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Consumers' Preferences for Bread: Transgenic, Cisgenic, Organic or Pesticide-free?

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Abstract

Consumers are apprehensive about transgenic technologies, so cisgenics, which limit gene transfers to sexually compatible organisms, have been suggested to address consumer concerns. We study consumer preferences for rye bread alternatives based on transgenic or cisgenic rye, grown conventionally or without the use of pesticides, relative to traditionally bred rye, grown with conventional or organic farming methods. Stated preference (SP) data from a choice experiment are combined with revealed preference (RP) data from market purchases from the same respondents. Results show that respondents prefer pesticide-free production methods, and that while cisgenics is preferred over transgenics, the majority of respondents favour traditional breeding methods. The distribution in preferences suggests that some respondents prefer bread from cisgenic crops produced without pesticides over traditional crops produced using pesticides. Preferences for organic bread are stronger than for pesticide-free products. From a policy perspective results suggest that excluding cisgenics from mandatory labeling in the EU, or including it in the voluntary non-GM labelling in the US, would cause welfare losses for consumers.

Keywords: *Choice experiment*; *combined revealed and stated data*; *genetically modified*; *new breeding techniques*.

JEL classifications: *D12, Q16, Q18*.

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1. Introduction

Environmental pressures from agriculture on surrounding ecosystems, notably nature reserves and forests, are growing, and it is argued that agricultural technology development should be directed towards sustainable intensification (Godfray *et al.*, 2010) to resolve these conflicts while supporting a continued increase in production levels for a growing population. One important aspect of sustainable intensification is to reduce the use of pesticides in food production. Organic production methods represent one attempt to this end. However, reduced pesticide use may also be achieved through biotechnological approaches, such as genetic modification (GM), while maintaining or enhancing yields (Andersen *et al.*, 2015; Palmgren *et al.*, 2015). These GM technologies are, however, debated (Frewer *et al.*, 2013) and remain controversial. Consumers are sceptical towards GM products and express unwillingness to buy them (Dannenberg, 2009; Qaim, 2009). Moreover, in several parts of the world these products face severe legal restrictions (Lusser and Davies, 2013). Partly, as a response to consumer antagonism, new breeding techniques with restricted gene transfer have been introduced (Nielsen, 2003). A case in point is *cisgenics,* where gene transfer is restricted to sexually compatible organisms; a restriction not present in the hitherto dominant *transgenic* GM technique (Schouten *et al.*, 2006).

The goal of this study is to investigate consumer preferences for rye bread alternatives based on transgenic versus cisgenic rye, grown conventionally or without the use of pesticides, relative to traditionally bred rye, grown with conventional or organic farming methods. Several studies suggest that there is a greater acceptance among consumers for cisgenics than transgenics, although crops produced by traditional breeding practices are preferred (Lusk and Rozan, 2006; Gaskell *et al.*, 2010; Delwaide *et al.*, 2015; Hudson *et al.*, 2015). From an economic point of view answering this question satisfactorily presents some difficulties as lack of market data means that existing studies have relied either on stated (Lusk and Rozan, 2006; Delwaide *et al.*, 2015) or lab-based methods (Colson *et al.*, 2011) for preference elicitation; in either case external validity remains an issue. We add to the literature by assessing the potential reception of cisgenics, using a combined data source approach (Ben-Akiva and Morikawa, 1990; Hensher and Bradley, 1993; Swait and Louviere, 1993), where data from a stated preference (SP) survey are enriched with actual purchase data from the same respondents. The motivation for this approach is to achieve greater external validity of the estimates compared to analysis based on pure survey data. While the choice experiment elicits preferences for the attributes of interest in this study (*cisgenic* and *transgenic* rye grown with or without the use of pesticides) the market data add reliability to the results. Based on results from previous studies (Lusk and Rozan, 2006; Gaskell *et al.*, 2010; Delwaide *et al.*, 2015), we hypothesise that traditional breeding is preferred over cisgenics, which in turn is preferred over transgenics. Eliminating pesticides in production is expected to be a positive feature, though we have no *a priori* expectations for the relationship between cisgenic bread produced without the use of pesticides and conventional bread.

The following section gives a background on consumer preferences for food products based on new breeding technologies, specifically cisgenics, and products produced without pesticides, e.g. organically. We also touch upon the methodological challenges. Next, the survey design and summary data are presented, followed by sections on the methodology, results and a concluding discussion.

2. Previous Work

2.1. Consumers preferences regarding pesticide use and new breeding technologies

Concerns over the environmental impacts of conventional agriculture are among the reasons for the growth in organic farming. The market for organic foods has grown over recent decades, but apart from a few specific countries (such as Austria and Denmark) it remains rather limited in size (Hughner *et al.*, 2007). Organic farming reduces the use of pesticides, which is also achievable using GM technology (National Academies of Sciences, 2016). However, GM technology also raises a number of social, moral and economic concerns (Palmgren *et al.*, 2015). Consumer preferences and willingness to pay (WTP) for various types of GM-based food products can provide useful information on the social feasibility of these alternatives. Several studies have documented that consumers' WTP for GM food is lower than for conventional counterparts (Lusk *et al.*, 2005; Dannenberg, 2009). On the other hand, stated preference studies have shown that acceptance for GM is higher when the GM product is associated with less or no pesticides (Loureiro and Bugbee, 2005; Schenk *et al.*, 2011).

Another aspect that may affect the attitude, and hence potentially the acceptance of GM food, is the perceived naturalness of the technology, although the meaning of naturalness is ambiguous and differs between individuals (Siipi, 2008; Mielby *et al.*, 2013). Cisgenic foods may be perceived as less unnatural than transgenic foods (Schouten *et al.*, 2006; Mielby *et al.*, 2013). A survey in the US and France found a greater willingness to eat ingenic[2] vegetables than transgenic, though the traditionally bred vegetables were the most preferred (Lusk and Rozan, 2006), and a study in the Netherlands found that consumers rated cisgenics more positively than transgenics, although the magnitude of the difference was small compared to the difference between cisgenics and traditional breeding (Schenk *et al.*, 2011). Kronberger *et al.* (2013) found that many do not differentiate between the technologies. In the Eurobarometer survey, 57% of the respondents found the technologies equally unnatural (Gaskell *et al.*, 2010) and in a Swiss study the figure was 40% (Haller *et al.*, 2009). To date, few studies have explored whether these attitudes translate into different WTP for cisgenic products relative to transgenic counterparts. Delwaide *et al.* (2015) conducted a contingent valuation survey in five European countries, and found that the discount required for cisgenic relative to traditional rice was smaller than for the transgenic rice. Similar results were found in experimental auctions in the US (Colson *et al.*, 2011). A survey on Indian consumers found that respondents did not value cisgenic and transgenic rice differently, but there was a positive WTP for no-fungicide, provided by the cisgenic and transgenic rice types (Shew *et al.*, 2016).

