Higher Minimum Quality Standards and Redistributive Effects on Consumer Welfare

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Abstract

This paper estimates an individual level demand model for eggs differentiated by animal welfare. Typically, after minimum quality standards for eggs are raised, the price of higher quality eggs falls. As a result, consumer welfare is redistributed from households who do not value animal welfare to households who are willing to pay a premium for animal welfare. In our analysis of German household data, we find that on average, households with higher income are willing to pay more for eggs that provide higher animal welfare. This provides evidence that higher minimum quality standards have a regressive impact. In counter-factual scenarios, we estimate the cost reduction that would be needed to offset the regressive effect, and find that as retailers' pricing power increases, the cost reduction must be higher. Finally, we consider hypothetical future scenarios that continue to increase the minimum quality standard until only the highest quality eggs remain on the market.

Keywords: Minimum quality standard, Product differentiation, Regulation, Consumer harm, Bayesian estimation, Heterogeneity

JEL classification: L11, L13, L50, H23

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1 Introduction

Today, policymakers and regulators are taking an increasingly paternalistic stance with regards to consumer health and safety, as well as environmental and ethical standards. Many government agencies have introduced higher minimum quality standards and product bans on a variety of products for a wide range of reasons, including environmental protection[1], consumer health and safety[2] to broader ethical standards, including animal welfare[3].

Such regulations in the form of minimum quality standards and product bans are a ubiquitous aspect of our everyday lives, but not much is known about their economic impact. While higher minimum quality standards are usually non-controversial from an ethical or ecological viewpoint, they can have unintended consequences for consumers. In this paper, we make an empirical analysis of the impact of a higher minimum quality standard on individual consumer welfare, taking into account how firms adjust prices for the product variants that are still available following the new regulation. Our counter-factual experiments offer guidance to policymakers on the potentially regressive effects of such a higher standard, particularly on lower-income households, and how those effects can be mitigated.

Faced with a restricted set of products, buyers will adjust their individual consumption. But also firms, notably retailers, will optimally adjust their pricing of the still available products and product variants. Understanding the mechanism of these adjustments is key, both to assess the overall impact of any given policy and to correctly anticipate the effect of any planned policy. We conduct such an analysis for the case of a ban on the sale of battery eggs in Germany, where animal welfare is an important dimension of product quality. In the EU, fresh eggs are grouped into four categories (battery, barn, free-range and organic) depending on different levels of hen welfare. The battery egg ban deprived German consumers of their lowest-quality, lowest-price alternative.

We argue in this paper that regulators should consider the possible equilibrium effects that raising minimum quality standards might have on individual consumer welfare. In equilibrium, one should expect a drop in prices for close substitutes. A firm that has some degree of pricing power, will aim to attract buyers who formerly bought the lowest quality product and decrease its margin for upper quality products. In the end, former low-quality product buyers are more negatively affected by the ban than high-quality product buyers, because a higher minimum

[1]For instance, the EU banned conventional light bulbs and nickel-cadmium batteries in 2009.

[2]For instance, the New York City Health Department banned large-sized soft drinks sold in restaurants, sports arenas and movie theaters in 2012. However, this initiative was refused by the state's highest court in 2014.

[3]For instance, the EU banned battery hen's eggs in 2012 and cosmetic tested on animals in 2013.

quality standard benefits consumers who buy upper quality products anyway. Hence, there are losers and winners, but the impact on total consumer surplus is ambiguous.

The theoretical literature on minimum quality standards has not made clear-cut predictions about their effect on social welfare in the absence of strict assumptions about market structure, cost functions, and consumer preferences. Even if we focus exclusively on changes in aggregate consumer welfare, the theoretical literature has been ambiguous regarding the impact of minimum quality standards.[4] Nor are we aware of any empirical study that explicitly addresses the effects of higher minimum quality standards on prices and consumer welfare in vertically differentiated product markets.

Technically, we use an empirical framework that is particularly well-suited to analyze heterogeneous consumer preferences in markets with vertical product differentiation. In our main analysis, we estimate a hierarchical Bayesian multinomial logit model with a flexible mixture of normals first-stage prior to allow for non-normal consumer heterogeneity in the estimation. We rely on a modified version of the standard Markov Chain Monte Carlo (MCMC) algorithm in Rossi, Allenby, and McCulloch (2005) that is described in Pachali, Kurz, and Otter (2018) and implement order constraints for the egg label intercepts to explicitly model vertical product differentiation in our demand framework.

The results show substantial heterogeneity in preferences for animal welfare-differentiated eggs across households. We demonstrate that prices for the majority of higher quality eggs fall after the increase in the minimum quality standard, which means that consumer welfare is essentially redistributed from households who do not value animal welfare to households who are willing to pay a premium for animal welfare. As higher-income households are willing to pay, on average, more for eggs that provide better animal welfare, this provides evidence that higher minimum quality standards have a regressive impact on households. Our findings suggest that equilibrium price reactions on the supply side are a major driver for the regressive impact of higher minimum quality standards. In contrast to other regulatory questions, such as merger approvals by competition authorities, equilibrium price effects and the resulting (possibly asymmetric) changes in consumer welfare do not seem to be considered ex ante by policymakers in product regulation cases.

Using counter-factual experiments, we show how consumer protection agencies can estimate the reduction in costs of the new minimum quality standard that would be necessary to offset the regressive effect. This cost reduction can be either achieved by implementing a subsidy or by

[4]See for instance, Besanko, Donnenfeld, and White (1987); Besanko, Donnenfeld, and White (1988); Crampes and Hollander (1995); Buehler and Schuett (2014).

other factors that lower the marginal costs of production such as economics of scale.[5] If the expected reduction in costs is close to the necessary level, the policy of increasing the minimum quality standard is less problematic in terms of harming low-income households. Otherwise, a tailored subsidy scheme could be introduced to soften the regressive effect. We identify the role of retailers' pricing power as an essential determinant of the level of the cost reduction required to protect consumers who would otherwise be harmed by the higher minimum quality standard. Finally, we examine hypothetical future scenarios in which the minimum quality standard is increased until only organic eggs remain on the market. We find that the cost reduction would have to be greater if the policymaker further raises the minimum quality standard.

The rest of this paper is organized as follows. The related literature is discussed in Section 2. Section 3 provides details on the German egg market and describes the data used in the analysis. The empirical model and estimation techniques are introduced in Section 4. The demand estimation results are discussed in Section 5. Section 6 discusses redistributive effects of increased minimum quality standards, the role of retailers' pricing power, and policy implications. Finally, Section 7 draws conclusions from our findings.

2 Related literature

As our analysis shows, any public policy intervention on a consumer product should take firms' optimal (price) responses and their impact on consumer welfare (at least in the long run) into account. In particular, policymakers should consider the possibility that even a simple intervention, such as banning one quality tier in a grocery product category, may have varied distributional consequences on households with different socio-demographic characteristics. While our empirical analysis is very specific as we study the ban of battery eggs in Germany, the economic mechanism that drives our results is very general and therefore relates to many streams of literature:

Structural models of demand and supply that provide an ex-ante evaluation of pressing policy questions discussed in the public debate. In a recent study, Dubois, Griffith, and O'Connell (2018) evaluate the equilibrium effect of banning advertising in junk food markets on consumer welfare and firms' profits. Ryan (2012) analyzes higher environmental standards in the cement industry, showing how this can discourage entry and thereby reduces social welfare. We combine both an ex-post evaluation of banning the lowest quality tier in the German egg

[5] Note that the argument of economics of scale is less appropriate for mature industries such as the egg market. However, for more emerging industries other than the egg market, marginal cost reductions can naturally occur by economics of scale due to a narrower product assortment.

market and an ex-ante analysis of banning even higher quality tiers. Our paper therefore provides a structural framework for policy evaluations in vertically differentiated product markets to study equilibrium effects on prices and the welfare impact on different consumer segments. Moreover, we also discuss how likely regressive effects of higher minimum quality standards can be mitigated through a tailored subsidy scheme.

The agricultural economics literature has published many studies on animal welfare regulation in general and hen welfare regulation in particular. This stream of literature deals with estimating willingness-to-pay (WTP) for animal welfare and/or product sustainability in different categories. For instance, Allender and Richards (2010a) and Andersen (2011) in the context of eggs, Zander and Feucht (2018) for seafood as well as Norwood and Lusk (2011) for pork meat and eggs. Identification of consumer's WTP for differentiated eggs is of central interest to our research question as well. We contribute to this stream of literature by showing that implementation of the vertical quality differentiation in our demand model is crucial for identifying household's WTP for animal welfare-differentiated eggs. We isolate the vertical product differentiation of perceived animal welfare and treat the four hen welfare labels in the German egg market as quality attributes. This is also reasonable as production costs increase when producers provide higher hen welfare and most consumers regard the four categories as reflecting different quality tiers.

