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Food for thought: Assessing the consumer welfare impacts of deploying irreversible, landscape-scale biotechnologies

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ABSTRACT

Genetically engineered insects have gained attention as regionally deployed pest control technologies, with substantial applications in agriculture for combatting intractable crop pests and diseases. One potential tool is a 'gene drive', using CRISPR-based gene editing. In gene drive, preferentially inherited, engineered traits are spread throughout a geographic area to reduce pest populations or inhibit disease transmission, while also potentially reducing pesticide use and crop prices. But the self-perpetuating nature of gene drives presents a consequence, in that consumers could eventually be limited to only host crops grown in the presence of these genetically engineered insects. In this study, we analyze potential consumer welfare impacts of these technologies using discrete choice experiment data from a representative sample of U.S. adults, examining preferences regarding gene drive use to control spotted wing drosophila in blueberries and Asian citrus psyllid in orange juice (OJ) production. We find smaller average discounts for gene drives versus increased conventional pesticide use or genetically modified crops. Only 27% and 25% of blueberry and OJ consumers, respectively, are estimated to derive disutility from gene drives. However, gene drive disutility for these consumers is so large that elimination of non-drive options from their choice sets results in negative (blueberries) or neutral (OJ) effects to aggregate consumer welfare when weighed against gains to other consumers from reduced prices. Positive welfare effects are recovered by retaining availability of non-gene-drive products. We argue that this type of analysis will be increasingly important as landscape-level biotechnologies are deployed to address challenges to agricultural sustainability.

1. Introduction

New types of biotechnologies are nearing deployment that have the potential to transform agricultural pest control, with important implications for consumer welfare. These biotechnologies – which may loosely be described as 'engineered self-spreading biocontrol' – are designed so that relatively small and short duration releases of a pest modified to carry desirable traits result in the permanent or semi-permanent spread of the organism through an agricultural region. Desirable traits could include decreased growth or survivability rates, altered host-plant preferences, enhanced susceptibility to pesticides, as well as disease inoculation (e.g. to prevent an insect-vectored plant disease). The two most developed examples of such biotechnologies are 'gene drives,' which use genetic engineering to insert desirable traits along with modifications to promote their biased inheritance (Fig. 1), and *Wolbachia*, a bacterium that infects pests, reduces their fitness, and achieves preferential inheritance by modifying the host organism's reproduction. Because of their intended scale and their non-chemical modes of action, these technologies have the potential to address some of the most pressing challenges to sustaining effective pest control in agricultural production (Oerke, 2006; Culliney, 2014), including increased pest pressure from climate change (Deutcsh et al. 2018), continued risks of invasive species spread (Paini et al., 2016), the environmental and human risks of pesticides (Larsen et al., 2017), as well as pesticide resistance (Gould et al., 2018).

Some of these technologies are already having significant effects on preventing vector-borne diseases (Pinto et al., 2021). There has still been no commercial deployment in agriculture, although applications are currently under development (Yadav et al., 2023). Meanwhile, concerns have been raised about the risks of such large-scale manipulation of ecosystems (NASEM, 2016; Kuzma, 2021), and previous research has shown that the public has concerns about these

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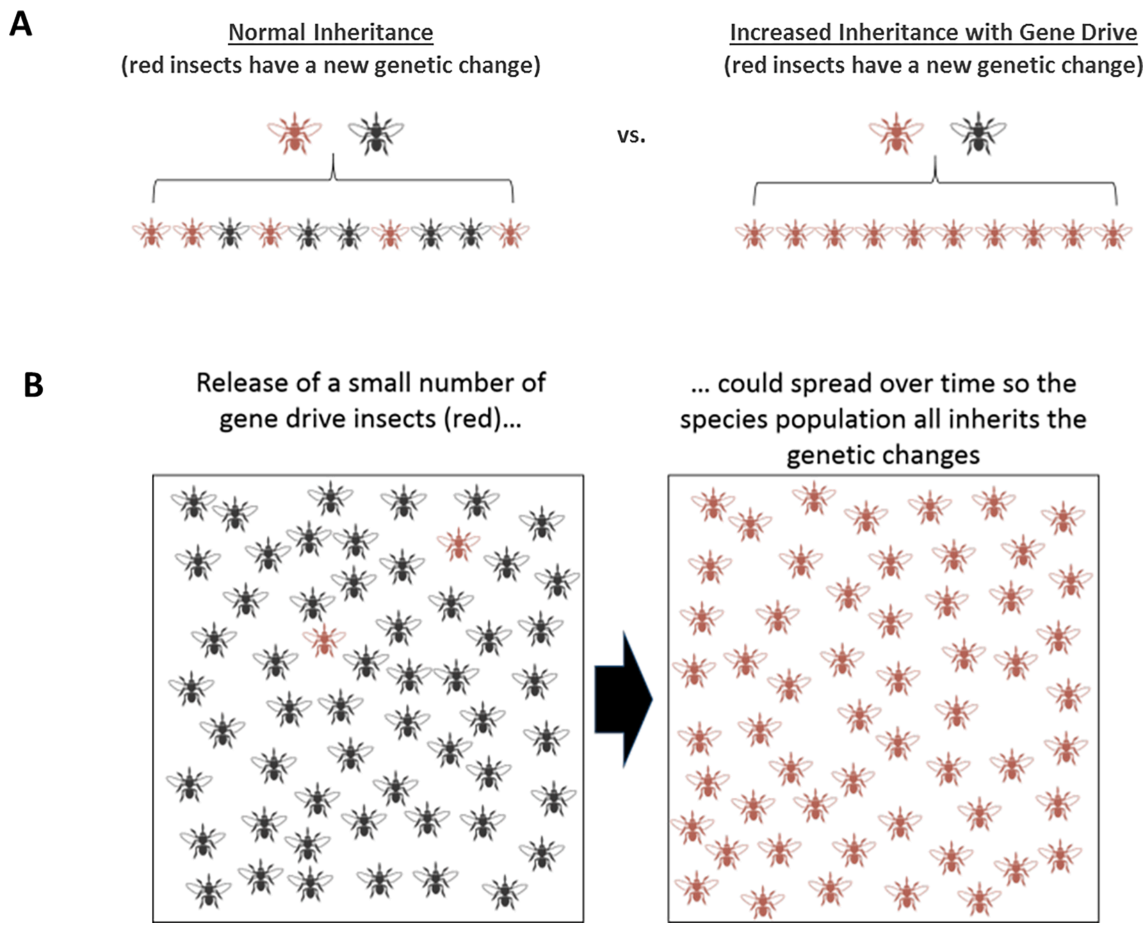

Fig. 1. Biased inheritance in gene drive (A) and potential for population spread (B). Note: Images created by the authors and present in a modified form in fielded survey to the public (see Supplementary Material for complete survey materials and wording).

technologies that may limit their acceptability in commercial agriculture, depending on how they are deployed (Jones et al., 2019). An extensive previous literature also documents consumers' decreased willingness to pay (WTP) for food produced using genetic engineering (GE) (Costa-Font, Gil and Traill, 2008; Frewer et al., 2011, 2013; Lusk, McFadden and Wilson, 2018).

