Landscape-level pest control externalities when consumer preferences are non-neutral

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Abstract

Biotechnology researchers are developing genetically engineered insects with substantial applications in agriculture. One strategy is a 'gene drive', using CRISPR/CAS9 gene editing. In gene drive, preferentially inherited, engineered traits are spread to reduce pest populations or inhibit their ability to spread disease. As a landscape-level biotechnology tool, gene drives have the potential to spread throughout all growing regions of host crops, efficiently facilitating reduction of pesticide spraying and crop prices due to management cost savings and yield loss mitigation. However, this strategy could also limit consumer choice to *only* host crops grown in the presence of gene drive insects. The net consumer welfare impacts from these interventions will thus depend upon the heterogeneous valuation of trade-offs between pesticides, prices, and drive insect presence. In this study, we administer an online survey to a nationally representative probability sample of 1,018 U.S. adults, gathering data on gene drive attitudes and impacts on willingness-to-pay (WTP) for two products that are host crops for insects under current drive research. Through a hierarchical Bayesian framework, we examine the consumer welfare implications of drive insect release scenarios that are either limited or unlimited in scope. Consumer preferences indicate lower marginal discounts for drive insect presence versus increased conventional pesticide use or a genetically modified crop. The mean and median consumer welfare impacts of unlimited drive releases are negative for fresh blueberries. For orange juice consumers, the mean surplus estimate is small, negative and statistically insignificant, while the median estimate is positive and statistically significant. We estimate substantial consumer welfare gains with limited drive systems that retain alternatives not grown in the presence of drive insects, though gains are more pronounced in blueberries than orange juice. Results provide insight into differential consumer valuations of biotechnology strategies as well as sorely needed data to inform debates on market impacts of drive insect releases.

Introduction

Effective and acceptable management of damaging, invasive species that threaten crops is a continual challenge for the agricultural sector. Biotechnology advances and CRISPR/CAS9 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 2016), 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). 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)).

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 (Emerson et al. 2017; NASEM 2016). 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). Public views on gene drives are also unlikely to be independent from previous controversy involving genetically modified organisms (GMOs) in food supplies (Baltzegar et al. 2018; Costa-Font, Gil, and Traill 2008).

Distinct components 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. For example, the genetic manipulation of pests instead of food products may 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 2016). 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, shifting the supply curve out 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 ecological risk assessments.

The objective of this study is to investigate the demand effects of gene drive insect use in growing environments against other chemical and biotechnological approaches to manage destructive and invasive agricultural pest species. Especially given impending implementation of the National Bioengineered Food Disclosure Standard, our study provides an important perspective on public values and preferences for mobile genetically engineered organisms in growing environments. Through a discrete choice experiment embedded within a nationally representative probability sample of 1,018 U.S. adults, we focus our analysis on willingness-to-pay for fresh and processed fruit products. We believe this is the first study of any genetically engineered insect's impact on consumer demand for an agricultural good. We further examine the impact of gene drive insects on the premium consumers are willing to pay for USDA-organic pest management regimes, providing important insights for the growing, multi-billion dollar organic industry (Willer, H. and Lernoud 2017). We also explicitly compare the consumer utility and willingness-to-pay impacts of crop genetic modification vs. gene drive insects for pest damage mitigation, providing an innovative understanding of how the public values unique biotechnology strategies in agriculture. Lastly, we simulate drive insect release scenarios that simultaneously alter multiple attributes in the choice sets and contextualize our findings with empirical estimates from the literature noting specific pest impacts on crop prices. We then draw conclusions about the value of geographically limited vs. unlimited gene drive insect releases from the lens of consumer welfare gains.

Background

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% and 25.8% in Florida bearing acreage and yield since the disease was found in 2005 (USDA-NASS 2017a). The bacterium is vectored by the Asian citrus psyllid (*Diaphorina citri*), 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 (*Drosophila suzukii*). 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). 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.

With the inherently commercial nature of agricultural applications, ex-ante consumer evaluations are crucial to project demand-side effects of gene drive insects. 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 expansion of the supply curve. 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 releases of non-drive versions of genetically modified crop pests (Zhang 2017). 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 – disproportionally 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 (Farnsworth et al. 2017; Van Timmeren and Isaacs 2013). 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 economically tenable 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 pay after the introduction of high spraying regimens to return to his/her 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?

Methods – Survey Design

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. The DCE is 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 receive 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 A). Respondents then reported attitudes on various contexts of gene drives for agricultural pest control and specific views on use in organic agriculture. The willingness-to-pay (WTP) portion was only completed by respondents affirming household purchase of fresh blueberries or orange juice in the last six months[1]. 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 reduce potential hypothetical bias in WTP estimates, a cheap talk script[2] was adopted in the DCE introduction (J. L. Lusk 2003).

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[1] 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.

[2] 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.)"

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 1. Respondents were instructed to imagine that 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 (Huber and Zwerina 1996), 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. Examples of blueberry and orange juice choice set designs are available in Appendix B.

Table 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
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], “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]; “Conventional insecticides applied every five days for several weeks while fruit ripens” [high conventional spray] – *Orange Juice:* “Conventional insecticides applied in the field 1-2 times per year” [low conventional spray]; “Conventional insecticides applied in the field 11-14 times per year” [high conventional 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). *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.

Conceptual Framework and the Econometric Model

Discrete choice models are grounded in random utility theory, allowing researchers to estimate the WTP for attributes describing product profiles in an experimental setting. This follows the Lancastrian concept of utility, where Lancaster (1966) argues that utility is not necessarily derived from a good itself; rather, utility is gained from the individual attributes composing a good. In this context, fresh blueberries and orange juice are viewed as a collection of production and quality attributes which are heterogeneously valued by consumers. We use the DCE approach for several reasons. First, because gene drive insects are not present in growing systems and thus, barring the use of deception, a revealed preference elicitation method such as experimental auctions is not feasible. 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 (Jayson L. Lusk and Hudson 2004).

Central to the idea of random utility theory is the assumption that economic actors seek to maximize their expected utility subject to the alternatives, or choice sets, they are presented. Based on Manski (1977), an individual's utility is a random variable because the researcher has incomplete information. In a choice experiment, an individual *i* maximizes utility attained from an alternative *j* at choice scenario (or time) t. Utility is decomposed into a deterministic [$V(\boldsymbol{X}_{ijt})$] and stochastic element (ε_{ijt}), represented here as:

$$(1) \qquad U_{ijt} = V(\boldsymbol{X}_{ijt}) + \varepsilon_{ijt}$$

When an individual faces a choice between two alternatives *j* and *k*, he or she is assumed to optimize utility such that probability of choosing *j* is:

(2) $$\pi_{it}(j) = Prob\{V\left(\boldsymbol{X}_{ijt}\right) + \varepsilon_{ijt} \geq V(\boldsymbol{X}_{ikt}) + \varepsilon_{ikt}\, ; j \neq k\}$$

In this context, $\boldsymbol{X}_{ijt}$ is a vector of fresh blueberry or orange juice attributes and ε_{ijt} is the random error term iid over all individuals, alternatives and choice situations (Revelt and Train 1998). The deterministic component of utility $V\left(\boldsymbol{X}_{ijt}\right)$ is assumed to be linear in parameters, where alternative *j* is a compilation of price, whether the plant is genetically modified, presence of gene drive insects in the growing environment, certified organic pest management (vs. high frequency conventional spraying), and low (vs. high) frequency conventional spraying. The experimental design was also powered to allow measurement of the interaction between gene drive insect presence and pest management practices, which provides critical insight into potential erosion of the value of certified organic production. The functional form for the deterministic component can be expressed as:

(3) $$V_{ijt} = \boldsymbol{\beta}'\boldsymbol{X}_{ijt}$$

In this context $\boldsymbol{X}_{ijt}$ is a 7 x 1 vector of product attributes,

$$\boldsymbol{X}_{ijt} = [Price_{jt},\ GM\_Plant_{jt},\ GD\_Insects_{jt},\ Organic_{jt},\ Low\_Conv\_Spray_{jt},\ (Organic * GD\_Insects)_{jt}, (Low\_Conv\_Spray * GD\_Insects)_{jt}].$$

The parameter vector $\boldsymbol{\beta}$ is to be estimated. Given the likely (confirmed) heterogeneity across consumers, we also utilize a random parameters, or mixed logit model. Following the familiar mixed logit specification (Revelt and Train 1998), the probability of a consumer *i* selecting alternative *j* in choice scenario *t* is:

(4) $$L(\boldsymbol{y_i}|\boldsymbol{\beta_i}) = \prod_{t=1}^{T} \frac{e^{V_{ijt}(\boldsymbol{\beta}_i)}}{\sum_j e^{V_{ijt}(\boldsymbol{\beta}_i)}}$$

where the unconditional probability is computed by integrating across all individuals' $\boldsymbol{\beta}_i$ and weighted by density, such that:

(5) $$P_i(\boldsymbol{y}_i) = \int L(\boldsymbol{y}_i|\boldsymbol{\beta}_i) g(\boldsymbol{\beta}_i) d\boldsymbol{\beta}_i$$

where $g(\cdot)$ denotes the density of $\boldsymbol{\beta}_i$. We employ a Hierarchical Bayes mixed logit model, generalized by Train (2001), for estimation of the parameter vector $\boldsymbol{\beta}$ using his well validated MATLAB code (Train 2009). Non-price base attributes distributed random normal with mean *b* and variance Ω and allowing for correlation of random coefficients. We test the price attribute as random log-normally distributed and fixed (non-random) across individuals. Interaction term coefficients are modeled fixed across individuals. Given classic normal priors on **b** and a diffuse prior on Ω which is inverted Wishart, the conditional posterior on $\boldsymbol{\beta}_i$ is:

(6) $$\Lambda(\boldsymbol{\beta}_i|\boldsymbol{b}, \Omega) \propto \prod_i L(\boldsymbol{y}_i|\, \boldsymbol{\beta}_i) \cdot g(\boldsymbol{\beta}_i|\boldsymbol{b}, \Omega)$$

Draws from the joint posterior are obtained via Gibbs sampling and the Metropolis-Hastings algorithm. In Gibbs sampling, a sequence of draws is estimated in which every draw for a parameter is estimated conditional on other model parameters in a hierarchical form. Beginning at initial values, a burn-in of 100,000 draws was specified, after which 1,000 draws were retained, thinning along every 100th draw to minimize the impact of autocorrelation, and verifying convergence visually (Train 2009) (Appendix G). As the mean (and variance) of a Bayesian posterior distribution of a parameter is asymptotically equivalent to a maximum likelihood estimator of that parameter, estimates from the Hierarchical Bayes model may be interpreted similar to classical procedures (Train 2009). Following prevailing reporting convention (e.g. Hynes, Hanley and Scarpa, 2008), the mean and standard deviations of the posterior draws are presented in a classical sense as the estimate and standard error for each parameter.

Willingness to pay (WTP) estimates of the marginal rate of substitution between price and non-price attributes are taken as the negative ratio of non-price and price coefficients, transforming the price coefficient where necessary in the lognormal specification. The coefficient on price proxies for the marginal utility of income, with WTP for product (non-price) attribute *m* given by:

$$(7) \qquad WTP_m = -\frac{\beta_m}{\beta_p}$$

We focus on specifications for preference (vs. WTP) space models since the main lens of analysis, welfare estimates from release scenarios of drive insects, are computed via preference space coefficients estimates[3].

Welfare Implications

While mWTP estimates are useful for single attribute changes in a purchasing environment with all options available to consumers, invasive species and gene drive insects may 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 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

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[3] WTP-space model results are quite similar to preference-space models in classical mixed logit model specifications and are reported in Appendix E.

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.

To answer these questions, we turn to the Small & Rosen (1981) classic discrete formulation of compensating variation (CV) from discrete choice estimates which is approximately equivalent to consumer surplus (McConnell 1995). This formula is derived from welfare theory and is noted to weight welfare effects by the probability that an alternative is chosen, which avoids erroneous aggregation of multiple changes by simply summing the WTP values (Lancsar and Savage 2004). The CV is the amount of money needed to return an individual to their original utility *after* a change in prices, attributes, or availability. A positive CV estimate would thus be a negative change in consumer surplus. As the random utility model provides direct estimates in utility space, we can use estimation results from the DCE directly. In this framework, the equation is:

$$(8) \qquad \Delta CS \approx -CV = \frac{1}{\lambda}\left[ln \sum_{j=1}^{J^1} e^{V_j^1} - ln \sum_{j=1}^{J^0} e^{V_j^0}\right]$$

where the marginal utility of income, λ, is proxied by the estimated price attribute coefficients $\widehat{\beta_{p\iota}}$ and scaled by average product prices. Indirect utility of each of the alternatives $j \in J$ are calculated from our preference space model specification and form the base V_j^0 and new V_j^1 choice sets in each state $t = \{0,1\}$.

Modeling Drive Insect Release Scenarios

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 example in gene drive debates and are widely discussed in the context of a self-sustaining, unlimited spread through the species population (NASEM 2016). For producers, 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 2)[4]. Self-sustaining releases simultaneously change multiple attributes in the choice set, modeled as moving to lower (pre-infestation), lower (pre-infestation) spray levels, and ubiquitous drive insect presence in growing areas. These two scenarios are the primary comparison of interest. Geographically 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

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[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.

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 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.

DCE Estimation Results

In Table 3 & Table 4, we present our preferred specification of the Hierarchical Bayes mixed logit model with correlated random coefficients and a log-normally distributed price coefficient. Model choice was guided by significant gains in log-likelihood compared to modeling price as fixed[5]. Our experimental design was specifically powered to measure interaction terms between gene drive presence and chemical/organic pest management levels and we present results with and without interactions included for transparency. Classical mixed logit models solved via maximum simulated likelihood also produce very similar results, with subsequent WTP estimates generally within 5% of Bayesian estimates, with little gain in goodness of fit measures. For transparency, we include these estimates in Appendix E, but we focus our discussion on Bayesian estimate coefficients that drive subsequent welfare analysis simulations.

In Table 3 & Table 4, 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 our priors and 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 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), 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 4), the GM plant mean is almost 2 times higher. This also aligns with our priors, given that those concerned with ingesting genetically modified organisms would face this personal 'risk' with certainty given a GM plant versus some positive, potentially low risk 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

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[5] 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%. HB model results with a fixed price coefficient in Appendix D.

juice, this disparity rises to a factor of three. In Figure 1, we present a summary of these main effect mWTP results for each product using estimates from the Hierarchical Bayes mixed logit specification with correlated random coefficients and price modeled as random lognormal (using column 3 WTP results from Table 3 & Table 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 insect presence does not significantly reduce WTP for organic or low conventional spraying vis-à-vis high conventional spray regimes.

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

Table 3: Hierarchical Bayes Mixed Logit Coefficients and WTP – Log-Normal Price Coeff. – Blueberries

	Coefficients				**Willingness-to-Pay**	
	(1) Without Interactions		(2) With GD Interactions		(3) Without Interactions	(4) With GD Interactions
Variables	Est. (se)	Var. (se)	Est. (se)	Var. (se)	Est. (se) [95% CI]	Est. (se) [95% CI]
GM Plant (v. not GM)	-1.220 (0.168)	5.216 (0.911)	-1.231 (0.171)	5.361 (0.974)	-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)	2.643 (0.452)	-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)	9.604 (1.517)	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)	4.635 (1.020)	0.835 (0.226) [0.41, 1.30]	0.907 (0.249) [0.45, 1.42]
Opt-out ASC	-4.969 (0.374)	37.015 (4.852)	-4.929 (0.417)	37.080 (5.202)	-5.806 (0.345) [-6.50, -5.15]	-5.753 (0.332) [-6.41, -5.13]
Price[a]	0.157 (0.068)	1.064 (0.139)	0.156 (0.073)	1.071 (0.135)		
GD Ins. X Organic			-0.138 (0.183)			-0.162 (0.214) [-0.60, 0.24]
GD Ins. X Conv. Low Spray			-0.147 (0.210)			-0.176 (0.249) [-0.67, 0.27]
Log-Lik	-2882.80		-2882.33			

[a] Untransformed, transform with $-e^{\widehat{\beta}_p}$. For WTP, compute $-\frac{\beta_k}{e^{\beta_p}}$. Note: *indicates the 95% credible interval does not contain zero.