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[2]Ingenic is comparable to cisgenics. There are a number of GM methods with restrictions on the type of genes that are inserted. For an overview and discussion see Baeksted Holme *et al.* (2013).

2.2. Obtaining WTP estimates

Many studies of the WTP for GM and organic food products have applied stated preference (SP) techniques to evaluate product attributes not yet on the market. However, such surveys often find a discrepancy between intentions and actual purchase behaviour (Shepherd *et al.*, 2005), most likely caused by the hypothetical nature of the surveys. Other studies on GM foods which apply lab-based experimental auctions, providing monetary incentives, find lower discounts for GM products (Lusk *et al.*, 2005); yet their external validity can also be questioned.

Market data, which reveal preferences (RP), have been used for studying preferences for organic products (Wier *et al.*, 2008; Smed, 2012). An inherent weaknesses with RP-data is, however, that there are often many unobserved factors that affect consumer choices – such as visibility (shelf space and promotion campaigns), appearance (package design, aroma), and direct or indirect measures of the well-being of the consumer (hungry, stressed, on a diet) – which makes it difficult to identify decisive factors. Furthermore, product attributes are commonly highly correlated, for market segmentation reasons, and therefore their individual value is hard to estimate. Importantly, market data do not allow one to infer product attributes not available on the market or about which no information is available. SP-data do not have this weakness and allow for product attributes to vary freely, as long as attributes are not technically correlated or tied, which enables estimation of attributes often highly correlated in market observations (Whitehead *et al.*, 2008).

Combining SP- and RP-data has become more common, especially in transport, environmental and marketing studies. An early empirical contribution on private goods by Swait and Andrews (2003) used scanner data and choice experiments on laundry detergents. The method is more rarely used in relation to foods. Brooks and Lusk (2010) assessed consumer preferences for milk from cloned cows, Resano-Ezcaray *et al.* (2010) studied preferences for ham from different regions, Thiene *et al.* (2013) and Nadhem *et al.* (2007) used a combination of SP- and RP-data on the choice of wine in relation to certificate of origin. Evidently, there are considerable difficulties in estimating models combining SP- and RP-data. While several studies find that combined models do not improve the model fit compared to using separate models on RP- and SP-data (Nadhem *et al.*, 2007; Resano-Ezcaray *et al.*, 2010), others show that the predictive power on consumer choices of the combined models is higher (Swait and Andrews, 2003; Brooks and Lusk, 2010), and the combined models may have improved external validity regarding predictions on relative preferences and WTP for attributes not on the market or hard to assess from market data. Econometric approaches to improve modeling of such combined data are being developed, in particular within transport research (Hensher *et al.*, 2008; Cherchi and De Dios Ortú Zar, 2011; Hensher, 2012).

3. Survey Design and Data Collection

A questionnaire instrument was distributed to a consumer panel managed by GfK ConsumerScan Denmark, where SP-data were collected from a choice experiment. Prior to the choice tasks, descriptions and symbols of the less familiar attribute (breeding technology) were provided. The descriptions and illustrations were designed to be an unbiased, informative and easily understood ‘translation’ of the highly sophisticated scientific concepts. Furthermore, these descriptions were checked for scientific accuracy by a plant breeding expert and tested for understanding in a focus group process.[3] The focus groups included participants from different age groups, and with varying income levels and level of education. The focus groups resulted in modifications in wording, and attribute descriptions used in the questionnaire. Prior to the distribution of the survey a pilot survey was carried out, resulting in 41 completed responses leading to further refinements.

The choice experiment included a number of choice sets, where consumers were asked to choose among rye bread alternatives. The following features motivated the use of rye bread for the study; it is based on a common crop, which may be grown with or without the use of pesticides; it is bought regularly by most consumers in Denmark and it comes in varieties allowing us to choose attributes that overlap between the choice experiment and the scanner dataset also made available from the consumer panel of GfK ConsumerScan Denmark. The purchase data for rye bread provide information about store type, price, and whether the bread is sliced, organic, prepacked, and if on promotion. The attributes and levels used in the choice experiment and the purchase data are presented in Table 1.

The organic label in the market data includes other factors than pesticide restrictions, and is strictly speaking not pesticide-free, but has restrictions in the type of pesticides that can be used (non-synthetic). Consequently, pesticide use cannot vary freely in the choice experiment if attributes are to overlap between the experiment and the RP data. This was solved by combining breeding type and pesticide use into one attribute with six levels in the choice experiment, whereas the market data only included two of these levels. Each choice set included three bread alternatives and the option not to purchase. An example of a choice set is shown in Figure 1. The experimental design was generated in NGENE (ChoiceMetrics, 2012), where the D-efficiency criterion was implemented, assuming a multinomial logit (MNL) model with interactions and linear utility functions. Previous studies have found that such MNL specifications perform well on mixed logit models with a panel specification, which is the model type estimated here (Hensher *et al.*, 2015). The D-error depends on the experimental design and on the true parameters in the model. While the true parameters are unknown before data collection, priors were obtained by estimating choice models based on the data from the pilot study. These parameters were used as fixed priors to generate the final experimental design, with an *ex-ante* d-error of 0.5911 (Ferrini and Scarpa, 2007; Hensher *et al.*, 2015). The design included 18 choice sets, and to avoid fatigue among respondents these were divided into three blocks, where each respondent faced six choice sets. Following the data collection the design of the experiment was evaluated (Scarpa and Rose, 2008), showing an *ex-post* D-error for the MNL model of 0.0046.