In this paper, we investigate a previously unconsidered consumer externality that could arise from these technologies, intended as they are to alter the agroecology of whole production systems. This externality comes from restrictions on consumer choice likely to result from large-scale deployment. For example, gene drive insect pests released at one location would spread out over large growing areas across multiple farms, replacing the extant pest population with GE organisms. Once deployed, this GE presence would occur regardless of whether individual growers in the area wanted the technology. If successful and widely deployed, this would limit the ability to grow crops in the absence of gene drive insects. Consumers who prefer food produced without these GE technologies would therefore find it more difficult or costly to find such products.[1] At the same time, were gene drive insect releases to prove effective at reducing pest damage, they could mitigate pest-induced food price increases, and could also offer a potential substitute for intensive application of chemical pesticides. Evaluating the consumer welfare impacts of such a technology would thus require simultaneous consideration of these effects.

This paper illustrates such a welfare analysis in two potential proposed applications of gene drives: one to control the soft-fruit pest spotted wing drosophila and the other to control the Asian Citrus Psyllid, the insect vector for Citrus greening disease. We measured the distribution of consumer preferences regarding the use of gene drives to control these pests in the production of fresh blueberries and orange juice. Because there still has been no commercial release of gene drives in agriculture, we measure preferences using stated choice experiments conducted on a probability-based representative sample of the US general public. The choice experiments were part of a survey in which detailed information was provided to participants about the prospect of using gene drives to control pests of these products (Jones et al., 2019). Estimating an array of discrete choice econometric models using these data, we find robust and novel evidence that, on average, consumers exhibit a lower WTP for these products when gene drives were used. However, the reduction in WTP associated with gene drive insects is significantly smaller than the WTP reductions associated with higher insecticide spraying or genetic engineering of the plant itself. Moreover, the majority of consumers are estimated to have no disutility associated with gene drive use in these products.

We then use these estimated preferences to evaluate the expected aggregate consumer welfare impact of gene drive releases for pest control in the production of these foods. In both cases, previous research has documented how recent pest invasion has resulted in significantly

[1] There is debate about whether consumers' aversion to GE food, and by extension gene drives, should be accounted for in welfare analyses, since many researchers point out that consumers are frequently misinformed about the risks of these foods. However, this debate misses the fact that even well-informed consumers can have values-based reasons for avoiding such foods, e.g. based on cultural or religious grounds (Atalan-Helicke 2015). Our approach in this paper is to try and obtain well-informed preferences for foods produced using gene drives, and to use these preferences in welfare analysis.

increased pesticide use and higher prices paid by consumers (Moss et al. 2014; Farnsworth, 2017). We use these documented estimates to construct gene drive release scenarios that produce complex changes to consumer choice sets, where gene drive insect releases mitigate increases in pesticide use and product prices but also remove non-gene-drive alternatives from the choice set. We calculate the minimum pest-induced consumer price increase under which a choice-restricting gene drive release would improve aggregate consumer welfare. In the case of spotted wing drosophila damage in the production of fresh blueberries, pest-induced price increases of over 30% would be necessary for a gene drive release to improve aggregate surplus for U.S. fresh blueberry consumers. In the case of a gene drive citrus psyllid aimed at eliminating citrus greening, disease-induced price increases of around 15% would be necessary. Previous estimates of price increases from either pest/pathogen have not approached these levels. If the costs of the gene drive deployment were borne by producers and passed on to consumer prices, then damage-induced price increases would need to be even higher for gene drives to improve aggregate welfare.

This paper provides two novel contributions. First, it provides ex-ante estimates of potential consumer WTP effects of gene drive use in agriculture. This contribution builds on recent papers examining how consumers value other next-generation agricultural biotechnologies like gene editing of crops or animals (McFadden et al., 2021; Yang and Hobbs, 2020). However, gene drives have very distinct implications compared to gene edited crops, with the former designed to engineer whole ecological systems as opposed to individual (consumed) organisms in the case of the latter. Our second contribution demonstrates how to conduct non-marginal welfare analysis for a suite of next-generation 'system-scale' agricultural biotechnologies on the horizon (e.g. Kaur and Upadhyay, 2022; Pfeifer et al., 2022). This contribution includes characterizing statistical uncertainty when analyzing aggregate consumer surplus effects of policy scenarios. This extension is still infrequent in the literature, which usually presents only point estimates of non-marginal welfare effects. Our use of a (now standard) hierarchical Bayes method for estimating the distribution of consumer preferences greatly facilitates the characterization of uncertainty.

The rest of the paper proceeds as follows: In the next section we provide background on gene drives in agriculture and a brief overview of the consumer and regulatory context. The third section describes the choice experiment design, data collection, summary statistics, and qualitative patterns observed in consumers' stated choices. We then describe the econometric methods used to obtain consumer welfare estimates, namely discrete choice modeling of heterogeneous consumer preferences. In the penultimate section, we present the consumer welfare analysis of different policy scenarios regarding gene drive releases. The final section concludes by discussing the implications of our findings.

2. Background on gene drive insects and two potential agricultural applications

To understand the consumer implications of the technologies introduced above, we first provide some background on how they work, how consumers might be impacted, as well as their regulatory context.

2.1. How gene drives work, with examples

There is a long history of using biocontrol techniques for managing invasive pest species in agriculture. One of the most prominent precursors to the technology we study is the sterile insect technique (SIT), which has had notable success in dealing with highly damaging pests for which no alternative control methods were available (Brown et al., 2019). SIT works by continually releasing sterilized insects into the environment to mate with wild-type pests, reducing the reproduction rate of the population. While it can be highly effective, it can also be highly expensive, requiring the continual rearing and release of sterilized insects until the population is eliminated or the outbreak is halted.

Recent innovations in biocontrol have introduced biological mechanisms that can sustain themselves and drive damage-reducing traits more permanently throughout a pest population after a much smaller initial release. These may include SIT-like traits that disrupt insect reproduction, or alternatively traits that could inoculate a disease vector from being able to transmit a damaging crop disease. The intention among developers is that these self-spreading mechanisms could dramatically improve the efficiency and sustainability of biocontrol as compared to SIT, by reducing the duration of modified insect releases needed to achieve pest elimination (Brown et al., 2019).

In this paper, we focus on a particular form of self-spreading biocontrol known as a 'gene drive' (Barrangou, 2014; NASEM, 2016). Gene drives work by engineering a parent insect to spread genetic elements to offspring at frequencies that are greater than the usual 'Mendelian' inheritance rate of 50%. Among their offspring, genes for engineered traits are copied from one parent's chromosome to the other, meaning the (now 'homozygous') surviving offspring will also go on to produce young who express these traits at very high rates. This mechanism allows desired genetic traits to spread rapidly within a population.[2]

While no gene drive pest has been released in the environment to date, researchers have actively pursued this strategy for some time and are making rapid progress. Much of this work has been primarily in the public health realm, targeting mosquito vectors of malaria (Hammond et al. 2021). Agricultural applications are farther behind, although multiple university research groups and private companies are now making more rapid progress (O'Brochta and Akbari, 2022; Scott et al., 2018; Yadav et al., 2023; https://biocentis.com/). We discuss two specific agricultural examples that were some of the very first attempts in the agricultural space and the specific drive designs required for each provide the context we focus on for the remainder of the paper. The first was an early attempt to use a type of gene drive to control Huanglongbing, or citrus greening, a bacterial disease (*Candidatus liberibacter* spp.) which has devastated the $3.3 billion U.S. citrus industry with declines of 21.5% in Florida bearing acreage and 25.8% in yield since the disease was found in 2005 (USDA-NASS, 2017a). The bacterium is vectored by the Asian citrus psyllid, an invasive species from East Asia. The proposed gene drive, funded by a grant from the US Department of Agriculture (Turpin et al., 2012), would have spread a strain of the citrus psyllid that is no longer 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. This early attempt failed for technical reasons, but there has been recent interest in renewing those efforts (Chaverra-Rodriguez et al., 2020).