Table 4: Hierarchical Bayes Mixed Logit Coefficients and WTP – Log-Normal Price Coeff. – Orange Juice

	Coefficients				**Willingness-to-Pay**	
	(1) Without Interactions		(2) With GD Interactions		(3) Without Interactions	(4) With GD Interactions
Variables	Est. (se)	Var. (se)	Est. (se)	Var. (se)	Est. (se) [95% CI]	Est. (se) [95% CI]
GM Plant	-0.949	5.402	-0.933	5.468	-0.848*	-0.826*
(v. not GM)	(0.168)	(0.938)	(0.166)	(0.929)	(0.167)	(0.163)
					[-1.20, -0.54]	[-1.16, -0.51]
GD Insects	-0.487	2.580	-0.420	2.517	-0.437*	-0.374*
(v. none)	(0.137)	(0.450)	(0.187)	(0.407)	(0.134)	(0.173)
					[-0.72, -0.19]	[-0.71, -0.06]
Organic	1.875	9.961	1.859	10.038	1.673*	1.643*
(v. Conv. High Spray)	(0.236)	(1.564)	(0.252)	(1.517)	(0.234)	(0.251)
					[1.21, 2.14]	[1.18, 2.16]
Conv. Low Spray	1.529	4.416	1.639	4.447	1.364*	1.448*
(v. Conv. High Spray)	(0.172)	(0.839)	(0.183)	(0.775)	(0.174)	(0.188)
					[1.03, 1.72]	[1.09, 1.84]
Opt-out ASC	-7.587	45.676	-7.631	46.271	-6.748*	-6.72*
	(0.513)	(6.594)	(0.510)	(6.681)	(0.330)	(0.315)
					[-7.42, -6.13]	[-7.36, -6.13]
Price[a]	0.116	0.914	0.126	0.915		
	(0.074)	(0.109)	(0.073)	(0.110)		
GD Ins. X Organic			0.040			0.036
			(0.235)			(0.207)
						[-0.38, 0.42]
GD Ins. X Conv. Low Spray			-0.233			-0.204
			(0.192)			(0.169)
						[-0.54, 0.13]
Log-Lik	-2674.96		-2674.01			

[a] Untransformed, transform with $-e^{\widehat{\beta}_p}$. For WTP, compute $-\frac{\beta_k}{e^{\beta_p}}$. Note: *indicates the 95% CI does not contain zero.

Table 5: Correlation between Random Coefficients – Non-price Normal; Price Lognormal

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

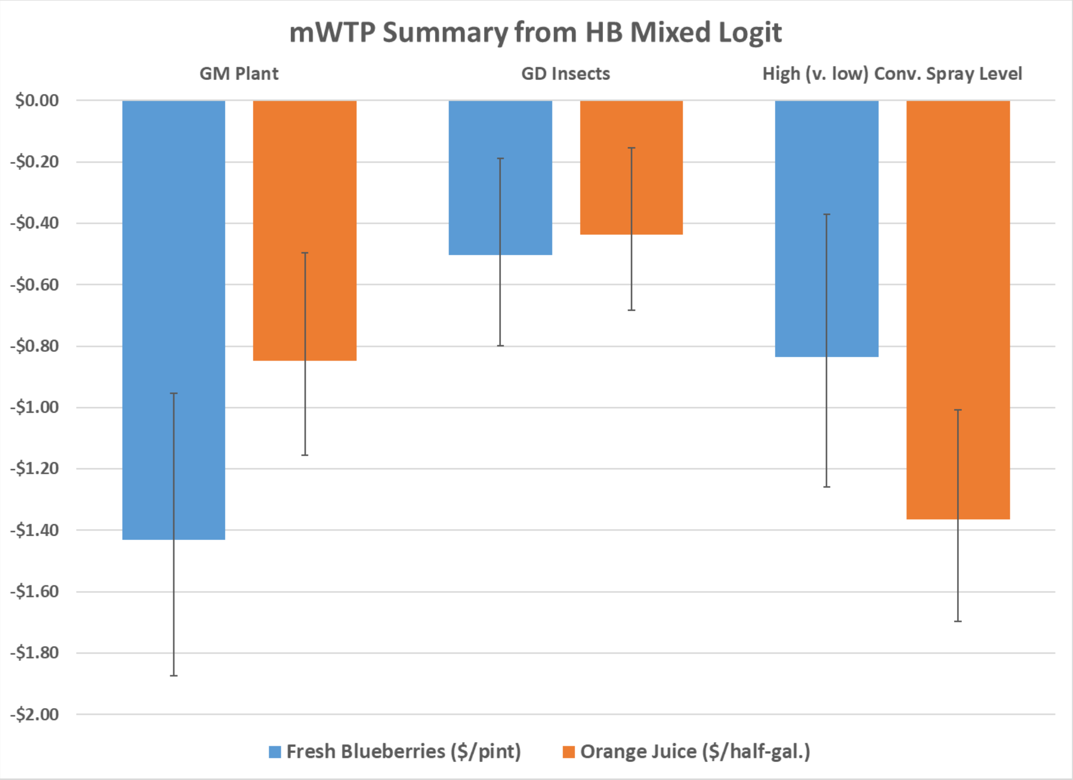

Figure 1: Comparing mWTP Estimates of Escalated Pest Management Strategies

Note: HB Mixed Logit model with correlated random main effects, price as random lognormal (Col. 3 of *Table 3* & *Table 4*). Comparisons of coefficients in this graph are only appropriate between attributes of the same product.

Welfare analysis

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 2, in which releases both reduce conventional pesticide spraying and prices. If a pest is more damaging and causes increased management costs and losses, this will generally result in increasingly higher retail prices. Thus the greater the pest's impact on retail prices of host crop products, ceteris paribus, the greater the ability to benefit from a reduction in pest damage via gene drive insect releases. Pests may disproportionately impact prices in the organic (vs. conventional) sector, as control options are often limited in scope and effectiveness (Burrack et al. 2019; Farnsworth et al. 2017; Van Timmeren and Isaacs 2013).

To contextualize relevant ranges of pest-induced price changes for each product, we use limited empirical examples from the economics literature as proxies for blueberries and orange juice. 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 the fresh blueberry market. Farnsworth *et al.* (2017) note that pest management is considerably more difficult in organic production and 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. As management techniques were less refined in "early" days, the initial impact on conventional market prices was considerably higher. For orange juice, we proxy with estimates from Moss *et al.* (2014) of Asian citrus psyllid-vectored citrus greening on fresh orange field box prices. In our initial simulation we assume proportional transmission of price changes in the orange juice market. Organic and conventional production are undifferentiated, though organic orange juice composes a very small portion of the overall market.

Unlimited Drive Releases

In Table 6 & Table 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 terms[6]. 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 important factors driving results.

For blueberries, the simulation suggests a mean $8.94 consumer surplus loss from unlimited drive insect release, 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. While median estimates are comparable whether price is fixed or lognormal, mean estimates are considerably higher in the random lognormal specification. Aside from lognormal distributional skew, this is driven in part by the negative correlation between the price and drive insect attribute coefficients (see: Table 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 improved management practices between "early" and more recent ("late" or "current") stages of spotted-wing infestation (Farnsworth et al. 2017), especially within conventional production, the potential reduction in prices from drive insect releases declines. Thus, consumers may benefit less (or be harmed more) from this type of area-wide intervention if releases are delayed past periods of

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[6] Assuming weekly shopping trips to convert our DCE "shopping trip" simulation to meaningful terms. Note that our 'per-capita' population are those whose households have purchased the product at least once in the six months before Nov/Dec 2017.

improved chemical and/or integrated pest 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, however, simulating an unlimited gene drive citrus psyllid release results in 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. Drive insect welfare losses are considerably lower than the estimated mean $9.46 per capita loss from Asian citrus psyllid-vectored citrus greening. However, a plurality of consumers would benefit from drive insect releases, with a small, statistically significant median surplus change of $0.73. More positive results for orange juice are driven, in part, by much greater relative disutility from increased insecticide versus drive insect presence (Table 3 & Figure 1). Estimates for orange juice consumers have less disparity between model specifications, though we note the significant, positive mean welfare estimate of $2.76 in a fixed price coefficient specification.

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 2, placing the empirical estimates in context. The range of scenarios assumes pests cause equal or disproportionately greater price increases in organic vs. conventional markets. Thus for blueberries in Figure 2a, simply switching from high spray and organic regimes to low spray and organic regimes, with ubiquitous drive insect presence and a hypothetical null price effect from initial invasions (0% change in conventional or organic prices), there is a mean welfare loss of about $11. Even if conventional prices were not impacted by spotted-wing (i.e. along the Figure 2a line for 0% ‘conventional price increase’), consumer welfare still improves if drive insects are able to reverse spotted-wing’s impact on organic prices. The Farnsworth *et al.* (2017) “late” period empirical point, with spotted-wing causing an increase in prices of 0.04% in conventional markets and 7.0% in organic markets, illustrates this type of gain.

Simulations indicate that spotted-wing Drosophila must induce fresh blueberry price increases well in excess of 20% for a mean positive consumer welfare gain from drive insect releases. Orange juice prices must increase over 12.4% due to citrus greening for a positive mean welfare estimate, just above 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 must have risen at least 14.0% for a positive mean welfare gain. To reach statistical significance for a positive mean welfare estimate, conventional prices must have increased >16% with organic price increases of >20%.

Simulations for median estimates across original price impacts are presented in Figure 3. A plurality of consumers would benefit from drive insect releases if spotted-wing had induced at least a uniform 10% price increase in conventional and organic markets (Figure 3a). If conventional prices only rose 8%, organic prices must have risen at least 20% to similarly achieve this plurality. With any non-zero price impact, median estimates for orange juice consumers are always positive (Figure 3).