Prior to the choice situations in the survey, respondents stated the typical price they pay for a rye bread of 800 grams, to anchor them in their typical purchase situation. The stated prices ranged from 5–59.5 DKK,[4] with a mean of 18.8 DKK, while the average bread in the market data cost 12.3 DKK and ranged from 3–44 DKK, indicating an upward bias in the stated values.

[3]The full descriptions and illustrations are available in the online supplementary material.

[4]1 USD ~ 7.00 DKK

Table 1
Attributes and levels in choice experiment and market data

	Choice experiment	Market data	Market share
Breeding technology and Production method	Transgenic with pesticide		
	Transgenic pesticide-free		
	Cisgenic with pesticide		
	Cisgenic pesticide-free		
	Conventional (pesticide)	Conventional (pesticide)	98.1%
	Organic (pesticide-free)	Organic (pesticide-free)	1.9%
Origin	Danish Imported		
Packaging	Store-baked	Store-baked	10.4%
	Prepacked	Prepacked	89.6%
Type	Whole	Whole	11.9%
	Sliced	Sliced	88.1%
Store type		Small supermarket	4.8%
		Ordinary Supermarket	36.2%
		Hypermarket	4.4%
		Soft discount store	45.2%
		Hard discount store	9.4%
Price (DKK)*,†	6,8,11,15,21,29	Continuous	

Notes: *1 USD ~ 6.88 DKK. †Price for 800 gram loaf of bread. The price for the market data was calculated by dividing the price paid by the weight and multiplied to compare to the price of 800 gram bread, which is the average weight in the market data.

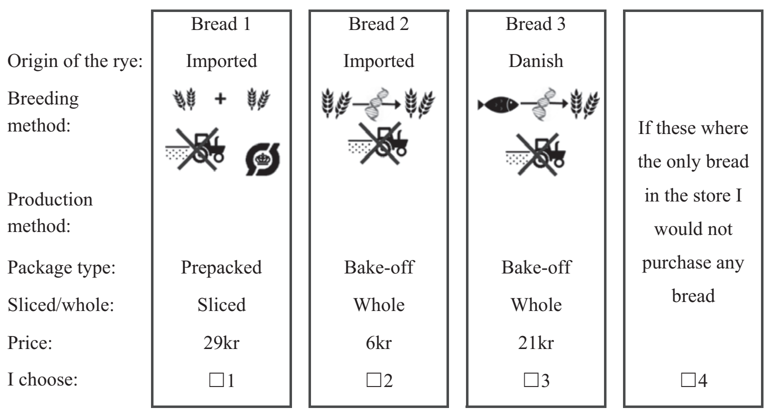

Figure 1. How the choice sets were presented to the respondents. The 'Ø' with a crown inside is the Danish state certified organic product logo.

The online survey was distributed in December 2014 to 1,525 panelists in the GfK consumer panel by GfK.[5] These panelists scan and report all their food purchases on a daily basis, enabling a match between the survey data and scanner data

[5]Part of the panel (425) report their purchases and answer surveys in paper format and they were provided with a hardcopy of the survey, but with the option to do it online.

for 2013. In total, 713 respondents answered the survey and had registered purchases of rye bread in the scanner data, and among those, 113 were excluded from the initial analysis, to be used as a holdout sample for testing the predictive power of the models. The sample corresponds well with the Danish population with respect to income and household size, while it is slightly underrepresented among those younger and those living in the capital area. There is a heavy overrepresentation of female respondents (77%), which is typical in consumer panels, as women to a greater extent are responsible for household shopping. Overall, the sample is considered a good representation of the consumers making the decisions in question. It is a well-known concern with consumer panels that the representativeness in other aspects is not known. Importantly, however, the participants in the GfK panel are not invited on the basis of their attitudes towards different foods such as GM, and thus we have no reason to assume that the sample is biased in this aspect.

The market data have the advantage of reflecting the respondents' actual behaviour, but are limited to information about the chosen alternative, and hence estimation of choice probabilities requires assumptions about the non-chosen alternatives. There were six store types, two types of package (prepack/store-baked), two types of bread (sliced/whole), and two production types (conventional/organic), providing 48 potential alternatives (Table 1). Initial data analysis suggested that some attribute levels were not available in all store types (e.g. only few, if any, organic types of bread are sold in hypermarkets and hard discount stores). Furthermore, purchases from specialty store bakeries were excluded as these are not comparable with the choice experiment. After excluding the incoherent combinations, 19 alternatives remained.

To achieve choice sets for the purchase data, prices for both the chosen and non-chosen alternatives need to be constructed. The price for both the chosen and non-chosen alternatives were set using the average price of that alternative among all purchases not on discount, while the price for chosen alternatives on discount was calculated based on the average of all purchases on discount for that alternative. This method implies that conventional, prepacked bread bought in a supermarket is predicted to have a different price compared to similar bread in a hard discount store. This is in line with the observed general price level differences between these store types. In this setup the store type is assumed to be part of the choice of bread; that is, consumers wanting to buy organic bread know that this is not available in hard discount stores and therefore choose a different store type. Correspondingly, consumers who chose a cheaper store type (hard discount or hypermarkets) are aware that they will not have the choice of buying organic bread. This choice set formation implies that the consumer knows the price and attributes available in the other store types, in line with the findings of Bjørner *et al.* (2004). While consumers cannot be expected to choose different stores for each product type, we assume that preferences regarding for example organic food are similar across product types. As an alternative the choice set may be assumed to only include the alternatives in the store of purchase. This alternative specification was tested, and similarly to Bjørner *et al.* (2004) it did not change the main results.[6]

[6]The models with the restricted choice set are available in the online supplementary material.