In another ongoing pursuit, researchers funded by the USDA (Li and Scott, 2016; Yadav et al., 2023), and separately by grower associations (Buchman et al., 2018), are seeking to design a *suppression drive* for spotted wing drosophila. Spotted wing is an invasive species in the United States that dramatically increases control costs (typically through spraying) and causes extensive damage to ripening berry and cherry crops worth over $4 billion in 2016 (Asplen et al., 2015; USDA-NASS, 2017b;

[2] In more technical terms: with natural Mendelian inheritance, when a GE insect homozygous for the engineered trait mates with a non-GE individual, the offspring will be heterozygous, harboring the GE trait on only one of its two chromosomes. With a gene drive, gene editing tools are coupled with the engineered trait in the germline cells of the pest. The result is that the target trait is copied from the GE parent's chromosome in the offspring over to the non-GE parent's chromosome, producing offspring which are homozygous for the trait. Those offspring then go on to mate and produce offspring which are again homozygous… and so one until the target trait spreads completely through the pest population.

Table 1
Choice experiment attributes and levels.

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

* 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.

Fan et al., 2020). Where the suppression drive spreads, a trait could be passed that inhibits reproduction of the pest, leading to eventual population collapse (Burt, 2003). A suppression drive would leave GE variants of the insect in the environment for some extended period, but potentially these too would dissipate in the long run in the event of a 'successful' population collapse. Given these first investments in gene drive target pests, we focus our analysis on fresh blueberries and orange juice to provide the most relevant data to inform the current debate.

2.2. How agricultural gene drives may impact consumers

A system designed for self-spreading GE traits in food production would naturally be expected to raise concerns among the public, as well as among growers concerned that consumers might react negatively to the technology. Public views on gene drives are also likely to be related but also distinct from views towards genetically modified organisms (GMOs) in food supplies (Costa-Font, Gil and Traill, 2008; Baltzegar et al., 2018). However, the genetic manipulation of pests instead of crops themselves may in fact reduce consumer apprehension. A survey by McFadden et al. (2021), for example, found that a plurality of consumers stated support for 'gene-edited' citrus trees or a 'gene-edited' citrus psyllid to control citrus greening and did not demonstrate statistically significant preferences for citrus produced through either method. However, the intentional – and potentially uncontrolled – spreading of genetic modifications through pest populations via gene drives, rather than (somewhat) field-isolated genetically modified material in GE crops, may increase public concern. This sentiment has been expressed by gene drive researchers and evaluators (NASEM, 2016). In a prior analysis of attitudinal data from the same survey we use here (Jones et al., 2019), we found that the general US public was relatively supportive of pursuing gene drive research in agricultural applications after being informed about the risks and benefits of the technology and as long as safeguards were included to limit the uncontrolled spread of the technology (which is more difficult to design from a bioengineering perspective).

Gene drive insects also have a high potential to cause structural changes in product availability. The goal to spread GE traits throughout the pest population may actually be achieved, meaning that in the medium- or long-term GE insects could replace their wild counterparts wherever that population is present. Consumers who prefer to purchase a certain food product not grown in the presence of gene drive insects may eventually no longer be able to find such products for sale. Changes in product availability induced by technological change are not a new phenomenon, but we argue there is amplified potential for such changes from a technology that is designed to spread and permanently establish itself across agricultural landscapes. From a consumer welfare perspective, some consumers are likely to view the removal of non-drive products from the choice set more negatively than others. Consumers who do not have any disutility from foods produced using gene drives would unambiguously gain if gene drives prevented pest-related price increases and substituted for less desirable forms of pest control. Our question in this paper is how disutility from gene drive insect presence compares in the aggregate to the utility of reduced chemical spraying and consumer prices.

2.3. How agricultural gene drives are likely to be regulated in the US

From a regulatory perspective, all substantive gene drive pursuits in agriculture involve genetic engineering and the insertion of foreign genetic material into insect pests. This means that their regulation in the US would be addressed within the Coordinated Framework on the Regulation of Biotechnology, which divides regulatory authority among the USDA, the EPA, and the FDA based on existing statutes. GE insect pests of plants and animals fall under the regulatory authority of the Animal and Plant Health Inspection Service (APHIS) within USDA, which handles permitting and regulation of movement into and within the United States under the authority of the Federal Plant Pest Act (FPPA) and the Virus-Serum-Toxin Act (VSTA).

Food labeling regulations administered by the USDA are also pertinent for gene drive insects. These include the organic label administered by the National Organic Program (NOP) and the National Bioengineered Food Disclosure Standard (NBFDS). Under 7 CFR Part 205, the NOP outlines prohibitions including transgenic (inserting a foreign gene, e.g. '*Bt*' crops) or non-transgenic gene editing methods[3]:

> *"Excluded methods: A variety of methods used 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;
> *Allowed and prohibited substances, methods, and ingredients in organic production and handling: To be sold or labeled as "100 percent organic," "organic," or "made with organic (specified ingredients or food group (s))," the product must be produced and handled without the use of […] excluded methods, except for vaccines*
> — 7 CFR §205.105

It remains to be seen how these labeling requirements will apply to gene drive insects since no commercial agricultural deployments have yet been made. While the NOP prohibits the use of GE technology in producing foods carrying the organic label, the adventitious presence of GE technology would likely not jeopardize a farm's organic certification. This may include the presence of gene drive insects deployed by other conventional farms which then spread onto organically certified farms. Policy memos from the NOP have detailed responses to questions about incidental adventitious presence of genetically modified material:

[3] https://www.ecfr.gov/current/title-7/subtitle-B/chapter-I/subchapter-M/part-205 (Accessed July 21, 2023).

Table 2
Summary of consumer behavioral and attitudinal patterns.