Limiting drive releases to retain market choice

There appears to be considerable welfare gain associated with retaining market alternatives without drive insect presence, even when those alternatives have higher prices and pesticide spray levels. As the distribution of ΔCS(GD+SQ, GD) is censored at a zero and unbounded in the positive direction, we concentrate analysis on median estimates in Table 6 & Table 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 is more modest, with a median $2.44 welfare gain. In Figure 4, we provide analogous welfare ranges across possible initial price impacts of the pest infestations, placing empirical literature estimates in context. Of course, the value of additional high spray and/or higher-priced, non-drive alternatives declines as the price of those alternatives increases.

The structure of the estimate distribution will always result in positive consumer welfare gains from limiting drive releases to preserve greater consumer choice. However, the scale of the estimates may be of immense interest to policymakers. 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 to what extent drive insect releases have the capacity to reduce price increases from pests. And while organic producers have disproportionately higher management costs and losses due to invasive pests, our data indicate that, on aggregate, there is significant consumer welfare gain to retaining organic options without any interaction with biotechnologies.

Table 6: Mean and Median Per-capita Annual Consumer Surplus Changes - Blueberries

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]**
ΔCS(SQ, Pre-SWD) **“current”** Original estimated change due to SWD introduction, with current prevailing practices	High spray & Organic, high prices (Conv. Price ↑0.04%; Org. Price ↑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]
ΔCS(GD, SQ) **“current” or “late”** After SWD infestation and *current* prevailing practices, release of GD SWD and ubiquitous presence	Low spray & Organic, low prices, with ubiquitous gene drive insect presence	High spray & Organic, high prices (Conv. Price ↑0.04%; Org. Price ↑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]
ΔCS(GD, SQ) **“early”** After SWD infestation with *initial* management, release of GD SWD and ubiquitous presence	Low spray & Organic, low prices with ubiquitous gene drive insect presence	High spray & Organic, high prices (Conv. Price ↑5.8%; Org. Price ↑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]
ΔCS(GD+SQ, GD) **“current” or “late”** Gain from limiting GD SWD presence given current prevailing practices	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]

[a] Using 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. CS(

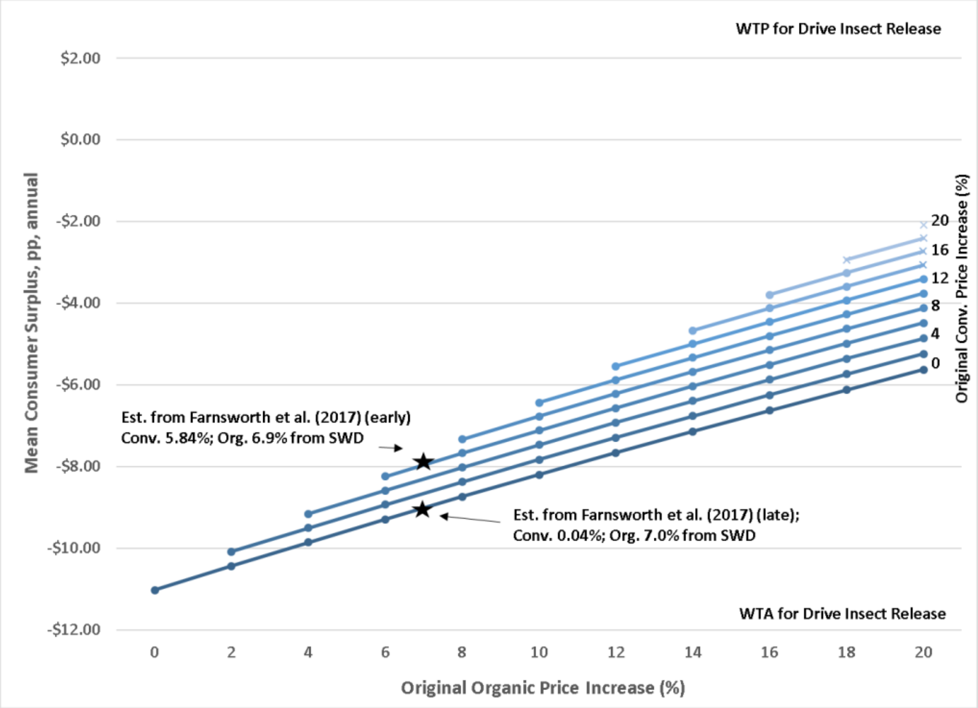
Table 7: Mean and Median Per-Capita Annual Consumer Surplus Changes – Orange Juice

Scenario	V^1 Alternatives	V^0 Alternatives	Price Lognormal Mean [90% CI]	Price Lognormal Median [90% CI]	Price Fixed (non-random) Mean [90% CI]	Price Fixed (non-random) Median [90% CI]
ΔCS(SQ, Pre-ACP) Original estimated change due to ACP introduction	High spray & Organic, high prices (All Price ↑11.99%[a])	Low spray & Organic, low prices	-9.464* [-10.296, -8.632]	-8.216* [-8.996, -7.436]	-7.124* [-7.592, -6.604]	-7.384* [-8.06, -6.708]
ΔCS(GD, SQ) After ACP infestation, release of GD ACP and ubiquitous presence	Low spray & Organic, low prices with ubiquitous gene drive insect presence	High spray & Organic, high prices (All Price ↑11.99%[a])	-0.364 [-1.924, 1.300]	0.728* [0.260, 1.352]	2.756* [2.028, 3.484]	1.560* [0.988, 2.184]
ΔCS(GD+SQ, GD) Gain from limiting GD ACP presence	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* [9.360, 12.272]	2.444* [1.924, 2.964]	5.252* [4.836, 5.668]	2.288* [2.028, 2.548]

[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.

Figure 2: Mean 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 prices 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 (Figure *2*.a)



Orange Juice (Figure *2*.b)

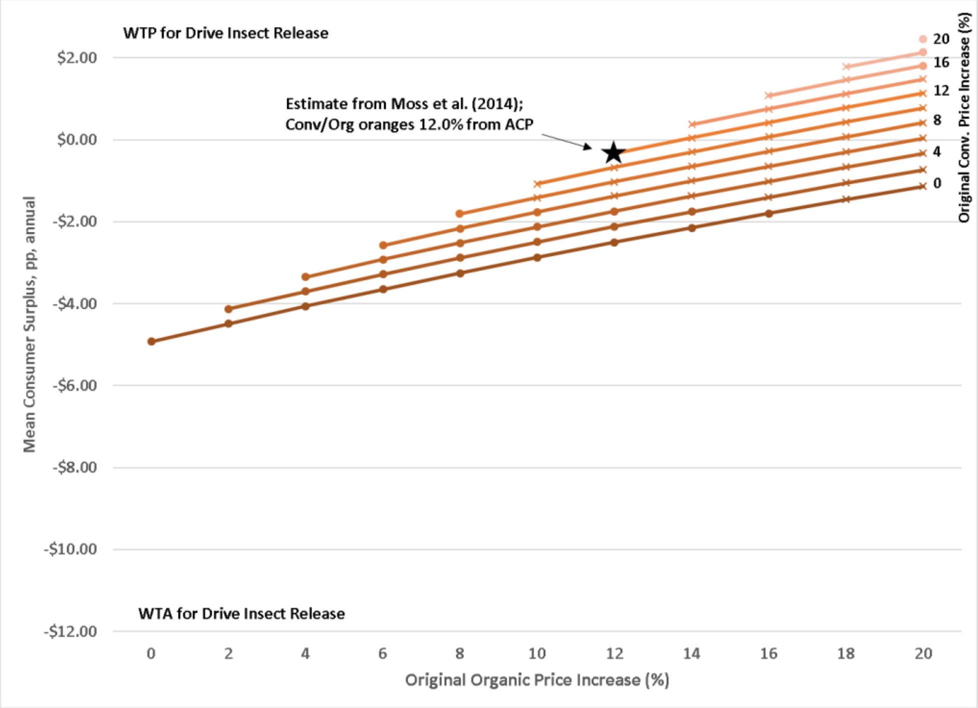
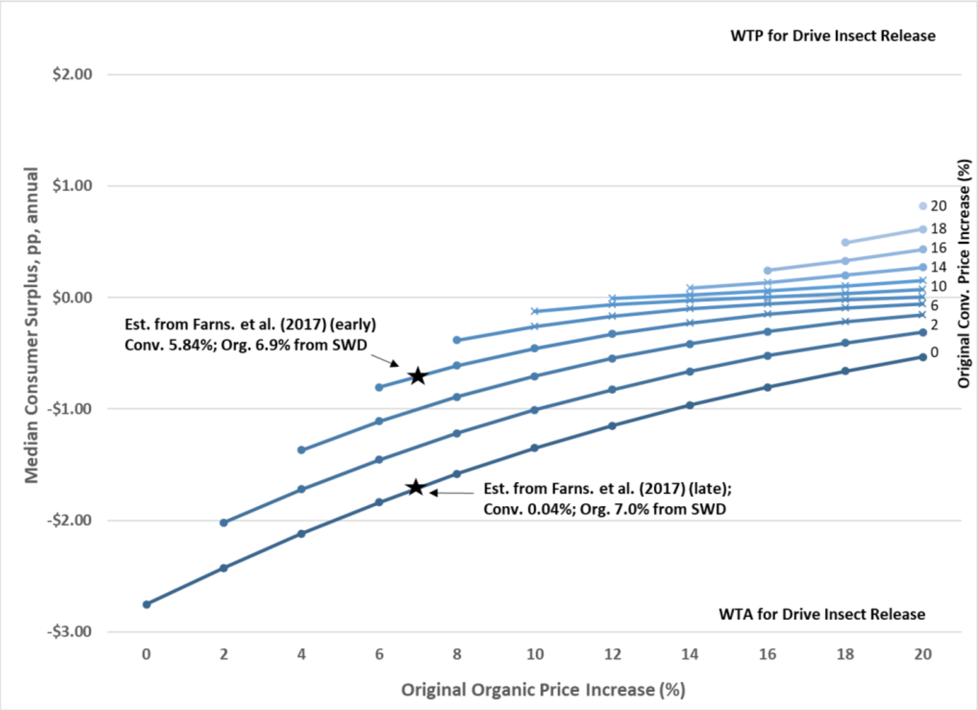