Battery eggs are not only banned in Europe but also in several states in the US. For the past decade, there has been a lively debate among US academics on the impact of hen welfare regulations on consumer welfare and egg prices (e.g., Sumner, Rosen-Molina, Matthews, Mench, and Richter, 2008; Norwood, Lusk, et al., 2009; Allender and Richards, 2010a; Norwood, 2011; Malone and Lusk, 2016; Mullally and Lusk, 2018a; Sumner, 2018; Mullally and Lusk, 2018b). The closest study to ours is conducted by Allender and Richards (2010a) who look into the impact of hen welfare regulation on consumers. Using a structural demand model for differentiated eggs, they examine the hypothetical impact on consumers of a cage-free egg production mandate in California. However, they can only make a distinction between regular cage eggs (circa 95% market share) and cage-free eggs (5 % market share) in their data on the Californian egg market. Likely equilibrium price effects are not taken into account as they do not model retailers' pricing decisions. Instead, the authors relate to Sumner et al. (2008) and assume that prices would rise by approximately 20% as a result of higher production costs after regulation. More recent studies provide an ex-post analysis of the Californian ban of cages for egg-laying hens in 2015. Malone and Lusk (2016) deliver an ex-post estimate of egg price evolution after the regulation in California took effect. They find a statistically significant impact on egg prices in California, with prices increasing by 33 to 70%. Mullally and Lusk (2018a) evaluate more data on the post-ban period to obtain an updated ex-post estimate of the effect of the Californian caged hen ban on egg prices. They find a 22% increase in the average price paid per dozen eggs due to stricter hen housing restrictions.

Apart from structural differences between the Californian and German egg market, our analysis is directly related to these studies. In our view, we contribute to this literature by explicitly modeling price evolutions of remaining quality tiers after banning lower quality alternatives in a fully developed structural model including demand and supply.[6] Unlike Malone and Lusk (2016) and Mullally and Lusk (2018a), we find that prices of remaining higher quality tiers typically fall after increasing minimum quality standards in the German egg market. The economic mechanism driving this result is very general and relates to the theoretical literature on minimum quality standards (see below), to the literature on pharmaceutical markets and the so-called brand-name price puzzle as well as to the literature on private-label entry in food and beverage industries (see Section 6.2 for a discussion of the link to the former two streams of literature). However, our results do not contradict the findings of the previous literature on the Californian caged hen ban since, as we show, price reactions after a ban depend simultaneously on multiple factors such as demand preferences, cost functions, and market structure. In this regard, we extend previous findings in our counter-factual simulations by further decomposing the drivers of the price reactions after imposing higher minimum quality standards. Nevertheless, the aggregation level of prices is also crucial for determining the price effect. If we had averaged egg prices across all animal welfare categories, we would observe an increase in egg prices as well but only because of the composition effect as consumers purchase more higher quality eggs. However, in terms of quality-adjusted prices, we show a drop in prices in the long-run.[7] Before making any statement on the impact of observed egg price evolution on consumer welfare, we argue that one has to account for the fact that these eggs are vertically differentiated, as many consumers have a greater willingness-to-pay for better animal welfare. Otherwise we would treat eggs in grocery stores as homogeneous goods, which stands in conflict with the observed price premium some consumers pay for eggs they understand were laid by better-treated hens. At

[6]Our demand framework is related to the model used in Allender and Richards (2010a) that considers eggs laid by hens grown under better conditions to be differentiated products as well. We adapt their model to the characteristics of the German egg market and implement order constraints to reflect perceived quality differences of the four different breeding categories instead of having a single demand parameter for the cage-free attribute. On the supply side, we add a structural model representative of the German retail market that we use to quantify evolution of egg prices for different quality tiers after the policy shift.

[7]Especially the literature on consumer price indexes deals with this "quality bias", as discussed for instance in Hausman (2003).

least for Germany, where there is sufficient demand for each hen welfare egg label, this would not be appropriate.

Minimum quality standards literature. Finally, retailers' optimal price response that we find in our model can be linked to the theoretical literature on minimum quality standards. The ban of low quality tiers in a product category always increases the minimum quality standard. Significant theoretical contributions were made by Mussa and Rosen (1978), Leland (1979), Shapiro (1983), Besanko et al. (1987), Besanko et al. (1988), Crampes and Hollander (1995), Panzar and Savage (2011) and Buehler and Schuett (2014). According to the theoretical literature, firms can extract more consumer surplus by using a product-line with quality-differentiated goods to segment consumers with respect to their willingness-to-pay for quality. This is especially relevant if firms cannot directly price discriminate between consumers with different valuations of quality. Any policy that affects the product-line of quality-differentiated goods, such as increasing the minimum quality standard, will trigger a price response by firms if they have some degree of pricing power. According to theoretical predictions, prices of remaining quality tiers that are close substitutes are expected to drop after the lowest quality alternative is removed from the market because firms lose a tool to discriminate between different consumer segments. This provides a theoretical explanation for our observed pricing pattern in the German egg market. The theoretical implications of minimum quality standards are well understood in the agricultural economics literature as well. See for instance Bockstael (1984) or Lapan and Moschini (2007), which provide theoretical treatments and examples for minimum quality standards in food markets. In terms of consumer welfare, there are no clear-cut predictions of the effect of higher minimum quality standards if consumers have heterogeneous preferences for quality. Typically, some segments of consumers with higher quality valuation will benefit and others with lower quality valuation will be harmed.

Our study contributes to all these literature streams by providing a framework as well as a full-fledged empirical analysis of the equilibrium effects on prices and different consumer segments in vertically differentiated product markets.

3 Market details and data

The market for fresh hen's eggs

The German market for fresh eggs is suitable to study the effect of higher minimum quality standards on consumer welfare in markets with vertical product differentiation for two reasons: first, since 2004, there has been an EU-wide requirement to state the breeding category on egg packages and to print a code on each egg indicating origin and breeding category.[8] Thus, consumers typically associate the four breeding categories with different quality levels: battery eggs $\precsim$ barn eggs $\precsim$ free-range eggs, and $\precsim$ organic eggs.

These perceived quality differences can be motivated by consumers seeking a "warm glow" who feel that the animals serving them have better than average living conditions and/or who find that eggs from happier hens do indeed taste better. Table 1 depicts the differences in living conditions for hens between the different egg categories. Production costs are different across categories. The better hen welfare an egg category provides, the higher are the production costs. The fact that there is sufficient demand for each category suggests that consumers are heterogeneous in their willingness-to-pay (WTP) for different levels of animal welfare/quality.

Table 1: Main differences between egg breeding categories

Egg label	Hens per m^2	Surface per hen in cm^2	Outdoor area per hen in m^2	Additional points
Organic	6	1667	4	Organic feed, no beak trimming, no regular use of antibiotics
Free-range	9	1100	4	Live in open barns
Barn	9	1100	0	Live in open barns
Battery	18	550	0	Live in cages

Source: http://www.deutsche-eier.info/die-henne/haltungsformen/; accessed 2 March 2016.

Second, in 1999 the EU decided that all member states had to ban the production of battery eggs by 2012. Germany already implemented the ban in 2010.[9] Nevertheless, battery eggs could still be imported from other EU countries until 2012 and an updated version of this breeding category called "Kleingruppenhaltung" was introduced to replace battery eggs. This category was slightly better but still worse than barn eggs in terms of animal welfare. The German retail sector, however, decided to completely delist battery eggs from its assortment of fresh eggs in the course of 2010 and to not introduce the eggs from "Kleingruppenhaltung". Some retailers pre-empted this delisting and already cut battery eggs out of their inventory several months before the official deadline. For example Lidl, a large retailer in Germany, stopped selling battery eggs already in 2009.[10] As a consequence, since mid-2010, German households have consumed battery eggs only indirectly as an ingredient of processed food products such as noodles, pastries and mayonnaise.

Data

Our analysis is based on Nielsen Homescan data, which tracks expenditures of German house-

[8] https://www.was-steht-auf-dem-ei.de/en/all-about-eggs/index.php; accessed 26 June 2018.

[9] Note that even after 2012 not all member states of the EU, especially among the new eastern member states, have implemented this ban. The EU commission plans to sue these countries for breaching the directive.