4. Methodology – Econometric Models

Following Lancaster (1966), individuals are assumed to choose the good that gives the highest utility, subject to a budget constraint. Choice models are commonly based on the Random Utility framework (McFadden, 1974), where the utility level comprises an observable component, the indirect utility V, and an unobservable component, the random error term ε. For individual i, the utility of choosing alternative k is:

$$U_{ik} = V_k + \varepsilon_{ik} = \beta' X_k + \varepsilon_{ik} \tag{1}$$

where β is a vector of taste parameters and X is a vector of attributes that describes the alternatives. In this study the indirect utility functions from the SP- and RP-data respectively can be expressed as:

$$\begin{aligned} V_k^{\mathrm{SP}} = \mu^{\mathrm{SP}} \times \big(&\beta^{\mathrm{SP}}_{\mathrm{Trans}}\mathrm{Transgenic} + \beta^{\mathrm{SP}}_{\mathrm{Cis}}\mathrm{Cisgenic} + \beta^{\mathrm{SP}}_{\mathrm{Pest-free}}\mathrm{Pestidcide\text{ - }free} \\ &\times (\mathrm{Transgenic} + \mathrm{Cisgenic}) + \beta^{\mathrm{SP}}_{\mathrm{Dom}}\mathrm{Domestic} + \beta^{\mathrm{SP}}_{\mathrm{Don'tbuy}}\mathrm{Don't\ buy} \\ &+ \beta^{\mathrm{SP}}_{\mathrm{Org}}\mathrm{Organic} + \beta^{\mathrm{SP}}_{\mathrm{Sliced}}\mathrm{Sliced} + \beta^{\mathrm{SP}}_{\mathrm{Prep}}\mathrm{Prepacked} + \gamma^{\mathrm{SP}}\mathrm{Price}\big) \end{aligned} \tag{2}$$

$$\begin{aligned} V_k^{\mathrm{RP}} = \mu^{\mathrm{RP}} \times \Bigg(&\sum_{s=1}^{S} \delta_s^{\mathrm{RP}}\mathrm{Storetype} + \beta^{\mathrm{RP}}_{\mathrm{Lag}}\mathrm{Same\ as\ previous\ purchase} + \beta^{\mathrm{RP}}_{\mathrm{Org}}\mathrm{Organic} \\ &+ \beta^{\mathrm{RP}}_{\mathrm{Sliced}}\mathrm{Sliced} + \beta^{\mathrm{RP}}_{\mathrm{Prep}}\mathrm{Prepacked} + \gamma^{\mathrm{RP}}\mathrm{Price}\Bigg) \end{aligned} \tag{3}$$

where β_{org}, β_{slice}, β_{prep} and γ are included in both utility functions while the remaining parameters are data source specific. We hypothesise that traditional breeding is preferred over cisgenics, which in turn is preferred over transgenics (*H1*: $\beta_{\mathrm{Trans}} < \beta_{\mathrm{Cis}} < 0$). Pesticide-free is expected to be positive (*H2*: $\beta_{\text{Pesticide-free}} > 0$, $\beta_{\mathrm{Org}} > 0$), while we have no expectations *a priori* for the relationship between GM bread without pesticides and conventional bread (*H3*: $\beta_{\mathrm{Trans}} + \beta_{\text{Pesticide-free}} = 0$, $\beta_{\mathrm{Cis}} + \beta_{\text{Pesticide-free}} = 0$).

When the error terms in the utility function are assumed i.i.d with a type I extreme value distribution the difference between error terms will take a logistic distribution and this results in the multinomial logit (MNL) model, with the probability function (McFadden, 1974; Train, 2003):

$$P_{ik} = \frac{\exp(\mu\beta' X_k)}{\sum_{j=1}^{J}\exp(\mu\beta' X_j)} \tag{4}$$

The variance of the error terms is not identifiable, but is normalised by a scale factor (μ) which is the inverse of the error variance ($\mu = 1/\sigma_\varepsilon$). The estimated parameters are hence compounds of preference parameters and scale, so direct comparison of parameters between models is not possible. While the scale of the parameters in MNL models is not identifiable, the relative scale between two data sources can be identified when estimated in a pooled model (Ben-Akiva and Morikawa, 1990; Hensher and Bradley, 1993; Swait and Louviere, 1993). When pooling data, common parameters are typically assumed and restricted to be equal while the scale is allowed to vary between data sources. By normalising $u^{\mathrm{RP}} = 1$ the relative scale (u^{SP}/u^{RP}) can be estimated. Swait and Louviere (1993) proposed an iterative process for identifying the relative scale, while holding the true, and common, parameters equal. Each data source is set to a branch in an artificial nested logit (NL) tree structure, and one of the branches is normalised to one while the relative scale of the other branch is estimated (Hensher and Bradley, 1993). The artificial NL model treats the data as cross sectional, and the variance in each dataset (nest) is assumed to be equal, implying IIA (Train, 2003). The mixed logit (ML) model relaxes the IIA assumption and allows for taste heterogeneity between individuals while preferences across choices for the same individual are stable, and such model specifications are increasingly used when pooling data sources (Hensher, 2008; Hensher *et al.*, 2008). The random taste parameters are described by a density function $f(\beta)$ specified to take the form $\beta_i = b + \sigma e_i$ for individual i, with the population mean b, the coefficient standard deviation σ, and a random error term e_i ~i.i.d. $N(0,1)$. The probability that an individual chooses a particular sequence of alternatives is conditional on the individual specific parameter β_i. The unconditional probability is the integral of the product of all the choice probabilities for that individual:

$$P_{ik} = \int \left(\prod_{n=1}^{N} \left[\frac{\exp(\mu^{SP}\beta_i^{SP}x_{kn})}{\sum_j^J \exp(\mu^{SP}\beta_i^{SP}x_{jn})} \right] \times \prod_{m=1}^{M} \left[\frac{\exp(\mu^{RP}\beta_i^{RP}x_{km})}{\sum_j^J \exp(\mu^{RP}\beta_i^{RP}x_{jm})} \right] \right) f(\beta|\sigma)\mathrm{d}\beta \tag{5}$$

N is the number of choices in the choice experiment and M is the number of purchases in the market data, where choices are linked for all individuals. The integral takes the dimension of the number of random parameters in the model. The parameters are estimated by simulation methods, since the probability function has no closed form solution (Train, 2003). Assuming the random parameters to be constant across choices (RP and SP) for each individual implies correlation over the choice sequences, and is achieved by using the same draw for all choices for each respondent when computing probabilities.