Figure 3: Median consumer surplus from uncontrolled drive insect releases that reduce pesticides and prices, across range of original pest-induced price increases for conventional and organic goods

Higher original price impacts from pests lead to greater prices 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 (Figure *3*.a)



Orange Juice (Figure *3*.b)

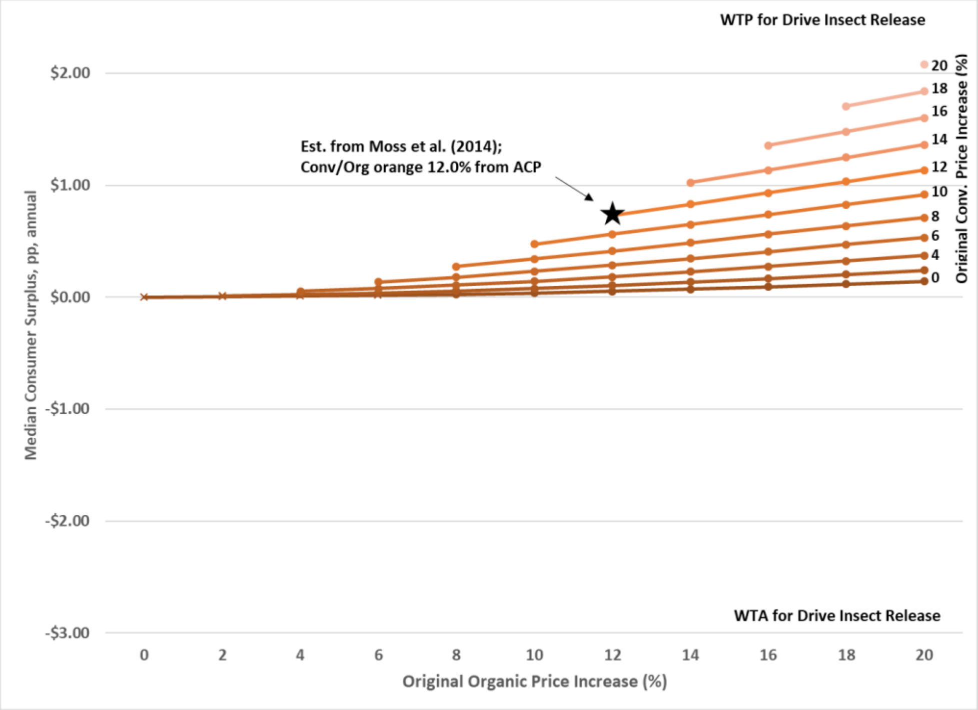
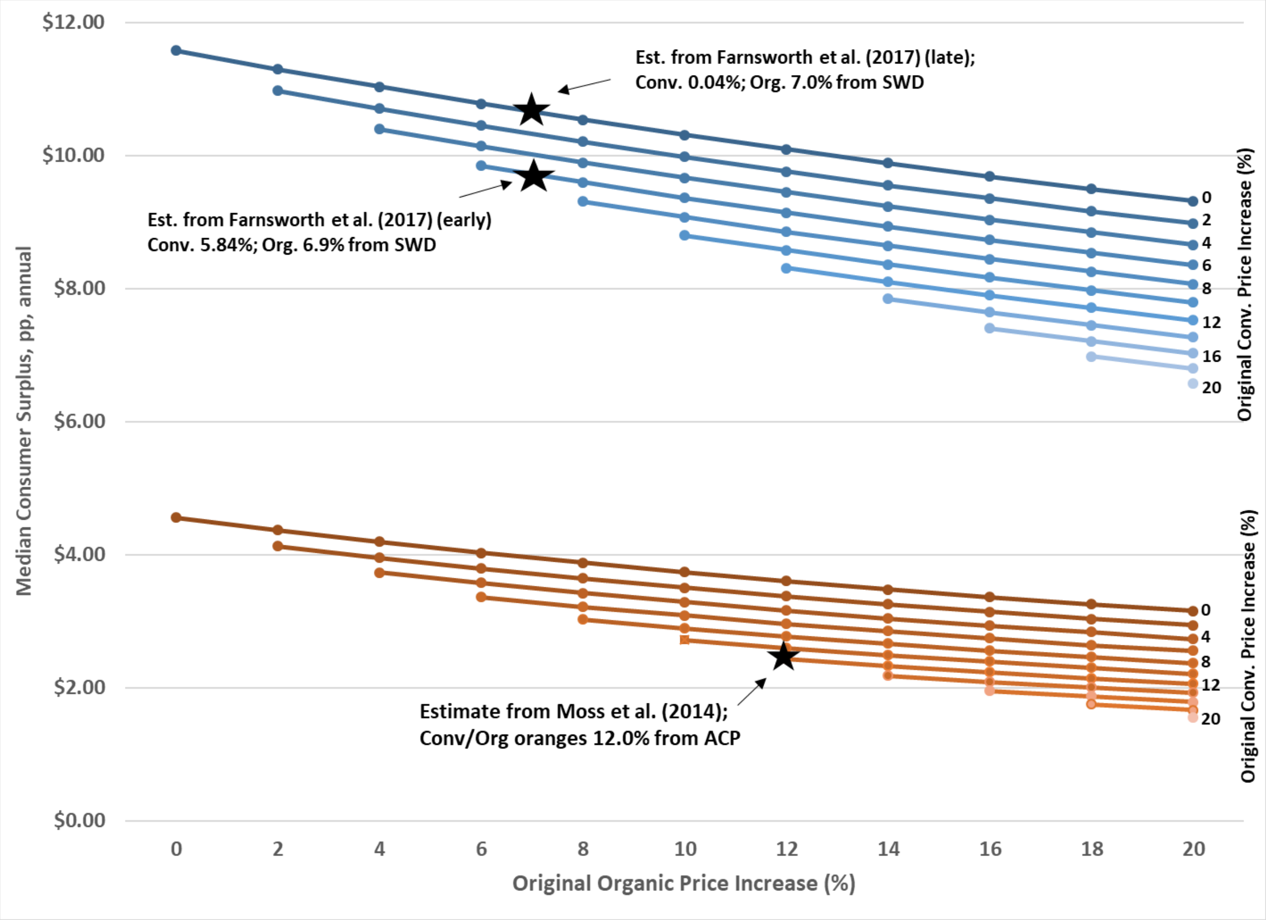


Figure 4: Median consumer surplus of limiting drive insect releases to retain market options for higher priced, higher spray alternatives (without drive insect presence in growing areas)

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).

Fresh Blueberries (top) and Orange Juice (bottom)



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 (Baltzegar et al. 2018; Emerson et al. 2017; NASEM 2016), 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, more pesticides are already a reality in these growing environments. Our results consistently indicate, across both fresh blueberries and orange juice experiments, that consumers had lower or statistically equivalent reductions in mean mWTP with gene drive insect presence in growing areas compared to current high (v. 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. It is logical that GMO organism presence 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 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. Among organic consumers, 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. This interactive effect dissipates and is not statistically significant for either product in more sophisticated and significantly more explanatory mixed logit specifications.