[10] https://albert-schweitzer-stiftung.de/aktuell/lidl-ohne-kaefigeier; accessed 12 December 2016.

holds on fast-moving consumer goods (FMCG).[11] All participants are surveyed once a year and several demographic variables such as age, household size, and income are recorded. For each year from 2008 to 2012, the Nielsen Company (Germany) GmbH drew a representative sample of German households. Households of the representative sample have projection factors (which may vary from year to year) to allow for extrapolation of sales and markets shares in Germany.

We focus on purchases of eggs in the German retail sector, specifically those discounters and full range supermarkets that sell around 80% of all fresh eggs in Germany.[12] Only purchases at the top ten retail chains were considered[13], because infrequent shopping trips to smaller chains make it difficult to impute prices for non-chosen alternatives and to cross-validate data. These sales represent approximately 75% of all egg purchases made in the German retail sector. For estimating our demand model, a product is defined as an egg category-package size-combination offered at one of the ten retail chains.[14] Similarly to Dubé, Hitsch, and Rossi (2010), we define an aggregate of purchase incidents in related product categories as an outside option.[15] As we analyze only fresh hen's eggs, we define boiled and painted eggs as well as eggs from other type of poultry, e.g. quails and gooses, as outside good. A similar approach of defining the outside option for estimating the demand of differentiated eggs can be found in Allender and Richards (2010a), where an aggregate of fringe brands is used as an outside good. Appendix A.1 describes how we impute prices for non-chosen egg alternatives.

Market shares, prices and model-free evidence

Figure 1 illustrates the seasonal patterns in egg purchases of inside goods (i.e. the sum of all battery, barn, free-range, and organic egg purchases) as well as the outside good. The left panel depicts monthly extrapolated sales and the right panel shows share of inside goods on total market size. We observe high peaks for inside good egg sales at end of the year (Christmas) and smaller peaks in the Easter period. The outside good, however, exhibits strong increases during Easter (as illustrated by the vertical dashed lines), which causes the market share of inside goods to decrease.

[11]We want to emphasize that only we authors are responsible for the contents, which do not necessarily represent the opinion of The Nielsen Company (Germany) GmbH.

[12]`http://www.daserste.de/information/ratgeber-service/lebensmittelcheck/wie-gut-sind-unsere-eier-fakten-rund-ums-ei-100.html`; accessed 12 December 2016.

[13]For reasons of confidentiality all brand and retailer names were made anonymous in this article.

[14]Specific brands of eggs are not considered here. We do not regard branding as important because in the data period most egg brands are private labels and there often exists only one brand within each retailer. The main differentiation here comes through the different egg labels. Furthermore, there is no advertising for egg brands in Germany.

[15]For example, Dubé et al. (2010) take any other fresh or canned juice product purchase as an outside good for refrigerated orange juice and any other margarine or butter than considered margarine brands as an outside option for margarine.

Figure 1: Seasonal pattern of egg purchases

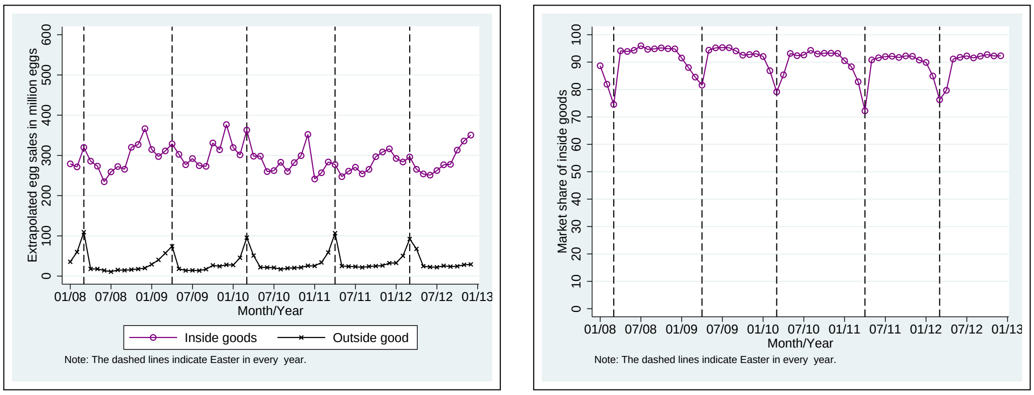


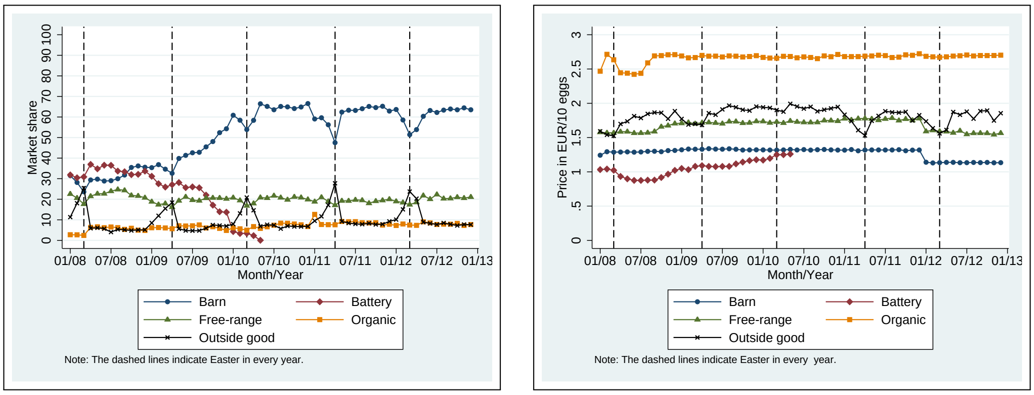
Figure 2 shows market share and price evolutions for different egg categories over time.[16] Market shares are shown in the left panel and prices in the right panel. Similarly as with the seasonal patterns in Figure 1, we observe that the outside good gains market share during Easter.
The price series points to the vertical product differentiation in the egg market. In the year 2008 where all egg categories are still available, we observe higher average prices as we move up from battery to organic eggs. From 2009 to the first months of 2010, prices of battery eggs increase until they almost match the prices of barn eggs. During 2009, we see that battery eggs become scarce as more and more battery egg henhouses reformed into barn egg houses, which explains the increase in battery egg prices observed in the figure. At the same time, some retail chains started to ban battery eggs from their shelves as well. As a consequence, more consumers switched to barn eggs as battery egg prices converged to prices of barn eggs. Finally, by the end of 2010, market shares of battery eggs were fully absorbed by barn eggs. In contrast, free-range and organic eggs could not substantially expand market shares after the ban.

Regarding price patterns observed in Figure 2, barn, free-range, and organic eggs seemed relatively stable (with the exception of organic egg prices in 2008) and we did not observe firms adjusting prices over the season. Only prices of the outside good exhibited a market response in form of lower average prices during Easter. The observed market share and price patterns motivate the specification of our demand model in Section 4.

In 2012, there was a drop in prices for barn and free-range eggs. This pattern can have two causes: First, there might have been a change in demand preferences. For instance, consumers have different valuations for egg categories after the ban of battery eggs and retail chains react to this demand shock. In the demand specification in our model, we control for that source by allowing consumers to have different egg preferences before and after the ban of battery

[16]We construct monthly market shares by using the extrapolated sales for each egg category and compute average prices in euros per ten eggs by dividing extrapolated revenues by extrapolated sales.

Figure 2: Monthly market shares and (sales-weighted) average prices across egg categories



eggs. Second, the regulatory intervention might have triggered retailers' price responses even if consumers' valuation for hen welfare-differentiated eggs had not changed. As the theoretical literature on minimum quality standards discussed in Section 2 concluded, firms can extract more consumer surplus by using a product line with quality-differentiated goods and segment consumers based on their willingness-to-pay for that quality. Banning lowest quality alternative battery eggs might therefore trigger a price response by retailers if they have some degree of pricing power. While retailers used battery eggs to compete for price-sensitive consumers before the ban, the role fell to barn eggs after the policy shift because they became the lowest quality tier. Accordingly, prices for the remaining quality tiers are expected to drop as firms lost one rung on their quality ladder. In Section 6, we isolate price effects of higher minimum quality standards in a structural model framework to verify and illustrate these hypotheses.