5. Results

Initially, models are estimated and results discussed for each of the data sources separately (SP and RP, respectively). This is followed by model estimates where the data sources are pooled, and based on these models the performance of pooling data sources is evaluated.

5.1. SP- and RP-models

To allow for preference heterogeneity among respondents, while assuming that each respondent has consistent preferences, ML models are estimated for each dataset. LR-tests show that this improves model fit significantly compared to the MNL models, where the LR-statistic for the SP model is 1,214.8 (compared with the critical value 15.5 for a 95% significance level) and for the RP model the LR-statistic is 5,922.6 (critical value 9.49). The ML models for SP- and RP-data are presented in Table 2. All product attribute parameters are specified with normal distributions, while the price parameter and the store-specific parameters are assumed non-random.

Table 2
The estimated SP and RP mixed logit models

		Model 1: SP	Model 2: RP
Retail type: (supermarket base)			
Hard discount store	Coefficient		–2.77** (0.13)
Hypermarket	Coefficient		–3.08** (0.14)
Small supermarket	Coefficient		–1.50** (0.19)
Soft discount store	Coefficient		–1.41** (0.09)
Production: (conventional base)			
Transgenic	Coefficient	–1.78** (0.21)	
	Std. dev.	1.50** (0.18)	
Cisgenic	Coefficient	–0.84** (0.15)	
	Std. dev.	2.00** (0.16)	
Pesticide-free * (trans + cis)	Coefficient	0.50** (0.10)	
	Std. dev.	0.50 (0.29)	
Organic	Coefficient	1.11** (0.15)	3.36** (0.35)
	Std. dev.	2.13** (0.20)	1.87** (0.16)
Other dummies			
Domestic	Coefficient	1.63** (0.11)	
	Std. dev.	1.40** (0.12)	
Same as previous purchase	Coefficient		1.22** (0.07)
	Std. dev.		0.90** (0.09)
Sliced	Coefficient	0.52** (0.09)	6.70** (0.27)
	Std. dev.	0.80** (0.14)	3.21** (0.31)
Prepacked	Coefficient	–0.81** (0.09)	–1.23** (0.49)
	Std. dev.	1.22** (0.13)	2.53** (0.41)
Don't buy	Coefficient	–0.76** (0.19)	
	Std. dev.	2.04** (0.16)	
Price	Coefficient	–0.06** (0.01)	–0.86** (0.03)
Observations/households		3,581/600	14,753/600
LL		–3,671.98	–15,906.23
LRI†		0.26	0.63

Note: Numbers in parentheses are robust standard errors. Asterisks (*,**) indicate statistical significance at the 5% and 1% level, respectively. †Adjusted Likelihood ratio index.

This specification is common practice in applied work (e.g. Hensher *et al.*, 2005) and allows for robust models.[7] The coefficients in Table 2 are the estimated population means and these are presented along with standard errors. For the attributes that are specified with a distribution, the standard deviations represent the variation in preferences around the mean, implying that a large standard deviation relative to the population mean suggests diversity in preferences for that attribute. The standard deviations are presented along with the standard errors of their estimate. Models were estimated in Biogeme 2.3 (Bierlaire, 2003) with 5,000 Halton draws and WTP

[7]Another option is to estimate the WTP estimates directly, by specifying a model in WTP space (Train and Weeks, 2005; Scarpa *et al.*, 2008), but this requires the price parameter to be the same across data sources which is not feasible in all our models.

estimates and standard errors were obtained with the Delta method (Hensher *et al.*, 2015).

All the parameter means in the SP-model are significant and have the expected signs but we note that there is significant and considerable preference heterogeneity on all attributes, with the absence of pesticides in the production process being the only exception. The mean parameters of the biotechnology attributes are both negative, with transgenic more negative than cisgenic. Considering the assumption of a normal distribution of preferences, we also note that a larger share of the population finds transgenic technology problematic compared to cisgenic. Producing GM bread without the use of pesticides is considered positive and equally so for both technologies.[8] Thus, if GM plants make this possible, the preference distribution will shift and fewer people on the market will prefer traditionally bred and conventionally produced bread to the GM variants. Organic is the most preferred among all production types, and its parameter is larger than the parameter for pesticide-free production (for transgenic and cisgenic). This suggests that additional aspects apart from pesticide use are reflected in preferences for organic products.

Consumers place large importance on the domestic aspect, which in the case of bread may be considered as a cue for freshness. The 'Don't buy' option is included to set the scale of utility to which other alternatives are compared, and this alternative specific parameter denotes the preference for not buying any bread relative to the base level bread (conventional, imported, whole and store-baked). The negative mean parameter and the large standard deviation for 'Don't buy' suggest that the majority of the respondents prefer the base level bread over no bread, but there is a non-trivial part of the sample that prefers no bread at all. This may be related to the considerable and homogeneous preferences for domestic over imported bread; some consumers simply do not want to buy imported bread.

The mean parameters in the RP-model are also all significant and in line with prior expectations. Organic is preferred over conventional, and people expect to pay less in discount stores and hypermarkets than in ordinary supermarkets. There is, however, considerable preference heterogeneity here too, in particular for the prepacked attribute. There is on average a positive preference for choosing the same type of rye bread as in the previous purchase, which is in line with previous literature on habit persistence and familiarity (Daunfeldt *et al.*, 2011). Evidence of the opposite sign, indicating variety seeking, has also been found in some studies (Daunfeldt *et al.*, 2011), and the significant and relatively large standard deviation of the preference distribution suggests this may also be true for some respondents in our sample. Importantly, the preferences for sliced over whole bread have the same sign as the SP-model, and the coefficient for prepacked over store-baked is negative in both models. This means that all the parameters that are included in both models have the same sign, which is important for the pooled model where the praxis is that only those can be set to be equal (Swait and Andrews, 2003; Whitehead *et al.*, 2008). A comparison of the relationship between the common parameters shows that the absolute value of the average preference parameter for organic produce is larger than for prepacked bread in

[8]For the SP-data, a model where the pesticide-free attribute was allowed to differ between transgenic and cisgenic is estimated and the LR-test indicates that the effect of pesticide-free is not significantly different between transgenic and cisgenic. LR-statistic: $-2 \times (-4{,}278.18 + 4{,}279.38) = 2.41$. The critical value for a 95% significance level and 1 df is 3.84. We therefore proceed with a common pesticide-free parameter.

both models, while the relationship between organic and sliced is not consistent between the models. The attributes sliced and prepacked are however highly correlated in the market data and this multicollinearity in the RP-model may explain the divergence with the SP-data. Finally we note that the relative size of the price parameter is quite different; we return to this below.