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 alternative 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. Consumer welfare estimation indicates that, using model specifications with the highest explanatory power, mean and median consumer surplus changes are negative for blueberries. 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 is quite large and should be carefully considered when weighing how (and if) to implement any release program for genetically engineered or gene drive insects. Thus the ecological risk concerns already expressed by scientists and regulators with self-sustaining gene drive insect releases (Delborne et al. 2018; NASEM 2016) are augmented by these marketplace concerns, given the inherently commercial nature of any agricultural gene drive pest application. But just as the National Academy of Sciences, Engineering, and Medicine (2016) report emphasizes for case-by-case risk assessment with gene drive organisms, our data indicate 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. Our experiment clearly labeled product features, though perfect information may not be available to many consumers in the marketplace. Further, while increased pesticide application may not be heavily publicized, impending trial releases of non-drive GM mosquitoes in Florida led to heavy media coverage (see: Allen (2016) and Servick (2016)). Gene drive insect releases may be similarly publicized, which could increase awareness and potentially lead to a greater overall market impact.

Further research is needed to connect underlying values driving the consistently differential impacts of plant vs. insect-based biotechnology solutions. In addition, 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.

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Appendix A: 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.

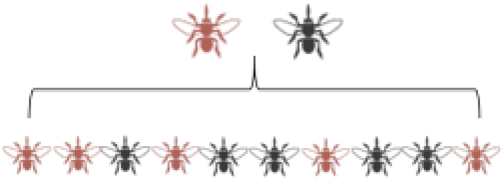
As you may have heard, a new strategy under development is called a ‘gene drive’, using a genetic engineering technology called CRISPR/CAS9 (pronounced “crisp-er”). **With this approach, scientists may be able to modify the genes of insect pests 1) to prevent them from being able to transmit diseases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

Panel 2:

“(Page 2 of 4)

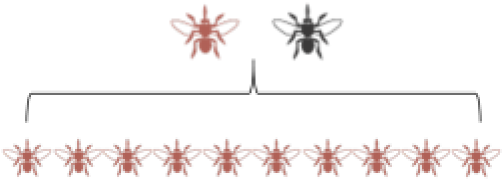
How does a gene drive work?

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.**



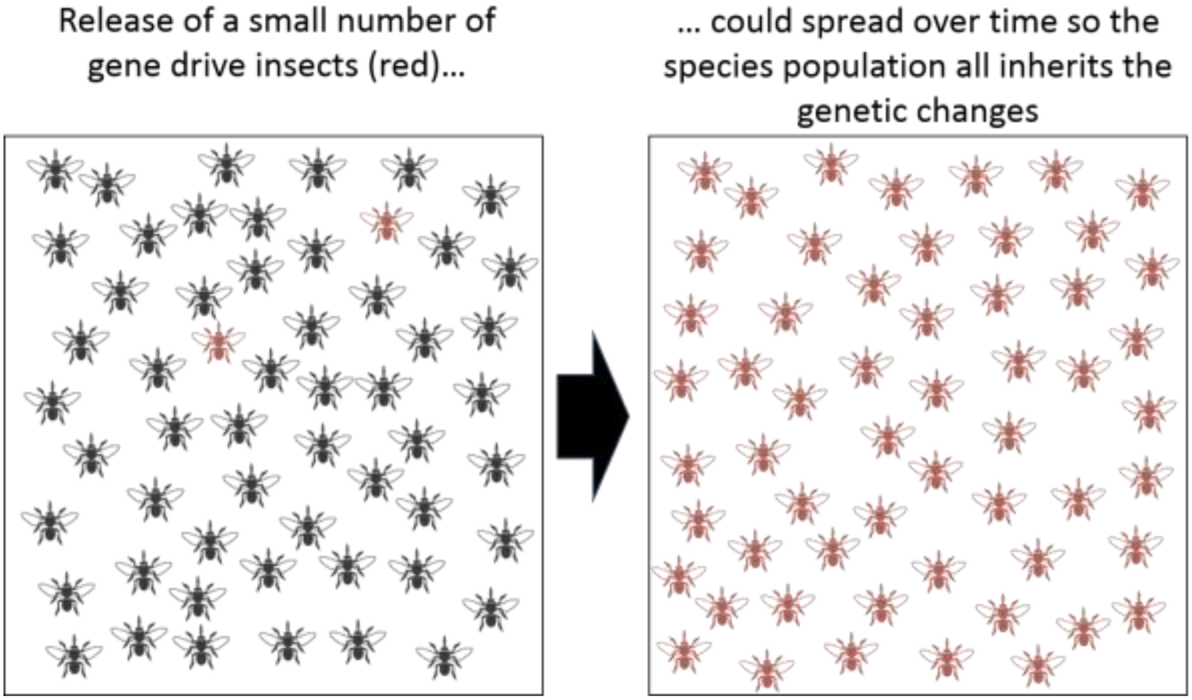
Normal Inheritance
(red insects have a new genetic change)

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.**



Increased Inheritance with Gene Drive
(red insects have a new genetic change)

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)

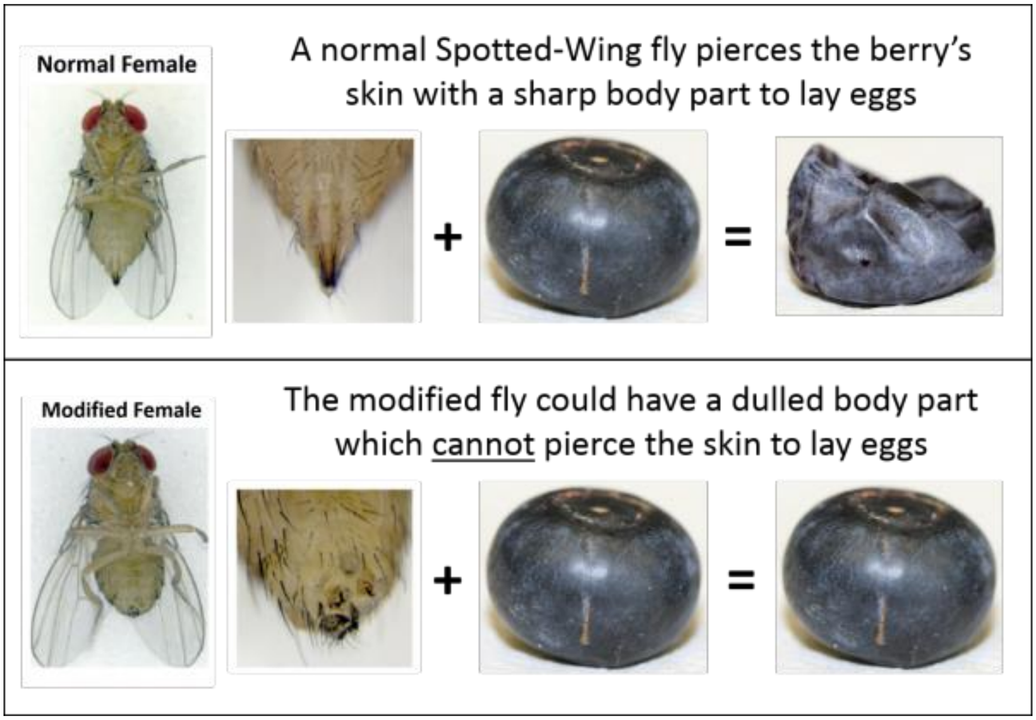
Gene drives could potentially be used to reduce or eliminate an insect population

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.


A normal Spotted-Wing fly pierces the berry's skin with a sharp body part to lay eggs

The modified fly could have a dulled body part which cannot pierce the skin to lay eggs

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.”

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 B. Choice Experiment Scenario Examples

Appendix B.1 Choice scenario example: Fresh Blueberries

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

Appendix B.2 Choice scenario example: Orange Juice

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

Appendix C: Sample Details

Appendix C1. Qualified completes socio-demographic details

N=1,018 completes	% Qualified Completes
Age Categories	
- 18-29	12.48
- 30-44	24.95
- 45-59	28.39
- 60+	34.18
Sex	
- Male	52.26
- Female	47.74
Education	
- <High School	7.07
- High School	25.25
- Some College	29.08
- Bachelor	21.02
- Masters	13.75
- PhD	3.83
Household Income	
- < 25,000	11.00
- 25k to <50,000	18.37
- 50k to <75,000	15.80
- >75k	47.45
Race/Ethnicity	
- White, Non-Hisp	72.89
- Black, Non-Hisp	7.47
- Other, Non-Hisp	4.91
- Hispanic	12.38
- 2+ Races, Non-H	2.36

Appendix D: Fixed Price Coefficient HB WTP Results

Hierarchical Bayes Mixed Logit Coefficients and WTP – Fixed Price Coefficient – Fresh Blueberries

	Coefficients				Willingness-to-Pay	
	Without Interactions		With GD Interactions		Without Interactions	With GD Interactions
Variables	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			

Hierarchical Bayes Mixed Logit Coefficients and WTP – Fixed Price Coefficient – Orange Juice