The price reactions illustrated in Figure 2 suggest that— assuming consumer preferences for different egg categories remain unchanged— typical battery egg consumers are likely harmed while typical barn and free-range egg consumers likely benefit from the ban on selling battery eggs. Over all, households with lower income are more price-sensitive, and tend to prefer battery eggs as the cheapest alternative. Figure 3 illustrates this conjecture by comparing evolutions of market shares for different egg labels across different income groups in our sample of households.[17]

Table 2 shows the percentiles for the net income per adult in household, which we use to form ten income groups. According to Figure 3, we observe that in 2008, the market share of battery eggs decreased as we moved up from the lowest income group (group 1) to the highest (group 10) . At the time, the lowest income group had virtually no demand for organic eggs. In 2012,

[17]We compute monthly net income per adult using the demographic information on households. Income is originally a categorical variable (see Table A.14 in the Appendix for its original coding). We constructed a continuous income variable for each household by drawing from a uniform distribution within the respective income range.

Figure 3: Yearly market shares for egg labels by income groups

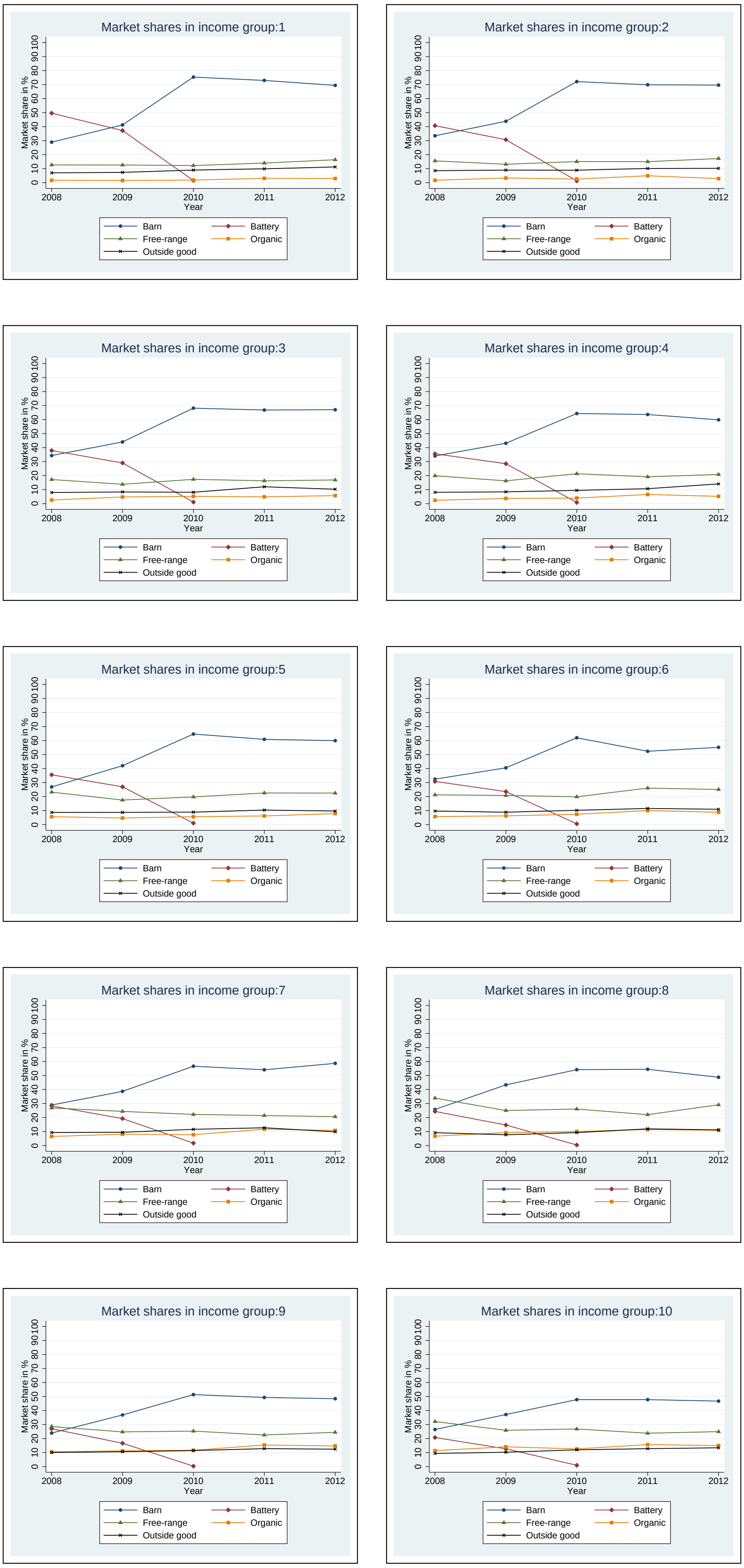


Table 2: Percentiles for income per adult in household

	10%	20%	30%	40%	50%	60%	70%	80%	90%
Income per adult in EUR	632	786	925	1052	1184	1337	1500	1744	2190

after the ban of battery eggs, barn eggs constituted around 70% of egg purchases by the lowest income group but less than 50% in the highest income group. We regard this as model-free evidence that the ban on battery eggs is regressive and particularly disadvantages households in lower income groups— a result that we further examine in the counter-factual analysis in Section 6.

Estimation sample

In order to meaningfully estimate individual preferences, we have to ensure that each household had at least one chance to choose from among all every egg category, e.g., battery, barn, free-range, and organic. However, the set of representative households in the Nielsen homescan data is not exactly identical over the years and a fraction of households are replaced each year by similar ones for a number of reasons, such as sample attrition or irregular recording patterns. For instance, if we observe barn egg purchases of households who got into the sample only after the ban of battery eggs, we cannot know with any certainty whether these households would have bought battery eggs instead of barn eggs if still available. For our estimation, we therefore consider only households who belong to the representative sample of 2008.[18] We further restrict our estimation sample and include only households who purchased eggs at least four times between 2008 and 2012, in line with a common practice in the demand estimation literature using household scanner data (e.g., Dubé et al., 2010; Erdem, Keane, and Sun, 2008). This leaves us with a total of 6,961 households for our estimation sample. We can match these households with their projection factors and demographics recorded in 2008, allowing for market simulations based on prices 2008 as we perform in Section 6. Table 3 compares our estimation sample with the full representative sample in 2008. We conclude that in terms of observable demographics, the estimation sample seems comparable to the full sample.

Table 4 displays market share-weighted average prices for a package of ten eggs and market shares for different egg categories based on the estimation sample. We regard the prices in 2012 as long-run new equilibrium prices after the ban on battery eggs. Basically, Table 4 is equivalent to Figure 2 with the difference that it depicts prices and market shares on a yearly basis. In 2008, when battery eggs were still listed by German retail chains, both barn and battery eggs

[18] Also because after 2008 some retail chains already pre-empted the ban and start delisting their battery eggs in 2009.

Table 3: Description of household sample and characteristics

	2008				
Variables	Mean	Stand. Dev.	Median	Min	Max
Full sample of households					
Household size	2.28	1.16	2.00	1.00	9.00
Monthly net income in EUR	2328.98	1329.69	2058.00	500.00	7996.00
Pet in household	0.45	0.50	0.00	0.00	1.00
Children in household	0.25	0.43	0.00	0.00	1.00
Age oldest household member	53.56	14.48	53.00	19.00	99.00
Female share in household	0.50	0.29	0.50	0.00	1.00
Urban dummy	0.75	0.44	1.00	0.00	1.00
No. of households			10843		
Estimation sample of households					
Household size	2.38	1.18	2.00	1.00	9.00
Monthly net income in EUR	2350.71	1313.33	2096.00	500.00	7996.00
Pet in household	0.48	0.50	0.00	0.00	1.00
Children in household	0.28	0.45	0.00	0.00	1.00
Age oldest household member	52.21	14.09	51.00	19.00	99.00
Female share in household	0.50	0.27	0.50	0.00	1.00
Urban dummy	0.75	0.43	1.00	0.00	1.00
No. of households			6961		

Note: The urban dummy equals one if the household lives in a municipality with at least 50,000 inhabitants.

exhibited similar market shares and together constituted around 65% of all egg purchases. The difference between average prices for ten eggs of both breeding categories was 0.34 EUR in 2008. Comparing average prices for a package of ten barn eggs between 2008 and 2012, we observe that they are 0.16 EUR lower in 2012, when battery eggs are no longer offered by retailers. In 2012, barn eggs account for around 60% of all egg purchases in our sample. By 2012, the price for free-range eggs has also dropped. As already explained above, the observed price patterns fit our theoretical predictions on the impact of increasing minimum quality standards.