In the RP-model in Table 2 we assume that consumers choose among all bread alternatives, even those that are in other store types, and hence implicitly choose store and bread on offer in combination. To test if this is plausible we estimated a model where consumers were assumed to choose only among the alternatives they face in the store of purchase. These estimations (available in the online supplementary material) do not allow for shop-specific coefficients, but all the attribute parameters are significant and have the same sign as the RP-model in Table 2, and the relative order of organic, sliced and prepacked (the SP-common parameters) do not change from the initial specification. This consistency in main results is in line with Bjørner *et al.* (2004).

For the market data the number of purchases varies considerably between households providing a highly unbalanced panel dataset. The number of purchases averages 24 and ranges from a minimum of 1 to a maximum of 161 purchases. This can be compared to six choice situations in the SP-dataset. We therefore estimated an RP-model, where each purchase weighs equally (i.e. 1/6), and these results are available in the online supplementary material. The sign and relative order of the SP-common parameters did not change; hence we proceed with the full model.

5.2. Pooled models

Table 3 presents the results of ML models where the SP- and RP-datasets are pooled while controlling for scale differences. In model 3 all parameters common for the two datasets are restricted to equality (sliced, prepacked, organic and price), while the price parameter is free to vary between the data sources in model 4. The model fit is significantly better in model 4, as the significant increase in the log likelihood value clearly shows. The scale parameter for the SP-data is small relative to the RP, which suggests that the variance of the error terms is larger in the SP-data. This is expected as many of the attributes in the SP choices are unfamiliar to the consumers; while the market data are based on choices where the included attributes are highly familiar and decisions are made frequently. Indeed, a larger error variance in the SP-data is typical for pooled models (Whitehead *et al.*, 2008). We note that when the price parameters are allowed to vary between the data sources (model 4), the SP scale parameter increases. The estimated standard deviations relative to the means for the common parameters (organic, prepacked, sliced) are notably smaller in the pooled models than in the SP-only model, which may also indicate that some of the preference heterogeneity in the SP-only model is captured by the scale parameter in the pooled models.

The coefficient means are statistically significant and have the expected signs in both models. In model 4, the price parameter for the SP-data is substantially smaller than for the RP-data. This lower price sensitivity may reflect the hypothetical bias associated with the choice experiment, and is also likely to be influenced by the unfamiliar and unconventional characteristics, which may have reduced price awareness. The relative difference between the price parameters lies in the range of previous studies on hypothetical bias (Loomis, 2011). To test if the large difference in the price parameters

Table 3
The estimated SP and RP pooled models with two different treatments of the price attribute

		Model 3: 1 price parameter	Model 4: 2 price parameters
Retail type: (supermarket base)			
Hard discount store	Coefficient	−2.70** (0.13)	−2.72** (0.13)
Hypermarket	Coefficient	−3.06** (0.14)	−3.07** (0.15)
Small supermarket	Coefficient	−1.48** (0.22)	−1.47** (0.21)
Soft discount store	Coefficient	−1.37** (0.08)	−1.38** (0.08)
Production: (conventional base)			
Transgenic	Coefficient	−43.30** (6.45)	−15.5** (2.34)
	Std. dev.	33.10** (4.53)	13.3** (1.73)
Cisgenic	Coefficient	−20.20** (3.42)	−5.51** (1.25)
	Std. dev.	31.1** (4.77)	13.4** (1.71)
Pesticide-free *(trans+cis)	Coefficient	6.79** (1.96)	2.80** (0.79)
	Std. dev.	14.3** (3.57)	4.82** (1.93)
Organic	Coefficient	3.88** (0.31)	3.71** (0.29)
	Std. dev.	1.97** (0.20)	2.14** (0.11)
Other dummies			
Domestic	Coefficient	27.8** (4.03)	10.9** (1.42)
	Std. dev.	24.2** (3.33)	9.69** (1.23)
Same as prev. purchase	Coefficient	1.79** (0.07)	1.86** (0.09)
	Std. dev.	1.10** (0.07)	1.16** (0.09)
Sliced	Coefficient	5.40** (0.26)	5.34** (0.23)
	Std. dev.	3.05** (0.28)	2.71** (0.23)
Prepacked	Coefficient	−1.50** (0.31)	−1.35** (0.28)
	Std. dev.	2.82** (0.27)	2.69** (0.28)
Don't buy	Coefficient	−19.30** (2.96)	−3.41** (1.54)
	Std. dev.	36.80** (5.32)	15.00** (2.03)
Price	Coefficient	−0.85** (0.03)	
Price (SP)	Coefficient		−0.27** (0.05)
Price (RP)	Coefficient		−0.86** (0.03)
Scale (RP = 1)†		0.05** (0.01)	0.12** (0.01)
Obs./households		18,334/600	18,334/600
LL		−19,647.39	−19,610.39
Adjusted LRI		0.59	0.59

Note: Numbers in parentheses are robust standard errors. Asterisks (*,**) indicate statistical significance at the 5% and 1% level, respectively. †Scale is tested against the value 1.

between the data sources is driven by a proportion of respondents that did not take the price into account in the choice experiment, we estimated SP-only models where the price parameter was assigned a discrete mixture of distributions with one fixed at zero, to capture those who are inattentive to price, and the other a free point distribution. The model also estimated the proportion of respondents allocated for each price parameter. This model did not fit the data better than the model with a non-random price parameter (model 1), and we proceed with specifying the price parameters as non-random as presented in Table 3.

