetic Pest Management, how Gene Drives work
 - "A new type of technology scientists are developing"
 - "Not something people have used outside of the laboratory right now"
 - **Play Jennifer Kahn's TED talk video on Gene Drive Insects:** focus on mosquitos, carp, mentions agriculture, presented in fairly plain, concise and accessible language.
 - https://www.ted.com/talks/jennifer_kahn_gene_editing_can_now_change_an_entire_species_forever

- Give out card, have participants write two words/phrases specifically about their response to the video and gene drive insects (**3-5 minutes**)

[At this mark, 45-50 min]

Questions/Vocal Feedback:

- “I know the woman in the video talked a bit quickly. This is a new technology that most people have never heard of yet, so if it seems unfamiliar then that’s completely normal.”
- “We know that was a lot of information, but we’d like to hear your impressions and thoughts about the strategies we brought up. X [assisting researcher 2] is going to help answer some of the questions you may have, though she might not know all of the answers.”
- (If needed):
 - “In particular, what are your thoughts on gene drives in insects?”
 - “Are these developments in gene drive insects generally a good or a bad thing? Or perhaps, you’re not sure yet?”

X [assisting researcher 2] Elaboration: Specific Gene Drive purposes and method of action

- Population control
- Population replacement
- Elaboration: Specific crop/pest examples
 - Spotted-wing Drosophila – as an elimination strategy
 - Asian Citrus Psyllid – as replacement strategy

Questions, comments [At this mark, about 70 minutes]

Key Questions: (about 20 minutes total)

X [moderator]

- “What benefits do you think gene drive insects in agriculture may offer?”
 - “Who would benefit?”
- “What strikes you as potentially negative about using gene drive insects in agriculture?”
 - “Who would it affect?”
- “What do you think farmers would say about gene drive insects?”
 - “How do you think it might benefit them?”
 - “How do you think it could negatively affect them?”

[Bathroom break at 90 minutes, give 5-10 minutes]

[At 100 minutes here]

X [moderator] [about 10 min]

- List most ‘important’ unknowns about Gene Drives present in the recent National Academy of Sciences report
 - Ask folks to list other questions to answer.
 - “What other questions could they be asking?”
 - “What more would you want to know?”
- Reaffirm that gene drives are new and many questions still exist
- [new: opportunity for best/worst evaluation?
 - Choose the most important and least important of the questions generated, including the NAS q’s]

[At this mark, about 120-130 minutes]

If time remaining (only in Raleigh group):

- “Who do you think would be most likely to do research in gene drive insects?”
 - “How do you think your opinion on GD insects would change depending on whether it was _____ or _____ funding this research?” (list examples)
 - “Does it make a difference if the USDA vs. the Department of Defense funds NC State to do the research?
- “Right now USDA has organic certification regulations which prohibit the use of synthetic pesticides and genetically engineered plants. No mention is specifically made about genetically engineered insects and discussions are ongoing to make a decision. What do you think the governments should decide about GE/GD insect material?”
 - “If [product] was produced under organic practices but in an area using GE/GD flies, is it still organic?”

Choice experiment testing exercises (~20 min)

- Run exercise as consumer (~10 min)
 - i. Run written, individually, asking people to choose between fruit examples with different attributes, differing uses of genetic engineering in plants/insects
 - ii. Afterwards, breakdown of thoughts on each choice (~10 min)
 - 1. “How did you find this exercise generally easy or hard to think about?”
 - 2. “Did the options for each choice seem realistic?”
 - 3. “What were the most important things you looked for when answering the questions?”
 - 4. “Which parts did you not care about as much?”
 - 5. “Did release of GD insects affect your choice in any way?”

Research prioritization exercise (varied in each location to try different formats)

Conclusion (<5 minutes)

- Summarize with confirmation; Review purpose and ask if anything has been missed; Thanks, dismissal, and compensation