Table 4: Data description of estimation sample

	Average price (EUR) per 10 eggs					Market share (%)				
Egg product	2008	2009	2010	2011	2012	2008	2009	2010	2011	2012
Organic	2.57	2.68	2.68	2.69	2.69	5.10	6.09	6.32	8.25	8.03
Free-range	1.60	1.71	1.72	1.75	1.56	21.80	18.79	20.01	19.71	21.15
Barn	1.29	1.33	1.32	1.32	1.13	30.54	41.30	63.50	61.29	60.16
Battery	0.95	1.08	1.21			34.78	25.78	0.96		
Outside good	1.67	1.81	1.92	1.73	1.72	7.79	8.04	9.21	10.75	10.65
No. of households						6961	6600	6045	5553	5224
No. of purchase incidents						87449	86513	77412	66061	63355

However, we want to point out that these changes in average prices and market shares alone should not be used to quantify the effect of banning battery eggs on prices and consumer welfare. While we think that most of the price decrease for barn and free-range eggs is due to the ban, we cannot rule out the possibility that other factors have simultaneously changed such as egg tier preferences or cost functions. However, as our aim is to isolate the impact of a higher minimum quality standard, in terms of banning battery eggs, on consumer welfare, we employ a structural demand model to estimate consumer preferences for different egg categories and control for seasonal effects and changes in preferences after the policy shift. For our structural model, we estimate individual demand parameters based on 380,790 purchase incidents of 6,961 households between 2008 and 2012. Furthermore, given these demand estimates, we characterize long-term equilibrium effects in Section 6 and study optimal pricing reactions due to the banning of a lower quality tier using a supply model of retail competition.

4 Empirical Framework

Demand specification

In our demand framework, we assume that a household makes a discrete choice among J_t egg products during each egg purchase occasion at time t (similarly as in Allender and Richards, 2010a,b; Andersen, 2011). We define the household's choice opportunity to be conditional on a purchase incident in the egg category and we do not model consumer choice of every trip to a retailer which would include trips of no purchases in the egg category at all.[19] As is usually the case with empirical demand estimation, we do not know the specific set of egg alternatives across retailers that a household might consider at the time of purchase. However, the structure of the data allows us to infer individual preferences for the ten retail chains (conditional on observing an egg purchase) that effectively locate the alternatives most likely to be considered and offer valuable information about the level of differentiation across retailers required for the counterfactual analysis below. Accordingly, we assume consumers have full information and include the egg alternatives of all ten retail chains into the individual consideration set. Household i's

[19] Moreover, we only observe purchases of multiple egg packages in 14% of total shopping trips. Since eggs are perishable goods (they should be consumed within approximately two to three weeks), stockpiling is an unreasonable explanation for observing multiple egg package purchases. We therefore treat the decision on the quantity of packages purchased as exogenous and predetermined, for instance because of household size or because the purchase is for a special occasion. Therefore, each egg purchase occasion at time t represents a discrete choice among J_t egg products independent of quantity.

indirect utility from egg product g in chain l at period t is specified as

(1)

$$U_{iglt} = \begin{cases} \gamma_{i,g}\mathbf{1}\{t = regular\} + \tilde{\gamma}_{i,g}\mathbf{1}\{t = Easter\} + \bar{\tilde{\gamma}}_{i,g}\mathbf{1}\{t = Christmas\}+ & \\ \quad +\alpha_i p_{glt} + \beta_i \mathbf{1}\{units_g = 6\} + \psi_{i,l} + \varepsilon_{iglt}, & \text{if } g = Battery \\ \gamma_{i,g}\mathbf{1}\{t = regular, t < RC\} + \gamma^{RC}_{i,g}\mathbf{1}\{t = regular, t \geq RC\}+ & \\ \quad +\tilde{\gamma}_{i,g}\mathbf{1}\{t = Easter\} + \bar{\tilde{\gamma}}_{i,g}\mathbf{1}\{t = Christmas\}+ & \\ \quad\quad +\alpha_i p_{glt} + \beta_i \mathbf{1}\{units_g = 6\} + \psi_{i,l} + \varepsilon_{iglt}, & \text{else} \end{cases}$$

Where $g \in \{Battery, Barn, Free\text{-}range, Organic\}$ and $l \in \{1, \ldots, 10\}$ in our application. The indicator variable, $\mathbf{1}\{units_g = 6\}$, denotes whether egg label g has the package size six instead of ten eggs. The price is given by p_{glt} and we normalize the mean utility of the outside option to zero, $u_{i0t} = 0$. We set $j := (g, l)$ to simplify notation in what follows and replace the deterministic part of utility by V_{ijt} for household i and every choice alternative j at time t. Assuming that ε_{ijt} follows a type I extreme value distribution, individual choice probabilities are given by a multinomial logit model

$$Pr_{it}\{j|p\} = \frac{e^{V_{ijt}}}{1 + \sum_{k=1}^{J_t} e^{V_{ikt}}}. \tag{2}$$

We have 26 parameters to estimate on the household level, denoted as: [20]

$$\theta_i = \Big(\alpha_i, \gamma_{i,Battery}, \ldots, \gamma_{i,Organic}, \tilde{\gamma}_{i,Battery}, \ldots, \tilde{\gamma}_{i,Organic}, \bar{\tilde{\gamma}}_{i,Battery}, \ldots, \bar{\tilde{\gamma}}_{i,Organic}, \gamma^{RC}_{i,Barn}, \ldots, \gamma^{RC}_{i,Organic}, \beta_i, \hat{\psi}_{i,2}, \ldots, \hat{\psi}_{i,10}\Big)' \tag{3}$$

Endogeneity of prices

As with most demand estimation problems, there are endogeneity concerns regarding the price variable. Our demand specification in Equation 1 therefore incorporates egg label specific seasonality control dummies for the Easter and Christmas periods[21] as well as regime change dummies.[22] The latter measure preferences for the remaining quality tiers after the ban on battery eggs. We include these controls to capture possible changes in egg preferences that may

[20] We estimate individual retail chain preferences relative to a baseline chain in order identify the likelihood. For $l \neq 1$, $\hat{\psi}_{i,l} = \psi_{i,l} - \psi_{i,1}$ measures household i's preference for the lth retailer relative to the first as the baseline level.

[21] The starting date of the season is set to one month before the actual event, like Easter or Christmas.

[22] The date of regime change is set to end of June 2010 when the last battery eggs were sold in the major retailers in Germany.

potentially lead firms to change their prices. A common endogeneity concern is that supply side reactions (pricing responses) on by the econometrician unobserved demand shocks may bias the price parameter estimate in Equation 1. For instance, according to Figure 2, we observe that the outside good gains market share during the Easter season while barn and free-range eggs lose shares at the same time. Even though this observation goes along with a drop in prices of the outside good, we cannot rule out that households have different preferences for the inside goods (relative to the outside good) in the Easter period —especially because the outside good incorporates painted eggs. Similarly, while retail prices appear to be relatively stable at the end of the year, Figure 1 indicates high peaks for sales of the inside goods during the Christmas season. We therefore include Christmas seasonality dummies to control for this pattern. Finally, policy regulations, such as the ban on battery eggs that we study, can affect public sentiment regarding animal welfare that might influence preferences of households. We include regime change dummies since we cannot rule out such preference changes according to Figure 2. The observation that market shares of organic eggs remained stable after the increase in relative prices of organic eggs at the end of year 2011 might be due to a preference shift of households towards organic eggs following the policy regulation or due to a more general shift towards consuming more sustainable egg products.
Figure 2 also indicates that the policy shift is probably the most important factor to identify price sensitivity. Battery egg average prices almost converged with barn egg prices until 2010, most likely because they became scarce as more egg suppliers upgraded their farms to barn egg production.[23] Most of the price variation is across egg labels. We control for that dimension through egg-label intercepts. Another dimension of price variation is across retail chains, e.g. low-price discounters vs. high-price, full-range supermarkets. We control for that dimension by including individual retail chain preference parameters that affect the likelihood of purchasing a certain egg label in a particular retailer.

Another possible approach to compensate would be to apply instrumental variable techniques. Cost shifters are natural candidates for instruments as they usually correlate with prices but do not directly influence demand. We have access to potential cost shifters in the form of monthly hen fodder prices as well as wholesale prices of battery, barn and free-range eggs from the agricultural commodities exchange in Germany.[24] Appendix A.2 tests the strength of these potential instruments. We find that the short-term variation in potential cost shifters is not

[23]We do not think it to be plausible that consumers valued battery eggs more in that process and that retailers' reacted to this as a demand shock by raising prices. In particular, this is implausible as their market shares also decrease.