Testing the model fit of the pooled models against the model fit of the separate models gives a LR statistic of 138.4 for model 3 and 63.6 for model 4, with critical values for a 95% level of significance of 12.6 and 14.1, respectively.[9] Thus, fitting independent models to the two datasets provides a significantly better fit, which is a common finding in the literature (Swait and Andrews, 2003; Whitehead *et al.*, 2008 Brooks and Lusk, 2010) and not at all surprising as every parameter constrained to be equal across samples will likely reduce and never increase the log likelihood.

Rejection of parameter equality does not necessarily imply that the pooled models are inferior (Swait and Andrews, 2003) from a policy point of view. Given that the objective of this study is to assess consumer preferences and to predict the reception of cisgenics if introduced to the market, the predictive power of the models is also a relevant performance measure and we tested this in several ways. The different models were therefore used to predict outcomes in the holdout sample of 113 households that were not used for model estimations, including both SP and RP choices.

For each data source (SP and RP), we evaluated the prediction performance for each of the four models. The parameters of the models that are not included in the data, such as the RP-specific store type parameters in the SP-data, are not used for generating the prediction. Moreover, the attributes in the data that do not have parameter estimates in the models, e.g. biotechnology in the SP-data when predicting with the RP-model, are assumed to take the value zero. Note that applying the models to the pooled out-of-sample dataset will merely produce a weighted average of the prediction measures obtained from the SP- and RP-datasets respectively, so we refrain from presenting these results. Several measures of the predictive power of each of the models are presented in Table 4. The out-of-sample log likelihood (OSLL), as specified in Norwood *et al.* (2004) penalises for high probabilities for non-chosen alternatives, while the LL summarises the natural logarithm of the predicted value for the chosen alternative.

Based on the predictive power of the models we conclude that both of the pooled models perform slightly better than the SP-model on the SP-data with respect to

Table 4

Out-of-sample predictive power metrics of the four models in Tables 2 and 3

Model	% correctly predicted	OSLL*	LL†
SP-data (Observations = 667, households = 113)			
SP	47.1	–1,346.06	–811.45
RP	28.8	–4,879.26	–3,877.53
SP + RP (1 price)	47.7	–1,535.72	–812.17
SP + RP (2 prices)	47.5	–1,345.82	–811.98
RP-data (Observations = 2,237, households = 113)			
SP	1.7	–9,120.18	–6,916.26
RP	64.1	–4,648.91	–3,290.74
SP + RP (1 price)	63.4	–4,798.41	–3,403.91
SP + RP (2 prices)	63.3	–4,826.44	–3,459.44

Notes: *Out-of-sample Log Likelihood: $\sum_{i=1}^{N}\sum_{k=1}^{K}\sum_{t=0}^{T}(1-\delta_{ikt})\times\ln(1-P_{ikt})+(\delta_{ikt})\times\ln(P_{ikt})$, where δ_{ikt} is 1 if individual i chooses alternative k on choice occasion t, 0 otherwise, and P_{ikt} is the corresponding predicted probability. †$\sum_{i=1}^{N}\sum_{k=1}^{K}\sum_{t=0}^{T}\delta_{ikt}\ln(P_{ikt})$.

[9]The LR-statistic is computed as –2 × [LL(Pooled) – LL(SP) – LL(RP)], and the degrees of freedom is K(RP)+K(SP)–K(Pooled).

percent correct predictions, although the differences are not statistically significant, and the prediction LL values are not statistically significantly different between the models either. The OSLL measure also shows that the pooled model with two price parameters (model 4) is not statistically significantly different from the SP-only model (model 1), while model 3 is significantly worse.

For the RP-data the RP-only model (model 2) performs best in all three measures, although there are no statistical differences on a 5% level. Unsurprisingly, the SP-only and RP-only models perform poorly on the opposite data source. The poor predictive power of the RP-model on the SP-data emphasise that market data are not suitable for drawing conclusions on the reception of new attributes.

In conclusion, for the RP-data the RP-only and the pooled model with one price parameter outperforms alternative models, but since the main focus of this study is to understand relative preferences and predict the reception if cisgenics was introduced, we will focus on the performance on the SP-data. Considering several measures of predictive power suggests that the pooled model with two prices performs equally well on the SP-data as the SP-only model. This suggests that even after restricting parameters to be equal across datasets, the pooled model is equally good at predicting choices in the SP-data, and moreover the pooled model is enriched with RP-choices which enable increased external validity to the results from the choice experiment. These results suggest that the pooled model with two price parameters is most suitable for the purposes of this study.

5.3. WTP estimates for GM technologies with and without the use of pesticides

The WTP estimates for the pooled model with two price parameters are presented in Table 5, and for comparison the RP- and SP-only models are also included. The WTP estimates for the SP- and RP-models are the ratio of the attribute parameter and the negative of the price parameter, while for the pooled model with separate price parameters the RP-specific price parameter is used to obtain 'pseudo-WTP' estimates. We argue that since the SP and RP parameters are obtained from the same respondents, the RP-specific price parameter more closely reflects these respondents' true marginal utility of income. Therefore, we use the price parameter from the actual purchases when calculating the WTP for the new attributes that are in the SP-data only, to approximate the true WTP for cisgenics and transgenics. Comparing the WTP estimates in the SP-only and these 'pseudo-WTP' estimates from the pooled model shows that the monetary magnitude is adjusted downward in the pooled model. Importantly, relative preferences remain much the same.

The WTP estimates show the monetary value required for the consumers to become indifferent between the baseline and the attribute in question. The baseline in the RP-model is conventional, whole, store-baked bread bought in a supermarket, and the average price for such bread in the sample is 15.8 DKK. The price for the baseline bread in the SP-model is 12.1 DKK (which is conventional, whole, store-baked and imported). Moving to the pooled model shows that the baseline bread is only valued to 4.0 DKK while the estimate for Danish over imported rye bread is large in magnitude relative to the typical price the respondents pay for rye bread. This may be explained by loss aversion; consumers are not used to non-Danish rye bread, and we suspect that consumers believe that they only buy Danish bread, and that they would require a large discount for imported rye bread. We therefore interpret this to mean that the WTP for domestic bread should be added to the negative of 'Don't buy' to

Table 5

Estimated mean WTP estimates for each of the independent models (Table 2) and the pooled model with two price parameters (Table 2)