	Fresh Blueberries	Orange Juice
Number of respondents	457	408
Choice tasks per respondent	9	9
Fraction of applicable tasks in which…		
Cheapest product purchased	0.511 (0.482, 0.539)	0.477 (0.448, 0.506)
Organic purchased	0.563 (0.535, 0.592)	0.412 (0.384, 0.440)
Product using gene drive purchased	0.426 (0.402, 0.450)	0.411 (0.386, 0.437)
Product using GM plant purchased	0.302 (0.277, 0.328)	0.344 (0.313, 0.374)
No product purchased	0.272 (0.246, 0.297)	0.302 (0.273, 0.331)
Fraction of respondents who…		
Regularly buy USDA-certified organic foods	0.283 (0.241, 0.325)	0.195 (0.156, 0.235)
Seek “non-GMO”-labeled foods	0.236 (0.196, 0.276)	0.201 (0.161, 0.240)
Oppose gene drives in agriculture	0.118 (0.0885, 0.148)	0.140 (0.106, 0.173)
In choice experiment…		
Always purchased a product	0.348 (0.304, 0.392)	0.343 (0.297, 0.389)
Never purchased a product	0.0328 (0.0164, 0.0492)	0.0368 (0.0184, 0.0551)
Always purchased cheapest product	0.131 (0.100, 0.162)	0.140 (0.106, 0.173)
Always purchased organic	0.177 (0.142, 0.212)	0.103 (0.0733, 0.133)
Never purchased product with high pest spraying	0.348 (0.304, 0.392)	0.343 (0.297, 0.389)
Never purchased product using GM plants	0.328 (0.285, 0.371)	0.292 (0.247, 0.336)
Never purchased product using gene drives	0.149 (0.116, 0.182)	0.142 (0.108, 0.176)
Oppose pursuit of gene drives but chose product	0.0635 (0.0410, 0.0859)	0.0956 (0.0669, 0.124)

95% confidence intervals for mean in parentheses, using asymptotic standard errors clustered by respondent. Respondents only completed one DCE: blueberries or OJ.

> *“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, 2011).

What is more ambiguous is whether an organic farm was, for example, a member of a grower association that supported the release of gene drive insects in the area from which the organic farm benefitted (as noted by Reeves and Phillipson, 2017). However, regarding the NBFDS, foods produced using gene drives would almost certainly be exempt from carrying the ‘Bioengineered’ label, because any incidental gene drive insect material on the food product through adventitious presence would constitute such a small portion of the food’s ingredients (significantly less than the 5% threshold under the regulation).

3. Survey and choice experiment description

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

The DCE was embedded within a larger web-based survey fielded in October and November 2017 through the survey firm GfK’s KnowledgePanel®, a representative probability sample of U.S. adults, which resulted in 1,018 completed questionnaires. All respondents received a basic explanation of gene drive technology, illustrations of the citrus psyllid and spotted-wing Drosophila applications described above and selected from seven frequently asked questions (full wording in Supplementary Material, SM). Respondents who failed inattention and speeding tests were removed from the sample based on an agreement between the researchers and the survey sample provider, and are not included in the reported 1,018-person sample size (see Jones et al., 2019 for details).

Respondents then reported attitudes on various contexts of gene drives for agricultural pest control and specific views on use in organic agriculture, which are summarized by Jones et al. (2019). That study did not analyze data from the DCE, which was only completed by respondents whose households purchased fresh blueberries or OJ in the last six months. From 1,018 total survey respondents, we draw WTP data from 457 fresh blueberry consumers and 408 OJ consumers who completed the DCE. Respondents purchasing both products were randomized to only one DCE exercise.[4] Following convention to reduce potential hypothetical bias in WTP estimates, a cheap talk script was adopted in the DCE introduction (Cummings and Taylor, 1999; Lusk, 2003) and a consequentiality statement was included at the beginning of the survey (Herriges et al., 2010).[5]

For both products, the DCE included attributes of price, gene drive insect presence in the growing area, crop genetic modification to resist pests, and varied traditional pest management regimes, which include a high conventional spray level, low conventional spray level, and the USDA-organic seal.[6] Product attributes and corresponding levels are

[4] 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), which is “a crowdsourcing marketplace enabling individuals and businesses (known as Requesters) to engage a 24/7, global distributed workforce (known as Workers) to perform tasks” (Amazon). Pretesting indicated 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.

[5] 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.)”.

[6] In principle, we could have also included multiple spray levels within organic products in the DCE. However, as opposed to conventional production, more frequent spraying by organic growers is not a realistic or effective response to these pests, since organic pesticide options and effectiveness are much more limited. Indeed, previous research that we discuss in detail later has shown that price increases in organic fresh blueberries owing to Spotted wing damage have remained elevated (whether through increased costs, losses, or diverted supplies to conventional markets due to expanded spray needs). In contrast, pest-induced price impacts for conventional blueberries eventually subsided as growers adapted (primarily by more intensive chemical applications). For the purposes of both parsimony and realism in the DCE design, we therefore omitted multiple spray levels in the organic attribute level.

outlined in Table 1. Respondents were instructed to imagine they are making a regular shopping trip in a grocery store and indicate which of two options, if any, they would purchase. A D-efficient design powered to estimate main effects and interaction between gene drive insect presence and other current pest management practices was generated and fielded to a pretest sample via Amazon MechanicalTurk (n = 300) to refine and 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. In contrast, we allowed organic certification to coappear with the use of gene drives in the same product, which was theoretically possible within USDA regulations at the time of the survey. Estimated coefficients from pretest models were used to generate more efficient, unique designs for each product for the main round (Ferrini and Scarpa, 2007), which yielded a total of 18 choice tasks. These were optimally blocked into two groups of nine choice sets for each respondent to avoid survey fatigue. See SM section 2.1 for details.

Table 2 summarizes the choice patterns from both the blueberry and OJ choice experiments.[7] The statistics in this table are selected to exhibit the variety of choice patterns observed in these simulated purchasing scenarios. On roughly half of choice occasions, consumers chose the cheapest product in the choice set, although only 13–14% *always* chose the cheapest alternative. A sizable group of consumers showed a clear desire for the products in both experiments: Thirty-four percent of both blueberry and OJ consumers never selected the opt-out ‘no product’ alternative in the choice experiment. Blueberry consumers chose an organic product in a little over half (56%) of choice occasions, whereas OJ consumers chose organic in a minority (41%) of choice occasions. Products using gene drives appear generally more preferred than those involving GM plants or high levels of conventional pesticide spraying.

Based on these descriptive statistics, the data appear well-suited for econometric demand estimation. First, they show clear and predictable responsiveness to price, as well as to all the production attributes considered in the DCE. Second, it does not appear that any of the attributes were dominating, dominated or lexicographic for a majority of consumers, which would have invalidated the use of the conventional random utility framework we use in the econometric analysis presented below. Although measurable portions of consumers demonstrated clear choice patterns for the cheapest product available or for organic or non-GMO (non-gene-drive) products, the evident heterogeneity and diversity in these choice patterns can still be accommodated in appropriately specified random utility models as we show below.

4. Econometric analysis

To obtain welfare estimates, we first use the DCE data to estimate a random utility model (RUM) allowing for unobserved heterogeneity in consumer tastes. We then use this estimated model to compute aggregate consumer surplus for a set of different policy scenarios which we detail in the next section.