[24]We note that wholesale prices from the agricultural commodities exchange in Germany are not complete as there was no access to corresponding prices for organic eggs.

directly transmitted to retail egg prices (see results shown in Table A.1) and conclude that we do not have good instruments available.

Finally, although there is never a guarantee to control for all possible factors that correlate with prices and also directly influence demand, it would not qualitatively change our findings in Section 6. As there is no individual pricing to consumers by retail chains, we should rather expect that a likely attenuation bias shifts the whole distribution of price coefficients towards zero. Thus, it should not change the ordering of price parameters across households. Second, if the price parameter distribution was biased towards zero, the calculated changes in consumer surplus would be rather underestimated in absolute terms. In that case, our findings of the redistributive effects across different consumer segments can be regarded as conservative estimates or lower bounds.

Estimation approach and prior constraints

As outlined in Section 3, we observe sufficient demand in each egg label category to make it particularly important to rely on a model that explicitly accounts for preference heterogeneity. We rely on a hierarchical Bayesian multinomial logit model with a mixture of normals first-stage prior to estimate individual demand parameters θ_i. This approach not only allows approximate deviations from standard normal heterogeneity distributions as described in Rossi et al. (2005), but is also well suited for the purpose of estimating reliable individual level coefficients when the amount of data provided by each panel unit is rather small. Table 5 shows the varying amount of information provided by each household in the sample. A hierarchical Bayesian approach that

Table 5: Distribution of the number of egg purchase incidents across $N = 6961$ individuals in the estimation sample

	Min.	1st Qu.	Median	Mean	3rd. Qu.	Max.
Purchases	4	21	43	55	77	338

effectively pools information across households through the prior and thereby shrinks extreme coefficient estimates (implied by a short history of observations on the individual level) towards the sample mean is usually considered more reliable. We believe that this is a desirable property in our application as, given the dimensionality of our model, we have only a rather short history of purchases for the majority of households in the sample. Moreover, the relatively small amount of within quality tier price variation as compared to price variation across quality tiers further motivates the use of a hierarchical model.

It is well understood in the literature that standard unconstrained hierarchical prior distributions often lack economic rationality (e.g., Reiss and Wolak, 2007; Allenby, Brazell, Howell, and

Rossi, 2014; Pachali et al., 2018). As a consequence, market simulations based on the posterior of the hierarchical prior can be misleading and produce counter-factual outcomes that lack face validity. In most applications, the reason is that individual level posterior distributions will reflect large amounts of posterior uncertainty about a specific household's preferences due to the limited amount of individual information usually available. We therefore need to distinguish uncertainty in posterior inference from irrational behavior and the specification of the hierarchical prior becomes important.

We want our model to provide estimates of $\{\theta_i\}$ in line with basic economic theory. This application represents the common situation with a mix of constrained and unconstrained coefficients in a hierarchical model. While we should not constrain preferences for the retail chains and the battery egg taste coefficients, which measures preferences for battery eggs over the outside good, it seems meaningful and actually important to constrain the remaining parameters. For example, a household that is only observed to purchase the highest price alternative (organic eggs) could be rationalized as exhibiting positive preferences for high prices in a model without economically motivated constraints. We therefore constrain the price coefficient to be negative for every household.[25] Similarly, an unconstrained model could misleadingly rationalize the choice pattern of a household that only purchased the lowest price alternative (battery eggs) based on higher (direct utility) preferences for battery eggs than for qualitatively superior alternatives.[26] However, everything else equal, a household should not be worse off consuming an organic egg instead of a battery egg if purchased at the same price. Preferences for the four different egg labels should therefore satisfy the ordering implied by the perceived quality differences. Lastly, households should not be worse off if they choose ten instead of six eggs, everything else being equal, and we restrict the package size six coefficients to be negative.

Table 6: Restricted attributes and constraints imposed on levels

Restricted Attributes	Constraints
Price	$\alpha_i \leq 0$
Egg labels (regular)	$\gamma_{i,Battery} \leq \gamma_{i,Barn} \leq \gamma_{i,Free\text{-}range} \leq \gamma_{i,Organic}$
Egg labels (Easter)	$\tilde{\gamma}_{i,Battery} \leq \tilde{\gamma}_{i,Barn} \leq \tilde{\gamma}_{i,Free\text{-}range} \leq \tilde{\gamma}_{i,Organic}$
Egg labels (Christmas)	$\bar{\tilde{\gamma}}_{i,Battery} \leq \bar{\tilde{\gamma}}_{i,Barn} \leq \bar{\tilde{\gamma}}_{i,Free\text{-}range} \leq \bar{\tilde{\gamma}}_{i,Organic}$
Egg labels (Regime change)	$\gamma_{i,Battery} \leq \gamma^{RC}_{i,Barn} \leq \gamma^{RC}_{i,Free\text{-}range} \leq \gamma^{RC}_{i,Organic}$
Package size	$\beta_i \leq 0$

[25] This practice can be also found in e.g., Dubois et al. (2018), Allenby et al. (2014) and Allender and Richards (2010a).

[26] For example, Table A.5 shows individual level inference for a typical household who mainly purchased the lowest quality alternatives in the unconstrained model to better illustrate this problem.

Table 6 summarizes the constraints we impose. Throughout the study we measure each household's individual WTP for a package of ten eggs from the respective category in comparison to a package of ten battery eggs (in the regular season before regime change) as

$$(4) \qquad WTP_{i,g} = \frac{\gamma_{i,g} - \gamma_{i,Battery}}{-\alpha_i} \text{ for } g = Barn, Free\text{-}range, Organic.$$

Without the sign and order constraints, we obtain some households with a lower WTP for organic eggs than for battery eggs, a problem that has already occurred in the literature. For instance, Andersen (2011) separates the two factors that increase a household's WTP for different egg product labels: animal welfare and product safety. The author's result, however, is a negative mean WTP for non-battery eggs compared to battery eggs and mean WTP becomes smaller as moving from barn, free-range to organic eggs.[27] This contradicts economic reasoning regarding vertical product differentiation and common market knowledge. More generally, valuations of vertically differentiated product features are difficult to estimate on a household level if only observational data is available with limited variation in prices. In our case, the everyday low pricing (EDLP) by German retailers (see Figure 2) does not provide sufficient variation to disentangle household's price sensitivity and preferences for quality tiers without the sign and order constraints. The rationality assumption we employ ensures to interpret households mostly purchasing low quality tiers or small packages as being price sensitive instead of having higher valuations for poor quality tiers or small package sizes.[28] For ease of comparability, we characterize differences of posterior inferences between the constrained and unconstrained model in Appendix A.4. Even though we believe the constraints are valid for the vast majority of consumers, they might still not hold for every household in the sample. For instance, households that face particular storage constraints of eggs might not be worse off by choosing the smaller package size, everything else equal. Our demand framework does not incorporate such behavior and we assume that households that buy the ten eggs and face storage constraints could get rid of the four additional eggs without losses in utility —which is probably not the case for all households. This could slightly bias egg label estimates (since not all egg labels were offered at smaller package sizes) or the price coefficient when households do not purchase small package sizes because of lower prices. Similarly, the vertical differences between egg labels might also not hold for all households due a lack of economic rationality in choice patterns caused by, e.g.,

[27] Andersen (2011), Table 2a p.574.

[28] Another example where economically motivated constraints are important is related to the trend in flight ticket pricing, where additional services such as extra luggage, priority boarding and flexible cancellation rights are extra charged. With market data we basically never observe that the same flight is offered at a lower price if additionally booking extra services. Thus, it will be hard to estimate the willingness-to-pay for these extra services if one does not include sign constraints reflecting that consumers should weakly prefer such services.

social costs, such as buying organic seeming as though one is uppity compared to the social reference group. As a consequence, we would overestimate price sensitivity when the order constraints were in fact violated for such households. However, the iid extreme type I error term in the utility specification still allows deviations from rationality to occur, although it cannot be explained by the deterministic part of the indirect utility.

The Bayesian implementation of our demand model follows the approach in Pachali et al. (2018). They propose a Markov Chain Monte Carlo (MCMC) algorithm similar to Rossi et al. (2005) that effectively samples from the posterior distribution of a model imposing sign and/or order constraints on some coefficients. The basic idea is that unconstrained coefficients have a standard normal prior while sign and order constraints are imposed through a log-normal distribution. MCMC inference is performed on a transformed space exploiting the property that coefficients are jointly normally distributed after the transformation.