	Model 1: SP-model	Model 2: RP-model	Model 4: SP + RP: (2 prices) - model
Retail type: (supermarket base)			
Hard discount store		−3.22** (0.15)	−3.16** (0.16)
Hypermarket		−3.58** (0.18)	−3.58** (0.19)
Small supermarket		−1.74** (0.20)	−1.72** (0.23)
Soft discount store		−1.64** (0.08)	−1.61** (0.09)
Production: (conv. base)			
Transgenic	−28.08** (4.98)		−18.01** (2.84)
Cisgenic	−13.23** (2.86)		−6.42** (1.50)
Pesticide-free (transgenic/cisgenic)	7.82** (1.89)		3.26** (0.92)
Organic	17.51** (2.43)	3.91** (0.34)	4.32** (0.25)
Other dummies			
Domestic	25.71** (3.35)		12.71** (1.72)
Same as previous purchase		1.42** (0.09)	2.17** (0.11)
Sliced	8.14** (1.47)	7.79** (0.20)	6.22** (0.29)
Prepacked	−12.81** (1.91)	−1.43** (0.55)	−1.57** (0.30)
Don't buy	−12.05** (2.77)		−3.98* (1.80)

Notes: Mean WTP estimates are point estimates in DKK. Numbers in parentheses are standard errors obtained by the Wald method. Asterisks (*,**) indicate statistical significance at the 5% and 1% level, respectively.

obtain the WTP for the base level bread. This results in a price of 16.7 DKK for domestic, conventional, whole, store-baked bread, which is well within the range of the RP-data.

The 'pseudo-WTP' estimates for the pooled model show that consumers differentiate between the breeding technologies. Transgenics is clearly not accepted by the consumers on average, the large negative WTP suggests that a large majority of consumers are not willing to buy such bread at all. The cisgenic technology also faces a significant penalty on average and is valued less than traditional. For both technologies, an absence of pesticides in the rye production reduces the negative WTP significantly, and in particular for the cisgenic technology it may motivate some consumers to prefer this bread to the conventional product.

6. Concluding Discussion

The objective of this study was to evaluate consumer preferences for the use of transgenic and cisgenic (within species) genetic breeding techniques relative to traditional breeding methods and to relate these to an important attribute which is a significant feature of organic production; the restricted use of pesticides in agricultural production. We believe our results are reasonably representative for the Danish consumer, as the sample corresponds well with the Danish population with respect to income and household size, although it is slightly underrepresented among those younger and those living in the capital area. There is a heavy overrepresentation of female respondents (77%), which is typical in consumer panels, as women are largely responsible for household shopping. Thus overall, the sample can be considered a good representation of the consumers making the decisions in question.

Results show that consumers differentiated between transgenics and cisgenics – preferring cisgenics over transgenics – while the traditional breeding method was still preferred by the majority of the respondents, which is consistent with previous studies. Technologies related to breeding and production methods develop rapidly, and, importantly, our results suggest that efforts to meet consumer concerns by restricting the origin of the inserted gene(s) in the breeding process may further reduce (or perhaps even close) the WTP gap of some consumers to traditional breeding techniques.

Respondents preferred pesticide-free products, and there was little variation among respondents in this preference. On average, respondents declined GM products relative to traditionally bred rye. But while the aversion to transgenics relative to traditional breeding was large and homogeneous, the distribution for cisgenics suggests that a non-trivial group of our respondents did not differentiate between cisgenics and traditional, and hence the positive preference for pesticide-free may have led more consumers to prefer cisgenic and pesticide-free food over conventionally produced.

It should be noted that this study was limited to study of the impact of restricted use of pesticides as a potential positive feature of new breeding technologies. Other product characteristics may be of greater value to the majority of consumers, and if cisgenic breeding enables improvements in these aspects, the findings may be different. If cisgenics for example enables improvements in taste or health properties of products, this may increase the willingness to compromise with breeding technology.

From a methodological point of view, this study contributes to the prevailing knowledge by utilising a combined data approach that improved external validity of results compared to existing stated preference or lab experiment studies. The study showed that although combining stated preference (SP) and revealed preference (RP) data were rejected in terms of model fit when compared to two independent models, the predictive power of the pooled model was not statistically different from the SP-only model, suggesting that the improved external validity of the pooled model could be achieved at no cost in the predictive power. In particular, the pooled model generates substantially lower estimates of WTP than the independent SP model, suggesting that pooling can help offset the almost inevitable hypothetical bias inherent in SP approaches.

The benefit of the combined SP-RP models is the potential ability to improve external validity of the estimated preferences for the product attributes not observable on the market and hence the WTP for these. Of course, among such attributes some may be easier to relate to than others, and may spur different reactions among people. The attributes we have focused on in this study are unfamiliar to most respondents and may be hard to comprehend when making consumption decisions. Thus, the reactions to the attributes might in our case be slightly more pronounced than would be the case in a real market situation. We have attempted to correct in part for this by calculating WTP based on revealed preference price sensitivity, but nevertheless we cannot exclude the possibility that true market reactions may be less pronounced. Moreover, the unfamiliarity with attributes among respondents implies a heavy reliance on the descriptions provided in the survey. While these descriptions aimed to be as neutral and yet informative as possible in their approach (which was tested in a focus group process), we acknowledge that the information and level of understanding is far less controlled and more heterogeneous between consumers in a real market situation.

In conclusion, while use of cisgenic breeding was evidently more acceptable than the previous GM versions (transgenic), on average the traditional breeding method remained preferred even when cisgenic methods allowed for no use of pesticides. Given these results it could be argued that consumers may request full information about the breeding method, which *could* be provided via a separate label for cisgenics. Evidently, the costs of implementing such a regime should be taken into account when deciding on the feasibility of implementing such a label. Nevertheless, from a policy perspective, our results suggest that while the current labeling regime is suboptimal, excluding cisgenics from mandatory labeling in EU, or including it in the voluntary non-GM label in the US, will cause welfare losses for consumers.

Supporting Information

Additional Supporting Information may be found in the online version of this article:

Data S1. Supplementary estimations referred to in the article.

Data S2. Survey administered to Consumer Panel. English translation of Danish survey.

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