For the RUM, the utility of product j on choice occasion t for individual i is assumed to be linear in the product’s attribute vector X_{jt} and an unobserved random utility component ε_{ijt}:

$$U_{ijt} = \boldsymbol{\beta}_i^{'} \boldsymbol{X}_{jt} + \varepsilon_{ijt} \tag{1}$$

where $\boldsymbol{\beta}_i$ is the vector of individual-specific marginal utilities associated with the attributes $\boldsymbol{X}_{jt}$. For our application, the vector $\boldsymbol{X}_{jt}$ is given by all of the attributes in Table 1, with the addition of an opt-out, ‘no purchase’ alternative-specific constant (ASC) and interaction terms between gene drive insects and organically-certified or low-spray products:

$$\boldsymbol{X}_{jt} = [GM_{jt}, GD_{jt}, org_{jt}, lospray_{jt}, nobuy_{jt}, price_{jt}] \tag{2}$$

where $GM_{jt}, GD_{jt}, org_{jt}$, and $lospray_{jt}$ are binary indicators for whether alternative j in task t was respectively produced with GM plants, gene drive (GD) insects, under USDA organic certification, or with a low level pesticide spraying (‘low’ v. ‘high’ spray levels, the latter being the default level of the spray attribute, were defined in detail for respondents in the survey; see Table 1 notes). The binary variable $nobuy_{jt}$ indicates whether alternative j is the opt-out, no-purchase alternative. Because the DCE was designed and powered to also test interaction effects between GDs and organic/low-spray attributes, we also extensively tested model specifications including $GD_{jt} \times org_{jt}, GD_{jt} \times lospray_{jt}$ in X_{jt}. However, in all the correlated random coefficients models, these interaction effects are statistically indistinguishable from zero (see SM Table S6). For parsimony, we therefore use (2) as our main specification in the

Table 3
WTP (USD) estimates from the discrete choice experiment – Blueberries (see equations 1–4).

	Mean [95% posterior]	Median [95% posterior]	Fraction $WTP = 0$ [95% posterior]
GM Plant	-6.1	-0.32	0.47
(v. not GM)	[-9.3, -4.0]	[-0.99, 0]	[0.38, 0.57]
GD Insects	-4.4	0.00	0.73
(v. none)	[-7.4, -2.5]	[0, 0]	[0.65, 0.79]
Organic	7.4	0.61	0.44
(v. Conv. High Spray)	[5.1, 11]	[0, 1.4]	[0.36, 0.52]
Conv. Low Spray	4.5	0.24	0.47
(v. Conv. High Spray)	[2.9, 6.9]	[0, 0.84]	[0.35, 0.59]
No-buy opt-out	-0.63	-3.9	0
	[-2.9, 2.7]	[-4.5, -3.6]	–
Total choice tasks	4,113		
Total decisionmakers	457		
Degrees of freedom	27		
Log-likelihood	-2,840		
Pseudo-R2	0.37		

Notes: Model estimates for mixed logit model with price coefficient distributed lognormally; GM Plant, GD Insects, Organic, and Conv. Low Spray coefficients distributed according to truncated normal distribution (with mass at $\beta = 0$), with correlation permitted between all random coefficients. Model estimated via Hierarchical Bayes method (Train 2009). Estimation based on 10,000 draws from the posterior distribution, after burn-in. See Supplementary Material for further technical specification and alternative model comparisons. Reported point estimates of WTP statistics are posterior distribution means; [95% posterior] refers to 95% interval of posterior distribution of these statistics.

Table 4
WTP (USD) estimates from the discrete choice experiment – Orange Juice.

	Mean [95% posterior]	Median [95% posterior]	Fraction $WTP = 0$ [95% posterior]
GM Plant	-4.7	0	0.62
(v. not GM)	[-8, -2.8]	[0, 0]	[0.53, 0.71]
GD Insects	-2.76	0	0.75
(v. none)	[-4.8, -1.5]	[0, 0]	[0.67, 0.83]
Organic	5.3	0.52	0.43
(v. Conv. High Spray)	[3.6, 7.7]	[0, 1.1]	[0.35, 0.52]
Conv. Low Spray	3.8	0.21	0.47
(v. Conv. High Spray)	[2.5, 5.7]	[0, 0.73]	[0.37, 0.58]
No-buy opt-out	-3.2	-4.9	0.00
	[-4.8, -0.9]	[-5.37, -4.5]	
Total choice tasks	3,672		
Total decisionmakers	408		
Degrees of freedom	27		
Log-likelihood	-2,621		
Pseudo-R2	0.35		

Note: See notes for Table 3.

[7] Not reported in the table are the response time statistics for the DCE: Median completion time for the nine choice tasks was 3:22 min; the first and 99th percentiles of completion time were 40 s and 44:30 min respectively, with an interquartile range of [2:18, 4:48] minutes.

manuscript (and the policy analysis that comes later); however, when presenting RUM results in the next section, we also refer to results regarding these interaction effects presented in SM.

Imposing the conventional assumption that ε_{ijt} are i.i.d. draws from a standardized Gumbel distribution, the probability that individual i selects product j on choice occasion t is given by:

$$P_{jt}(\beta_i) = \frac{\exp\{\boldsymbol{\beta}_i^{'}\boldsymbol{X}_{jt}\}}{\sum_{k\in t}\exp\{\boldsymbol{\beta}_i^{'}\boldsymbol{X}_{kt}\}} \tag{3}$$

Preference heterogeneity is incorporated into this model by allowing the $\boldsymbol{\beta}_i$ to vary between individuals. In general, we assume this heterogeneity is unobserved, and that $\boldsymbol{\beta}_i$ is distributed i.i.d. according to a multivariate probability density function (pdf) $f(\boldsymbol{\beta}_i|\Omega)$, where Ω is a vector of parameters governing the distribution (e.g. a mean and covariance matrix if $f(\cdot)$ is multivariate normal). Given Ω, the expected likelihood that individual i makes a sequence of choices $j_{i,1}, \cdots, j_{i,T}$ across choice occasions $t = 1, \cdots, T$ is given by:

$$l_i(\Omega) = \mathbb{E}\left[\prod_{t=1}^{T} P_{j_{i,t}t}(\boldsymbol{\beta}_i)|\Omega\right] = \int \prod_{t=1}^{T} P_{j_{i,t}t}(\boldsymbol{\beta}_i)f(\boldsymbol{\beta}_i|\Omega)d\boldsymbol{\beta}_i \tag{4}$$

Depending on the specification of $f(\cdot)$, this integral may be computed analytically or using numerical simulation, and is amenable to estimation of Ω using either maximum likelihood estimation (MLE) or using Bayesian methods.

We employ a variety of alternative assumptions about the distribution of preferences as reflected in different functional forms for the mixing distribution $f(\cdot)$. In SM section 3, we detail extensive specification testing regarding the form of $f(\cdot)$. In summary, we evaluated mixed logit models with uncorrelated and correlated multivariate normal, lognormal, truncated, triangular and skewed mixing distributions; latent class models with up to 10 classes; so-called '2^K' latent class models evaluating attribute non-attendance (ANA) (Hensher and Greene, 2010); as well as recently developed 'logit mixed logit' models with flexible mixing distributions (Train, 2016). Results summarizing these model evaluations are in SM Table S2.

Based on measurements and comparisons of model fit and parsimony (Bayesian and Akaike information criteria), our preferred specification is a mixed logit model in which the GM plant and GD insect marginal utilities are distributed according to an upper-tail zero-truncated normal distribution (with positive mass at zero), the organic and low-spray marginal utilities are distributed as lower-tail zero-truncated normal distributions, the no-purchase ASC distributed normally, the marginal utility of price distributed lognormally, and the interaction terms' utilities fixed. Correlation is permitted and estimated among all heterogeneously distributed utilities; in specification testing, allowing for this correlation was the most impactful factor in improving model performance.