We specify our constraints on θ_i by defining the functional form $g : \mathbb{R}^k \rightarrow \mathbb{R}^k_c$ mapping conditionally normally distributed variates θ_i^* to sign and order constrained coefficients θ_i that enter the likelihood, where k denoting the number of coefficients in θ_i. The hierarchical prior is specified as follows in this application

$$
(5) \quad \theta_i^* = \begin{pmatrix} \alpha_i^* \\ \gamma_{i,Battery}^* \\ \gamma_{i,Barn}^* \\ \gamma_{i,Free\text{-}range}^* \\ \gamma_{i,Organic}^* \\ \tilde{\gamma}_{i,Battery}^* \\ \vdots \\ \tilde{\gamma}_{i,Organic}^* \\ \bar{\tilde{\gamma}}_{i,Battery}^* \\ \vdots \\ \bar{\tilde{\gamma}}_{i,Organic}^* \\ \gamma_{i,Barn}^{RC*} \\ \vdots \\ \gamma_{i,Organic}^{RC*} \\ \beta_i^* \\ \hat{\psi}_{i,2}^* \\ \vdots \\ \hat{\psi}_{i,10}^* \end{pmatrix} = g^{-1}(\theta_i) = \begin{pmatrix} ln\big(-\alpha_i\big) \\ \gamma_{i,Battery} \\ ln\big(\gamma_{i,Barn} - \gamma_{i,Battery}\big) \\ ln\big(\gamma_{i,Free\text{-}range} - \gamma_{i,Barn}\big) \\ ln\big(\gamma_{i,Organic} - \gamma_{i,Free\text{-}range}\big) \\ \tilde{\gamma}_{i,Battery} \\ \vdots \\ ln\big(\tilde{\gamma}_{i,Organic} - \tilde{\gamma}_{i,Free\text{-}range}\big) \\ \bar{\tilde{\gamma}}_{i,Battery} \\ \vdots \\ ln\big(\bar{\tilde{\gamma}}_{i,Organic} - \bar{\tilde{\gamma}}_{i,Free\text{-}range}\big) \\ ln\big(\gamma_{i,Barn}^{RC} - \gamma_{i,Battery}\big) \\ \vdots \\ ln\big(\gamma_{i,Organic}^{RC} - \gamma_{i,Free\text{-}range}^{RC}\big) \\ ln\big(-\beta_i\big) \\ \hat{\psi}_{i,2} \\ \vdots \\ \hat{\psi}_{i,10} \end{pmatrix} \sim N\left(\bar{\theta}^*, V_{\theta^*}\right)^{(\mathrm{ind}_i)},
$$

for the mixture of S multivariate normals as a first-stage prior model on the transformed coefficients and ind_i is the latent indicator variable denoting component membership of household i, with $\mathrm{ind}_i \in \{1, \ldots, S\}$. The specification in Equation 5 nests the set of constraints illustrated in Table 6:

$$\begin{aligned}
\alpha_i &= -e^{\alpha_i^*} \\
\gamma_{i,Barn} &= \gamma_{i,Battery} + e^{\gamma_{i,Barn}^*} \\
\gamma_{i,Free\text{-}range} &= \gamma_{i,Barn} + e^{\gamma_{i,Free\text{-}range}^*} \\
\gamma_{i,Organic} &= \gamma_{i,Free\text{-}range} + e^{\gamma_{i,Organic}^*} \\
\tilde{\gamma}_{i,Barn} &= \tilde{\gamma}_{i,Battery} + e^{\tilde{\gamma}_{i,Barn}^*} \\
&\vdots \\
\bar{\tilde{\gamma}}_{i,Barn} &= \bar{\tilde{\gamma}}_{i,Battery} + e^{\bar{\tilde{\gamma}}_{i,Barn}^*} \\
&\vdots \\
\gamma_{i,Barn}^{RC} &= \gamma_{i,Battery} + e^{\gamma_{i,Barn}^{RC*}} \\
&\vdots \\
\beta_i &= -e^{\beta_i^*}
\end{aligned} \tag{6}$$

Appendix A.3 provides more details about the MCMC approach and information about prior specifications.

Discussion of consumer choice set

The specification of our demand model assumes that all households have complete information about the egg products offered by the ten retailers. In our framework, the final purchase decision is not only determined by the egg product itself (e.g., an egg label in a given package at a particular price) but also by the preference for the specific retail chain, $\psi_{i,l}$, where the product is offered. For the individual demand specification in Equation 1, we expect retail chain preference coefficients become very negative —potentially approaching negative infinity— for those chains from which a household never or very infrequently purchased eggs. If a retail chain is estimated to be extremely unattractive to a consumer, the egg prices charged at this chain will not affect this consumer's egg-purchasing decisions, independent of the consumer's actual price knowledge set. This mechanism attenuates a likely bias in the estimate of preference coefficients caused by including alternatives the household did not consider at time of purchase. In Section 5, we empirically illustrate how estimated retail chain coefficients essentially drop egg alternatives of those chains from which a household never purchased eggs. However, this mechanism does not eliminate that across-retail chain price variation will have an impact on individual choices for households that purchased eggs in multiple chains during the period of observation. This might cause bias in the estimates of price coefficients for households that do not account for the prices in other —previously and/or still to be visited— chains when purchasing eggs at any given point in time. The direction of this possible bias is ambiguous. If the chosen egg product is more expensive than the egg label equivalents in the other equally valued retail chains, individual price sensitivity will be underestimated when the household was in fact not aware of the price differences at time of purchase. Similarly, price sensitivity will be overestimated in the reverse case.[29] Appendix A.5 shows robustness of egg preference estimates based on our full information choice set approach by comparing implied WTP heterogeneity distributions with corresponding distributions obtained with a stricter, limited information choice set assumption.

5 Estimation results

We estimate the model described in Section 4 and Appendix A.3 with a successively larger number of mixture components to compare models with more flexible prior heterogeneity specifications and compute their log marginal likelihoods using the Newton-Raftery method on the values trimmed by 1 % on the bottom and the top of likelihood draws, as suggested in Dubé et al. (2010) and Gamerman and Lopes (2006).[30] According to Table 7, the one normal component model dominates for model fit based on our estimates of log marginal likelihoods.[31] Figure 4 shows marginal posterior densities of the egg preference coefficients implied by the one

Table 7: Log marginal likelihood values for demand models

	Value
One normal component	-527838.9
Five normal component	-528434.9
Ten normal component	-528760.1

component model. The left panel of the figure illustrates posterior densities of the price and the six-egg package size coefficients. As restricted in the hierarchical prior, both densities only support values in the negative domain. The marginal posterior density of the price coefficient represents several households in its left tail with a low parameter value being very sensitive to changes in the price of egg products. The marginal posterior density of the package size six coefficient, on the other hand, peaks near zero but also supports households with a strong negative

[29] Preferences for egg labels will not be affected as quality tier assortment is relatively homogeneous across chains.

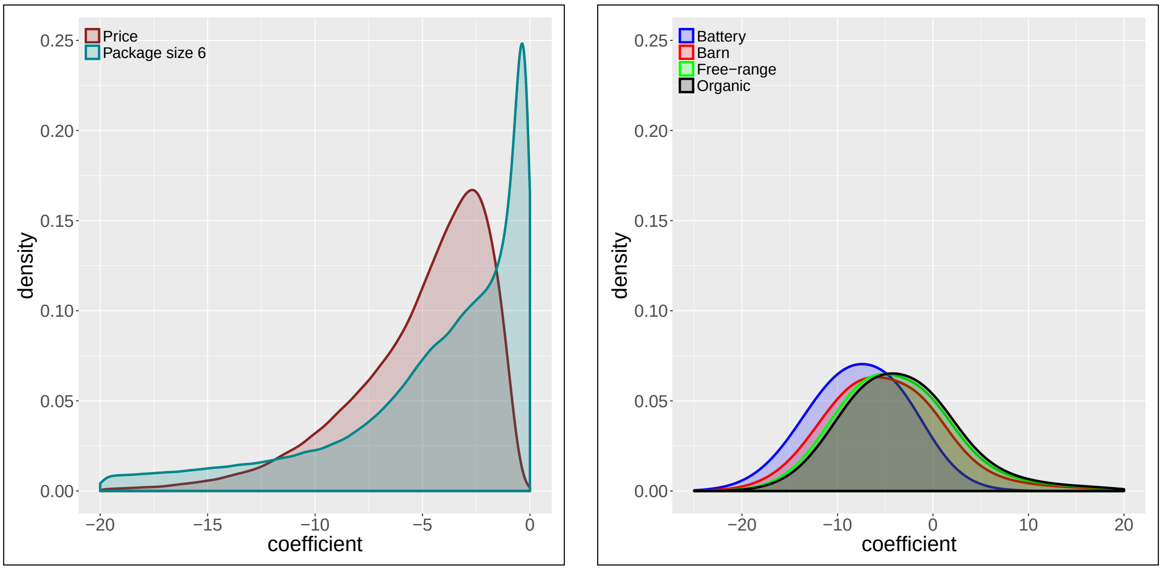
[30] We run the sampler for $R = 400,000$ iterations and keep every 100th draw. We decided to burn the first 2000 kept draws after inspecting time series plots of individual level posterior distributions as well as draws from the posterior of upper level model parameters. Posterior inference is based on 2000 draws from the converged posterior distribution.