	Coefficients				**Willingness-to-Pay**	
	Without Interactions		With GD Interactions		Without Interactions	With GD Interactions
Variables	Mean (SD)	Var (SD)	Mean (SD)	Var (SD)	Mean (SD) [95% CI]	Mean (SD) [95% CI]
GM Plant	-1.018	5.153	-1.028	5.142	-0.908	-0.913
(v. not GM)	(0.152)	(0.781)	(0.151)	(0.788)	(0.135)	(0.131)
					[-1.18, -0.65]	[-1.19, -0.67]
GD Insects	-0.713	1.767	-0.556	1.793	-0.637	-0.495
(v. none)	(0.106)	(0.315)	(0.153)	(0.324)	(0.096)	(0.137)
					[-0.82, -0.45]	[-0.75, -0.20]
Organic	1.812	8.842	1.903	8.894	1.617	1.691
(v. Conv. High Spray)	(0.198)	(1.245)	(0.216)	(1.262)	(0.17)	(0.19)
					[1.28, 1.95]	[1.30, 2.06]
Conv. Low Spray	1.289	3.42	1.395	3.359	1.151	1.24
(v. Conv. High Spray)	(0.141)	(0.565)	(0.157)	(0.586)	(0.126)	(0.137)
					[0.92, 1.41]	[0.97, 1.52]
Optout	-5.641	12.287	-5.589	12.285	-5.032	-4.965
	(0.308)	(1.622)	(0.313)	(1.699)	(0.196)	(0.194)
					[-5.43, -4.67]	[-5.38, -4.58]
Price	-1.121		-1.126			
	(0.046)		(0.047)			
GD Ins. X Organic			-0.175			-0.156
			(0.196)			(0.175)
						[-0.49, 0.18]
GD Ins. X Conv. Low Spray			-0.245			-0.217
			(0.162)			(0.144)
						[-0.49, 0.05]
Log-Lik	-2851.04		-2849.6			

Appendix E: Classical MSL mixed logit modeling results

Fresh Blueberries

Conditional Logit Results

Model estimation begins with a preliminary conditional logit model in utility space (Table 5, col. 1&2) which assumes homogeneous preferences across consumers. Fresh blueberry consumers negatively value genetic modifications to the plant itself as well as gene drive insect presence. However, the mean disutility for gene drive insect presence is less than half that induced by a GM blueberry plant, which is important as future biotechnology alternatives are considered. Consumers prefer both low spray and certified organic pest management practices to a high conventional pesticide spraying regime, which is largely representative of current conventional practices. We can also interpret the negative of the low spray coefficient as the utility associated with moving from a low to high spray regime. In this framing, mean drive insect impacts are statistically indistinguishable from a high spray regime ($p=0.630$).

In this model, gene drive insects appear to statistically significantly impact the marginal utility of pest management regimes, decreasing the marginal value of more environmentally friendly methods. In particular, there is a modest but statistically significant 23.9% ($p<0.001$)[7] reduction in marginal utility for certified organic status, a ratio which directly translates to a percentage decline in willingness-to-pay. This result would indicate a decline in the value denoted by the certification, though this result softens as we relax IIA in the mixed logit model.

Mixed Logit Results

A mixed logit model (Table 5, col. 3&4) accounting for unobserved heterogeneity provides marked improvements in model likelihood. The relative impact of biotechnology strategies for

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[7] Standard error calculated via Delta Method (using *nlcom* command in *Stata*)

pest mitigation remains roughly unchanged – the mean effect of a genetically engineered plant is nearly twice that of gene drive insects, resulting in a mean $1.07/pint reduction in WTP for a GM plant and $0.55/pint reduction for gene drive insect presence (Table 6). Compared to a high frequency conventional spraying regime, there is a mean $1.82/pint premium for certified organic management and a $0.63/pint premium for low frequency conventional spraying. Allowing attribute interactions but retaining independent random coefficients, the heterogeneity in gene drive insect impact remains across pest management regimes though the difference is now only significant for certified organic production (column 4). While the organic premium in the absence of drive insects is $1.91/pint, this decreases by a modest but statistically significant 22.5% ($0.43/pint) when drive insects are present.

When we allow all non-price random main effects coefficients to be correlated (T5, col. 5&6), we see important shifts in results which we are still exploring. The disutility from a GM plant continues to double that of drive insect presence. Further, the disutility from a high spray conventional regime, remains greater than drive insect presence in the main effects model (col. 5). Regarding impacts on organic valuation, the interaction coefficient with gene drive insects is attenuated and much noisier in the fully correlated model, with a statistically insignificant 6.8% reduction in organic WTP (Table 6). The sensitivity of the results to this fully correlated specification – which has much higher explanatory power –merits further exploration to determine appropriate policy recommendations.

Appendix E, Table 1: Fresh Blueberries - Preference Space Estimates

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

Appendix E, Table 2: 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 Present	-0.302*	0.0004	-0.554*	-0.319*	-0.693*	-0.634*
(v. Absent)	[-0.488, -0.116]	[-0.263, 0.264]	[-0.724, -0.383]	[-0.582, -0.056]	[-0.900, -0.487]	[-0.922, -0.345]
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)

Orange Juice

Conditional Logit Results

When assuming homogeneous preferences among orange juice consumers, disutility derived from gene drive insect presence is statistically equivalent to that of a genetically modified orange tree (Table 7, col. 1; p=0.973). Each biotechnology strategy is associated with a mean $0.55/half-gallon reduction in WTP (Table 8). Compared to a high frequency conventional spray regime, there is a $1.49/half-gallon premium for certified organic production and a $0.92/half-gallon premium for a low frequency spray regime. The presence of gene drive insects decreases marginal utility (and WTP) for organic certification by a statistically significant 20.28% (p=0.014).

Mixed Logit Results

However, when incorporating continuous heterogeneity across respondent preferences, the mean reduction in WTP for a GM orange tree is nearly 47% greater than the reduction for gene drive insect presence. While meaningful, this difference between biotechnology strategies remains lower than that found for blueberry production. Mean reduction in WTP from gene drive insects, as well as premiums for organic production and low spray regimes, are relatively unchanged in the mixed logit specification and further allowing for correlated random coefficients does not qualitatively change WTP estimates.

For both mixed logit models, the magnitude of the relative reduction in WTP for organic pest management when drive insects are present is on the order of 10-11%, but this estimate is not statistically significant. Modeling heterogeneity across respondents continues to be key to understanding policy-relevant impacts of these new technologies.

Appendix E, Table 3: Orange Juice – Preference Space Estimates

VARIABLES	(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***	-0.607***	-1.023***	-1.026***	-1.078***	-1.086***
	(0.0313)	(0.0312)	(0.0399)	(0.0401)	(0.044)	(0.045)
Plant GM	-0.336***	-0.336***	-0.867***	-0.870***	-0.944***	-1.069***
	(0.0710)	(0.0702)	(0.117)	(0.117)	(0.136)	(0.146)
GD Insects	-0.333***	-0.252***	-0.590***	-0.477***	-0.628***	-0.473***
	(0.0547)	(0.0633)	(0.0788)	(0.124)	(0.094)	(0.144)
Organic (v. High Spray)	0.904***	1.006***	1.555***	1.640***	1.674***	1.811***
	(0.0908)	(0.101)	(0.133)	(0.160)	(0.180)	(0.210)
GD insects x Org.		-0.204**		-0.170		-0.204
		(0.0905)		(0.176)		(0.195)
Low Spray (v. High)	0.558***	0.569***	0.980***	1.036***	1.200***	1.345***
	(0.0680)	(0.0895)	(0.0893)	(0.109)	(0.122)	(0.143)
GD insects x Low Spray		-0.0515		-0.151		-0.259
		(0.0898)		(0.147)		(0.158)
Opt-out	-2.804***	-2.785***	-5.421***	-5.396***	-5.515***	-5.561***
	(0.175)	(0.179)	(0.252)	(0.253)	(0.290)	(0.300)
SD[1]						
Plant GM			1.774***	1.765***	4.401***	4.735***
			(0.133)	(0.133)	(0.661)	(0.743)
GD Insects			0.723***	0.729***	1.431***	1.310***
			(0.122)	(0.123)	(0.285)	(0.270)
Organic			1.763***	1.755***	8.045***	8.497***
			(0.158)	(0.159)	(1.073)	(1.126)
Low Spray			0.945***	0.940***	2.568***	2.614***
			(0.124)	(0.124)	(0.487)	(0.465)
Opt-out			2.722***	2.724***	11.503***	12.025***
			(0.183)	(0.183)	(1.400)	(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. [1]For full covariance matrix of col. 5&6 models with correlated random coefficients, see appendix (omitted here for space).