The use of truncated normal distributions for the production-related attributes in our best-performing model was selected for evaluation on theoretical grounds: Truncated normals with probability mass at zero allow for a portion of consumers to have zero marginal utility associated with a given attribute. For those with non-zero utility, this distribution restricts these utilities to be positive (left-tail truncation) or negative (right-tail truncation). Our specification therefore rules out the possibility that consumers have positive marginal utilities directly owing to GM plants or gene drives (rather than just lower prices or spraying resulting from these products), or negative marginal utilities owing to organic and low-spray production systems. Further, by permitting a positive probability of consumers having marginal utilities of zero, this mixed logit specification also facilitates the simultaneous study of possible ANA in the choice experiments; this is explored in detail in SM section 5 (Balcombe et al., 2011).

To estimate our preferred specification, we perform now-standard hierarchical Bayes estimation (HBE) assuming a noninformative prior distribution (Train, 2009). We interpret results from this estimation method from a classical perspective: Since HBE of mixed logit with an uninformative prior is asymptotically equivalent to classical MLE, our use of HBE is driven first by the difficulty we encountered in getting the MLE of this mixed logit specification to converge. The second reason we employ HBE is that it greatly facilitates characterization of statistical precision in the welfare analysis because HBE produces both posterior distribution draws of the model parameters Ω (in our specification, the mean vector and covariance matrix of a multivariate normal distribution) and draws of the marginal utilities $\boldsymbol{\beta}_i$. This advantage is illustrated in more detail in the policy analysis section later in the paper. Technical details about our implementation of HBE and comparison to MLE results of the same RUM (the two are very close to one another) are provided in the SM sections 3 and 4. The main model was estimated in the Matlab® computing environment using HBE code provided by Train, although the R package Apollo, NLogit and Stata were all used in model evaluations and comparative testing.[8] Data and estimation code for replication are available at https://www.openicpsr.org/ openICPSR (ID# openicpsr-193063).

5. RUM results

Tables 3 and 4 display the main HBE results for our preferred mixed logit specification. For concision and interpretability, these tables report estimates of the population mean and median WTPs (i.e. $\beta_i^A/\beta_i^{price}$ for each non-price attribute A directly rather than statistics regarding the marginal utilities in $\boldsymbol{\beta}_i$. SM section 4 provides full estimates of underlying marginal utilities (i.e. population means and standard deviations for the $\boldsymbol{\beta}_i$'s).

The tables also report the estimated fractions of the target populations (fresh blueberry and orange juice consumers) that have zero marginal utility associated with each of the four production-related attributes. Note that a probability mass at zero results directly from specifying truncated normal mixing distributions for these attributes, which also imposes sign restrictions on the marginal utilities (negative for GM plants and GDs, positive for organic and low v. high conventional spraying). This precludes the use of p-values (or a Bayesian analogue) for testing whether the means of these marginal utilities are significantly different from zero. However, in simpler conditional logit models as well as in mixed logit models with unrestricted support, all the attributes' mean utilities are significantly different from zero (and of the expected sign). Again, the selection of the truncated normal in the preferred econometric specification was driven both by theory and primarily by statistical performance of the model for the purposes of policy analysis described in the next section.

Overall, the RUM results point to greater consumer acceptance of GD insects versus GM food, as well as when compared to the intensification of conventional chemical-based pest control. For both fresh blueberries and orange juice, we find that consumers' estimated mean reduction in WTP for products using gene drives is less than that associated with GM plants as well as that associated with high v. low levels of conventional pesticide spraying. These differences are statistically significant (i.e. 95% interval on the posterior distribution of these differences does not contain zero). In addition, supermajorities of consumers (73% for blueberries, 75% for OJ) are estimated to have no disutility associated with GDs, with the 5th percentile of the posteriors being greater than 50% for both products (i.e. from a classical perspective, we could reject the null that $\Pr\left[WTP_i^{GD} = 0\right] \leq 0.5$ at less than the 5% level). Larger estimated portions exhibit disutility associated with GM plants, as well as high v. low levels of conventional spraying. This estimated lack of disutility from GDs for a majority of consumers mechanically means that the median WTP estimate associated with GDs is zero for both products.

[8] https://eml.berkeley.edu/Software/abstracts/train1006mxlhb.html.

Table 5
Policy scenario analysis and consumer surplus (CS) impacts.

	Fresh Blueberries	Orange Juice
Pre-invasion status quo		
Conventional price	\$3.19 per pint	\$4.64 per half-gallon
Organic price premium	40%	40%
Conventional spray level	Low	
Mean CS at baseline	\$6.48 per grocery trip [\$5.24, \$8.11]	\$4.80 per grocery trip [\$3.89, \$5.93]
Pest invasion impacts		
Conventional price effects	+0.04%	+11.99%
Organic price effects	+7.0%	+11.99%
Conventional spray level	High	
Mean ΔCS	-\$0.56 per grocery trip [-\$0.79, -\$0.39]	-\$0.90 per grocery trip [-\$1.10, -\$0.75]
Uncontrolled GD release after pest invasion		
Price effects	Back to pre-invasion baseline	
Conventional spray level	Low	
Non-GD products available?	No	
Fraction of consumers with ΔCS > 0	75% [68%, 81%]	80% [75%, 86%]
Mean ΔCS | ΔCS > 0	+\$0.40 per grocery trip [\$0.28, \$0.55]	+\$0.78 per grocery trip [\$0.65, \$0.94]
Mean ΔCS | ΔCS ≤ 0	-\$4.10 per grocery trip [-\$6.35, -\$2.56]	-\$3.08 per grocery trip [-\$4.83, -\$1.91]
Overall mean ΔCS	-\$0.72 per grocery trip [-\$1.30, -\$0.29]	+\$0.03 per grocery trip [-\$0.38, \$0.34]
Controlled v. uncontrolled GD release		
Price effects	Non-GD: prices at post-invasion levels GD: price return to pre-invasion levels	
Conventional spray level	Non-GD conventional spray is high GD-conventional spray is low	
Mean CS gain v. uncontrolled GD	+\$1.61 per grocery trip [\$1.18, \$2.23]	+\$0.94 per grocery trip [\$0.65, \$1.35]

Notes: CS statistics computed from respective HBE mixed logit model results summarized in Tables 3 and 4 based on equations (5) and (6). Bracketed intervals are 95% intervals from posterior distributions of respective statistics. Units of CS estimates are per grocery trip for blueberry/OJ consumers. For 'high' and 'low' conventional spray definitions, see note in Table 1.
Note: **Plant Type Wording** - "The plant and fruit are genetically modified to resist pest damage" [genetically modified; GM_Plant], "The plant and fruit are not genetically modified" [non-genetically modified]. **Pest Management Regime wording** – *Blueberries*: "Conventional insecticides applied only when pest populations are high" [low conventional spray; Low_Conv_Spray]; "Conventional insecticides applied every five days for several weeks while fruit ripens" [high conventional spray; High_Conv_Spray] – *Orange Juice:* "Conventional insecticides applied in the field 1–2 times per year" [low conventional spray; Low_Conv_Spray]; "Conventional insecticides applied in the field 11–14 times per year" [high conventional spray; High_Conv_Spray]. Low v. high spray regimes represent predominate pest management regimes before and after the arrival of spotted-wing Drosophila (blueberries) or citrus psyllid (orange juice). See App****endix B for choice scenario examples.