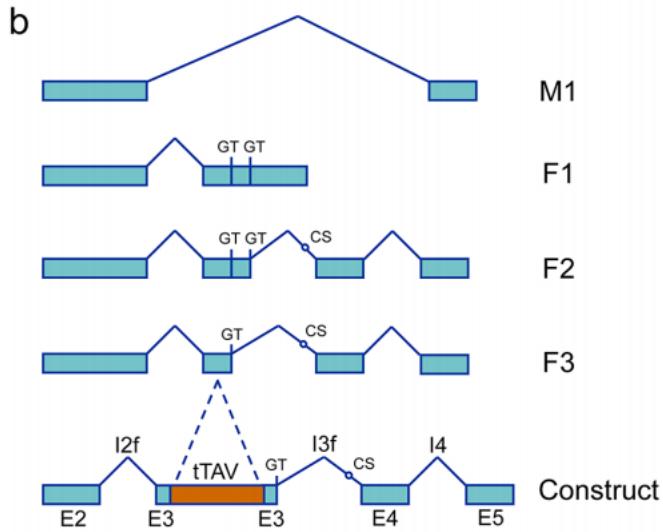
Appendix G. Elaboration of transgenic diamondback moth OX4319L

The following three figures (Ga-Gc) are from Jin *et al.* (2013) in which the development of the transgenic strain of diamondback moth OX4319L is explained.

a

		Sex	
		Male	Female
Tet	+	1	1
	-	1	0

The OX4319L strain of diamondback moth carries a repressible female-lethal gene. This means that the lethal gene, though carried by both males and females, will only kill females, and it is repressible. The on/off switch used for this gene is the antibiotic tetracycline (tet), and in the presence of tetracycline the lethal gene is turned off. Tetracycline is added to the diet of mass reared moths, so in the facility, females can survive and mate almost as well as wild-type females. When released into the wild where tetracycline is typically absent from the diet, or only present at extremely low quantities, the lethal gene is turned on, and females die. Since males survive and mate with wild-type females, they pass down this gene to their offspring and thus only their male children survive to the juvenile stage. This distorts the normal sex ratio, and in the severe absence of females in the next generation, the population crashes. The figure shows the survival rate of each moth given its sex, and given the absence (-) or presence (+) of tetracycline.



The mechanism for having a female-lethal gene, as opposed to a bi-sex lethal is the strategic positioning of the transgene. The lethal gene (tTAV) is positioned within the gene *doublesex* which is part of the sex determination pathway in many insects including moths (lepidoptera), flies (diptera) and beetles (coleoptera). *doublesex* is alternatively spliced in males and females. As part of the protein coding pathway, genes are translated from DNA to pre-messenger RNA (pre-mRNA), then the introns of the gene are spliced (the non-coding regions of RNA are cut out and discarded), then the mRNA is transcribed to amino acids, which combine to form proteins. Cell machinery can alternatively splice mRNA by recognizing alternative splice sites, and therefore make multiple distinct protein products from a single DNA sequence. Part B depicts the alternative splicing of *doublesex*, the top being the male transcript, and the following three being alternative spliced products for females. Males splice out exons 3 and 4, whereas females keep exon 3. The bottom shows the transgenic version of *doublesex*, with the lethal gene sandwiched within exon 3. Males will inherit the transgenic version of *doublesex*, but splice out exon 3, therefore making them immune to the lethal gene. No matter which of the three ways females splice *doublesex*, they always make the lethal transcript.

Appendix H: Derivation of fitness costs for homozygous and heterozygous RIDL insects (KK, Kk) and Bt resistant insects (ss, Ss).

Population level effect of fitness costs associated with repressive, female lethal transgene (derived from values in Harvey-Samuel et al., 2014)

$$KK: W_{RR} = 0.477$$

$$Kk: W_{R,-} = 0.736$$

$$kk: W_{-, -} = 1$$

$$1 - s = 0.477$$

$$s = 1 - 0.477$$

$$C_k = \mathbf{0.523}$$

$$1 - hs = 0.736$$

$$1 - h(0.523) = 0.736$$

$$h(0.523) = 1 - 0.736$$

$$h_k = \frac{1 - 0.736}{0.523} = \mathbf{0.505}$$

Population level effect of fitness costs associated with Bt resistance

Low Fitness cost (Yi et al., 2015)

Mortality in non-Bt environment

	ss	Ss	SS
Survival	90	93.3	93.3
Normalized	0.965	1	1
$W_s = 0.965 = 1 - C_s$			
$C_s = \mathbf{0.035}$			
$h_s = 0$			

High Fitness Cost – Bt : Groeters et al. (1994)

	ss	SS
Survival	44	58
Weight	5.29	5.18
Time	13.21	13.29
Eggs	180	208
Egg hatch	69.9	79.9
Total	38686625.287	66357932.83
Normalized	0.583	1
$W_s = 0.583 = 1 - C_s$		
$C_s = \mathbf{0.417}$		
$h_s = \text{unknown}$		