Appendix E, Table 4: Orange Juice - WTP Estimates

VARIABLES	(1) Cond. Logit - Base	(2) Cond. Logit – Full	(3) MXL Uncorrelated Base	(4) MXL Uncorrelated Full	(5) MXL Correlated Base	(6) 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]

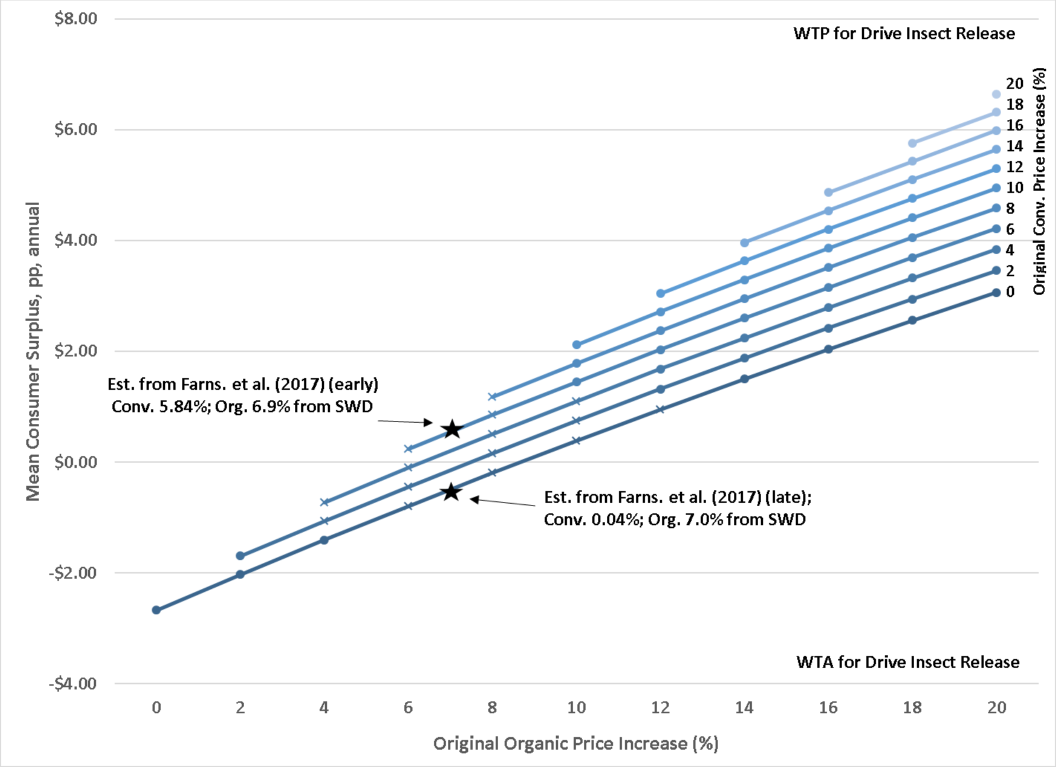
Note: 95% confidence intervals constructed by Delta method (Hole 2007)

Appendix F: HB MXL, with correlated random coefficients and price modeled as fixed/non-random

Table 1: Mean 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 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).

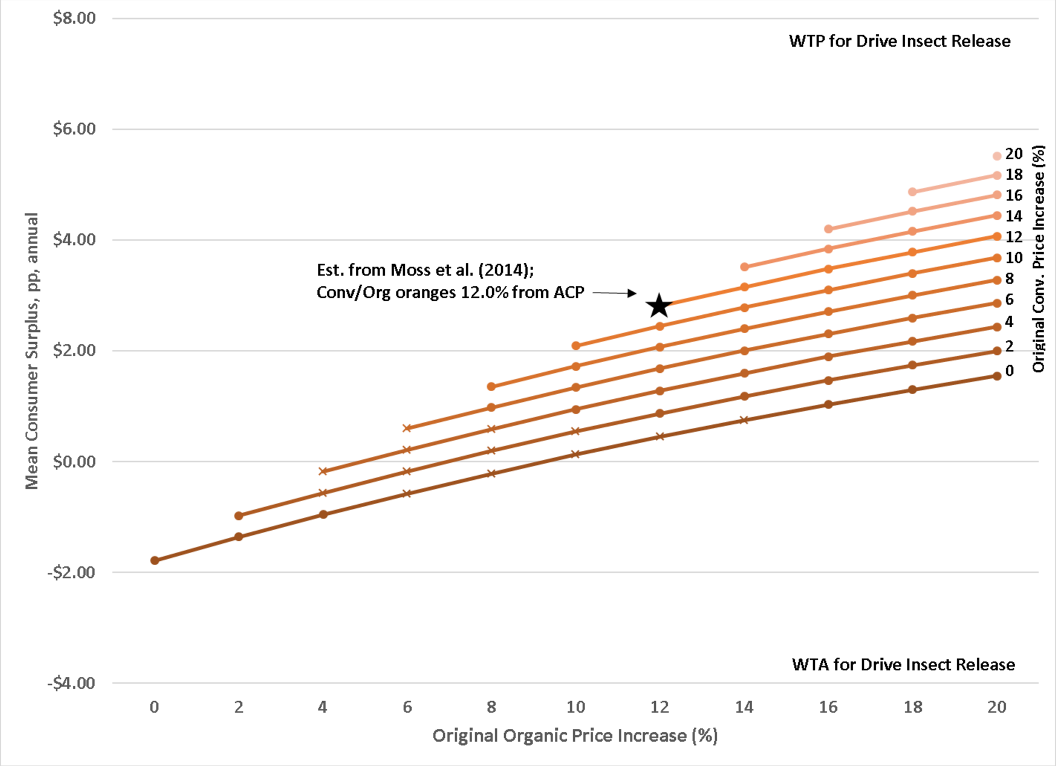
Fresh Blueberries



Est. from Farns. et al. (2017) (early)
Conv. 5.84%; Org. 6.9% from SWD

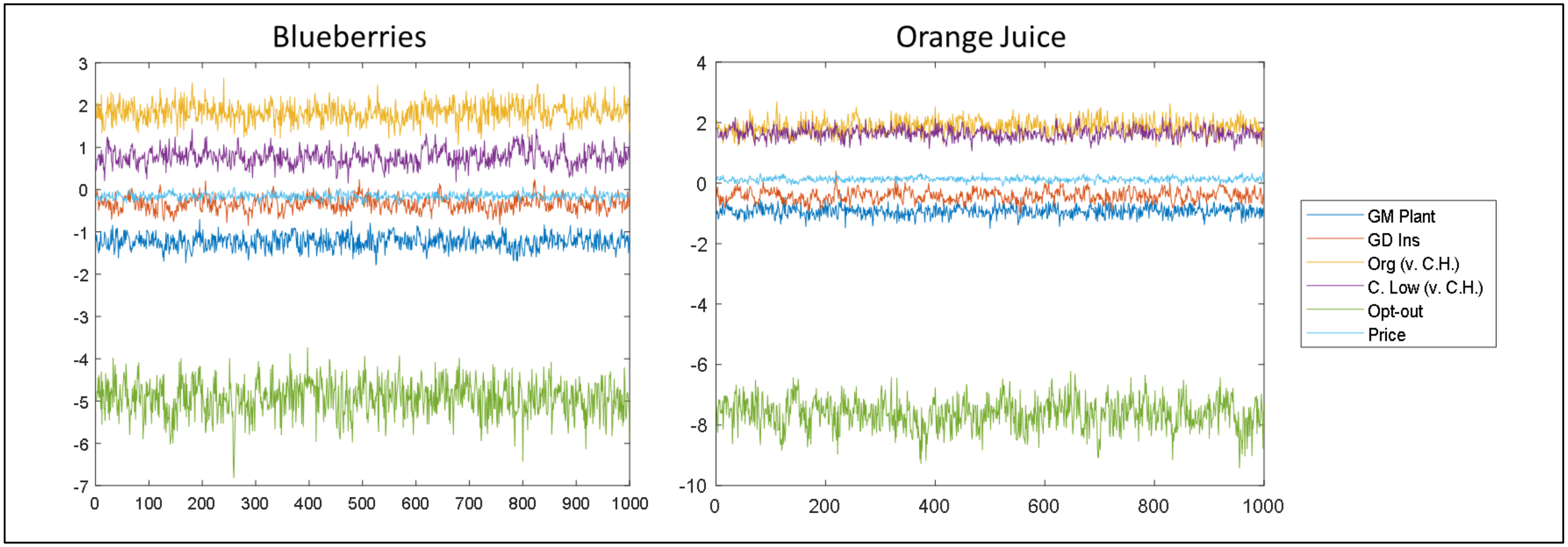
Est. from Farns. et al. (2017) (late);
Conv. 0.04%; Org. 7.0% from SWD

Orange Juice



Est. from Moss et al. (2014);
Conv/Org oranges 12.0% from ACP

Appendix G: Convergence of HB model coefficients



Note: Burn in of 100,000 draws; followed by 1000 retained draws, thinning every 100th draw. Non-price attributes modeled random normal, price as random lognormal.