We also note that utility associated with conventional pest control obeys the ordering we would strongly expect, with the mean WTP for the organic attribute exceeding the mean WTP low conventional spraying which is itself positive (meaning greater WTP for the low-spray attribute versus high-spray omitted base level).

Not shown in Tables 3 and 4 are results on the estimated interaction effects between GDs and the organic/low-spray attributes. As noted earlier, after testing models with these interaction effects (see SM Table S6) there is no evidence that these interactions provide any additional explanatory power in the RUM, which is the reason that for concision we exclude these effects from our main specification in Tables 3 and 4 and in the policy analysis below. However, this null result regarding the interaction effects is policy relevant. It implies that consumers' WTP for a USDA-certified organic product does depend on whether the product was grown in the presence of GD insects. We do note that this null result only emerges from the RUM estimation when we allow for heterogeneous preferences in the model *and* when we allow the $\boldsymbol{\beta}_i$'s to be correlated between the attributes. As SM Table S6 shows, the conditional logit (and the mixed logit, in the case of blueberries) results assuming uncorrelated $\boldsymbol{\beta}_i$ imply these interaction effects are statistically significant. However, as the model comparison in SM Table S2 shows, allowing for correlation in the $\boldsymbol{\beta}_i$'s is one of the most consequential specification decisions improving model performance. The significant interaction effects arising only when correlation in the $\boldsymbol{\beta}_i$'s is suppressed suggests such findings of significance are spurious. In summary, the picture that clearly emerges regarding preferences towards GD insects is that a minority of surveyed consumers appear to care about these technologies being used in production of their food.

6. Policy analysis

Given the heterogeneous preferences estimated in the RUM regarding GDs, it is not obvious whether their deployment in the two case studies considered would increase or decrease aggregate consumer welfare. Recapitulating, a key distinction of GDs vis-à-vis currently deployed agricultural biotechnologies is their potential to biologically alter entire agricultural production systems, not just individual food products. If GDs spread ubiquitously through growing areas, then non-GD alternatives may be removed from consumers' choice sets. This could harm consumers seeking to avoid these technologies, depending on the effects to food prices. Actual deployment scenarios may also differ according to how much control scientists and bioengineers exert over the technology to limit its area of spread and thereby retain non-GD alternatives' availability to consumers (Jones et al., 2019).

To model the potential aggregate consumer surplus (CS) impacts of these different policy scenarios, we use our estimated RUMs to evaluate three different policy scenarios: (a) a baseline scenario estimating the CS impacts of pest invasion in the two case studies, (b) a scenario modeling the CS effects of uncontrolled GD release that eliminates non-GD alternatives from the consumer choice set and (c) a scenario modeling the gain in CS to be had from the use of a controlled-v-uncontrolled GD that preserved availability of non-GD alternatives.[9]

Given the mixed logit structure of the RUM, the surplus of a given choice set $\mathscr{X} = \{X_j\}_{j=0,\cdots,J}$ to an individual consumer with preferences $\boldsymbol{\beta}_i$ can be estimated using the familiar 'log-sum' formula for such models (Small and Rosen, 1981):

$$c(\mathscr{X}|\boldsymbol{\beta}_i) = \frac{\log\left(\sum_{j=0}^{J}\exp\boldsymbol{\beta}_i^{'}\boldsymbol{X}_j\right)}{\beta_i^{price}} \tag{5}$$

Conditional on the RUM parameters Ω governing the β_i's distribution across the whole consumer population, aggregate CS is given by:

$$CS\left(\mathscr{X}^{policy}, \mathscr{X}^{SQ}|\Omega\right) = \int \left[c\left(\mathscr{X}^{policy}|\boldsymbol{\beta}_i\right) - c\left(\mathscr{X}^{SQ}|\boldsymbol{\beta}_i\right)\right] f(\boldsymbol{\beta}_i|\Omega)d\boldsymbol{\beta}_i \tag{6}$$

where $\mathscr{X}^{policy}, \mathscr{X}^{SQ}$ are the choice sets for the policy change and the SQ, respectively. Because HBE provides a posterior distribution for Ω instead of an MLE-based point estimate and covariance matrix, we obtain statistical central tendency and precision measures of aggregate CS by evaluating these with respect to the estimated distribution of $CS(\mathscr{X}^{policy}$,

[9] Note that scenario (c) necessarily results in a gain in CS relative to scenario (b) because (c) only increases consumer choice versus scenario (b), meaning that in our modeling no consumer can be left worse off by preserving non-GD alternatives in the choice versus uncontrolled deployment.

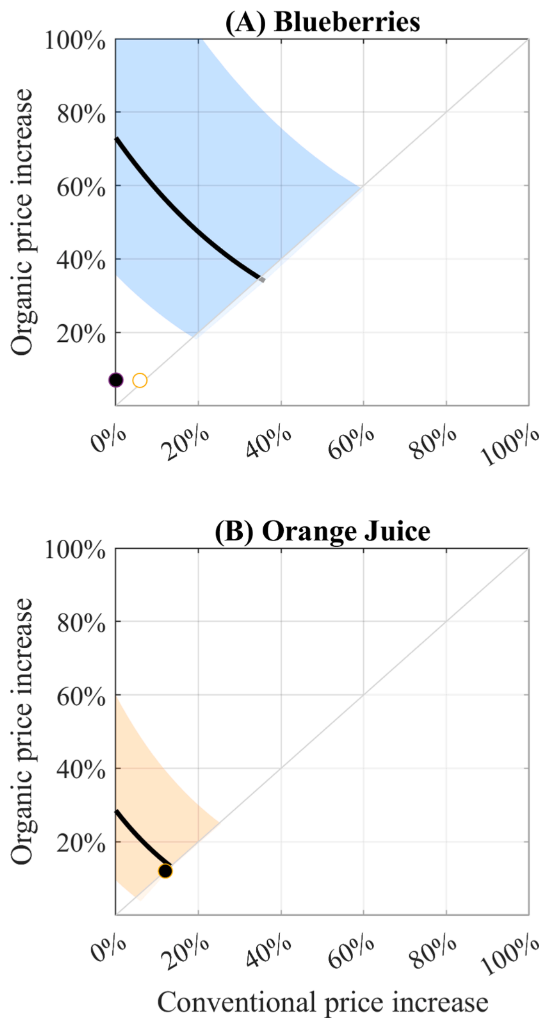

Fig. 2. Breakeven consumer surplus impacts from unlimited gene drive insect releases. Solid lines are sets of conventional and organic price increases from pest invasion that yield zero mean consumer surplus effects of unlimited gene drive releases. Shaded areas are 95% confidence sets. Circles are empirical estimates, from Farnsworth et al. (2017) in Panel (A) (open circle is early and closed circle is late-stage infestation) and from Moss et al. (2014) in Panel (B).

$\mathscr{X}^{SQ}|\Omega)$ produced from Ω's posterior distribution.[10]

Table 5 provides the details of each policy scenario and the estimated CS effects. The pre-invasion SQ consists of organic and conventional alternatives available for sale at the lower prices that prevailed prior to invasion by the pest. In addition, the conventional alternative has a low level of pesticide spraying in the SQ. The pre-invasion price for conventional produce is assumed to be $3.19 per pint for fresh blueberries and $4.64 per half-gallon for OJ, which are simple averages of the price levels used in the DCE (themselves based roughly on prevailing market prices at the time of the data collection, FDC, 2020). The organic price premium for both products is assumed to be 40% (Lin et al. 2008). Based on these assumptions, and applying (5) to our RUM results, we retrieve mean CS estimates of $6.48 and $4.80 per grocery trip for fresh blueberry and OJ consumers respectively.

The pest invasion impacts on CS under scenario (a) therefore consists of increased prices as well as higher levels of spraying in conventional production. For SWD invasion in fresh blueberries, we refer to Farnsworth et al. (2017): These authors estimate that for fresh *raspberry* production, SWD invasion in California at first caused increases of 5.84% and 6.9% in conventional and organic prices respectively. Eventually, price increases in conventional raspberries declined to 0.04%, as growers learned to adapt to SWD (primarily by spraying insecticides more intensively), whereas organic prices increased slightly further to 7% over the pre-invasion SQ due to few options available to organic growers for adapting to SWD. Without direct estimates for fresh blueberries available, and given roughly comparable production systems and pest exposure, we use these same relative price effects in policy analysis. For OJ, we refer to Moss et al. (2014), who estimate that citrus greening spread caused a 12% increase in orange prices (they do not differentiate between conventional and organic effects). Applying equations (5) and (6) under these assumptions, our RUM results imply that SWD in fresh blueberries and citrus greening in OJ produced a mean $0.60 and $0.91 per grocery trip reduction in CS for US blueberry and OJ consumers respectively, or 9% and 20% respectively of baseline, pre-invasion CS.

For scenario (b), to model the changes to CS resulting from uncontrolled GD deployment, we first set the status quo choice set as the post-invasion state, with increased prices and high levels of pesticide spraying in conventional production. The choice set under the policy change is then specified as consisting of the conventional and organic products available at their pre-invasion price levels and pesticide spray level. However, *all* the alternatives (except for 'no purchase') under this policy change have the GD attribute activated. This policy change necessarily improves welfare for those who see no harm in the use of GDs in the production of their food. For those who do view GDs negatively, CS can be positive or negative depending on their relative preferences for price and pesticide reductions versus avoiding GDs. This means that the level of GD nonattendance in the DCE (73% for blueberries and 75% for OJ) provides a lower bound on the percentage of beneficiaries from an uncontrolled GD release. As Table 5 shows, 75% and 80% respectively are estimated to benefit from uncontrolled GD releases. The mean gain in CS for these beneficiaries is $0.40 and $0.78 respectively, whereas the loss in CS to those experiencing a reduction in welfare is $4.10 and $3.08.[11] The weighted sum of these impacts produces net loss of $0.72 for blueberry and a net gain of and $0.03 for OJ consumers, or −11% and +1% of baseline, pre-invasion CS. Moreover, the 95% interval on the posterior distribution of these aggregate CS impacts does not include zero in the case of blueberries but does in the case of OJ. So, our RUM results imply that the uncontrolled GD release in scenario (b) would be welfare-reducing for SWD in blueberries, whereas for citrus greening in OJ the CS effects are statistically indistinguishable from zero. It is important to emphasize that these implications are both generated by comparing the minority of consumers who would experience a disproportionate CS loss compared to supermajorities who experience a small CS gain.

[10] The alternative to this procedure, if MLE had been used, would be to apply the Delta method or a parametric bootstrap on the statistic.

[11] There is a standard limitation of DCE estimates in measuring quantity effects. Implicit quantity-based assumptions in our CS analysis include: (a) that consumers do not shop more or less frequently as a result of the policy changes we analyze, (b) that consumers who are not regular consumers of the products studied are not at increased likelihood of becoming consumers of these products as a result of the policy changes, and (c) consumers do not change the quantities purchased as a result of the policy changes when making their product choices. Assumption (c) is perhaps the most consequential. We lack scanner data that would shed light on the variation in quantities/sizes purchased for fresh blueberries and OJ, and simply note from personal observation there is near uniformity in fresh blueberry and OJ (pint and half-gallon, respectively) container sizes at the wide range of supermarkets visited (with bulk retailers like Costco offering larger sized packages, but still mostly uniform within the store). And we have rarely seen consumers purchasing multiple units at a time. (It is also advantageous for our study that both products are highly perishable and thus are unlikely to involve purchases for long-term storage, except to the – likely small – extent that consumers purchase fresh blueberries to freeze them, given cheaper frozen retail options.).

Fig. 2 provides complementary analysis of scenario (b), by computing the combinations of conventional and organic pest/disease-induced price increases that would be necessary to make an uncontrolled GD release welfare-improving, based on our RUM results (the area below the 45° line is not plotted, on the assumption that organic pest-induced price increases would necessarily be greater than conventional). The solid line in the figure is the welfare-neutral set of price increases. As the figure shows, a minimum pest-induced price increase for blueberries in excess of 35% would be needed for an uncontrolled GD to be welfare-improving. A 60% price increase needed for the improvement to be statistically significant. For OJ, price increases in excess of 10% would be needed for welfare improvement (and over 20% for statistical significance of the improvement).

Finally, we turn in scenario (c) to the potential welfare gain of controlled v. uncontrolled GD release. In this scenario, the prices and spray levels of non-GD alternatives remain elevated at post-invasion levels, whereas the GD alternatives' prices and spray levels return to pre-invasion levels just as in scenario (b). Because this scenario contains the same choice set as in scenario (b), but with the addition of non-GD products, this scenario does not decrease welfare for any consumer. As Table 5 shows, this scenario recovers a mean gain of $1.61 and $0.94 in CS for the two cases, or 25% and 20% respectively of baseline, pre-invasion CS.

7. Conclusions

This paper highlights a case study of how a prospective, landscape-scale agricultural biotechnology could affect consumer choice and welfare. With major global changes forecasted for agricultural production systems over the coming decades because of climate and technological change (Rockström et al., 2017), this type of economic evaluation is likely to have an increasing role to play in policy analysis. More broadly, any technology aimed at increasing productivity at the expense of product variety has ambiguous effects on consumer welfare, requiring careful quantitative evaluation of who gains and loses – and by how much.

This study's limitations include all of those that normally apply to stated preference methods. Despite using best practices in the design, implementation, and analysis of the choice experiments that form the empirical basis for this paper, we cannot be certain that the estimated preferences would closely match those that would be revealed by actual purchase behavior (and indeed we would fully expect there to be some discrepancy between the two approaches). As such, revealed preference analysis of agricultural gene drives that were actually deployed would be important for further assessing the validity of the analysis here. However, it is worth emphasizing that revealed preference methods are of limited applicability in conducting welfare analysis of such technologies that can permanently and irreversibly alter production systems and product variety: To be useful for policy – namely, to inform the decision whether to permit deployment of the technology – welfare analysis must be conducted prior to actual market behavior being observed. In this regard, ex ante public and consumer consultations, using surveys, focus groups, and other methods, should be an integral part of these policy decisions. This paper demonstrates how ex ante welfare evaluation can inform these consultations.

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The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary material

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