[31] We note that adding seasonality and regime change dummies in our demand specification substantially increases fit. Namely, log marginal likelihood is -538645.6 based on the best performing five component model in the simplified demand specification without controls.

valuation of small package sizes in its left tail. Notably, the variance or implied heterogeneity of the density seems to be much larger compared to the price coefficient. The right panel of the figure plots the marginal posterior densities of the egg label intercepts. All coefficients reflect the order constraints specified in Section 4 and the densities indicate heterogeneous preferences for the different egg labels across German households. For all four egg-label coefficients, the marginal posterior densities have some households in the left tails with negative preferences for the respective egg label (compared to the outside good) while supporting households with strong preferences in the right tails as well.

Table 8 summarizes quantiles and first two moments of the marginal posterior distributions of all estimated coefficients implied by the one component model. The numbers confirm the key observations derived from Figure 4. Notably, marginal posterior distribution of the six-egg package size coefficient exhibits, by far, the largest standard deviation. Table 8 also includes

Figure 4: Marginal posterior densities of the egg preference coefficients $(\alpha, \gamma_{Battery}, \ldots, \gamma_{Organic}, \beta)$ for the one component model



marginal posterior distributions of egg label intercepts interacted with Easter and Christmas seasons as well as regime change. Compared to the regular estimates, it is apparent that households have smaller valuations of barn, free-range, and organic eggs relative to the outside good during Easter, which is in line with the model-free evidence presented in Section 3. Furthermore, it seems that battery eggs are slightly more positively valued compared to the outside good during Christmas. It is not clearly evident that preferences shifted after the regulation based on inspecting marginal posteriors of egg labels after regime change. Table 9 therefore adds a Bayesian equivalent of a significance test for control dummies. The table depicts 95% credi-

Table 8: Quantiles and first two moments of the the marginal posterior densities for the one component model controlling for seasonality and regime change

Coefficients	Quantiles						
	5%	25%	50%	75%	95%	Mean	Stand. Dev.
Price	-11.856	-6.871	-4.310	-2.677	-1.327	-5.207	3.535
Battery	-16.082	-11.170	-7.600	-4.062	0.280	-7.684	5.036
Barn	-14.097	-9.084	-5.149	-0.956	7.444	-4.059	10.535
Free-range	-12.677	-7.889	-4.061	0.099	10.045	-2.610	11.808
Organic	-12.169	-7.349	-3.490	0.634	11.123	-1.943	12.441
Six-pack	-53.563	-10.541	-4.072	-1.255	-0.164	-13.820	52.008
Battery × *Easter*	-15.516	-10.997	-7.657	-4.271	-0.183	-7.694	4.728
Barn × *Easter*	-14.428	-9.840	-6.259	-2.368	3.541	-5.619	8.036
Free-range × *Easter*	-13.205	-8.714	-5.232	-1.390	5.344	-4.395	8.537
Organic × *Easter*	-12.642	-8.049	-4.469	-0.634	6.467	-3.631	8.673
Battery × *Christmas*	-15.696	-10.842	-7.332	-3.876	0.476	-7.418	4.962
Barn × *Christmas*	-13.628	-8.818	-5.111	-1.225	5.591	-4.349	9.007
Free-range × *Christmas*	-12.464	-7.788	-4.115	-0.188	7.878	-3.048	10.052
Organic × *Christmas*	-11.634	-6.965	-3.298	0.563	8.812	-2.224	10.081
Barn × *RC*	-13.694	-8.992	-5.372	-1.670	3.771	-5.064	6.410
Free-range × *RC*	-12.487	-7.875	-4.269	-0.481	6.608	-3.333	11.310
Organic × *RC*	-11.773	-7.075	-3.380	0.459	8.290	-2.349	11.648
Chain 2	-11.337	-5.435	-0.221	5.332	11.304	-0.084	7.120
Chain 3	-5.238	-1.100	1.739	4.931	9.083	1.874	4.372
Chain 4	-8.549	-3.538	0.150	3.563	8.480	0.035	5.182
Chain 5	-14.007	-7.848	-3.308	1.208	7.397	-3.312	6.537
Chain 6	-8.428	-4.001	-0.670	2.529	6.944	-0.723	4.699
Chain 7	-7.579	-3.152	-0.064	3.207	7.732	0.012	4.662
Chain 8	-8.386	-3.659	-0.276	3.159	7.992	-0.239	4.987
Chain 9	-8.354	-3.812	-0.406	2.970	7.574	-0.411	4.871
Chain 10	-16.553	-10.445	-6.023	-1.612	4.484	-6.022	6.429

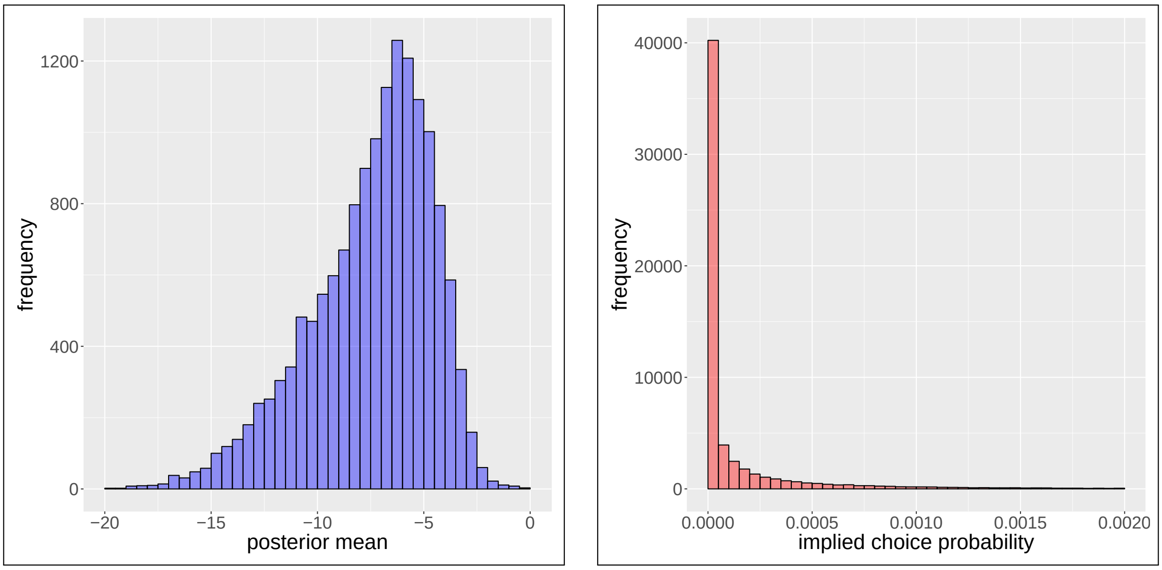
Table 9: Significance of control dummies based on marginal posteriors of mean parameter in the hierarchical prior

	2.5%	25%	50%	75%	97.5%
Battery × *Easter*	-0.122	-0.050	-0.020	0.010	0.072
Barn × *Easter*	-0.745	-0.693	-0.667	-0.639	-0.585
Free-range × *Easter*	-0.689	-0.631	-0.606	-0.578	-0.520
Organic × *Easter*	-0.507	-0.449	-0.420	-0.387	-0.323
Battery × *Christmas*	0.134	0.221	0.266	0.311	0.396
Barn X × *Christmas*	-0.031	0.055	0.107	0.152	0.235
Free-range × *Christmas*	-0.034	0.057	0.106	0.149	0.253
Organic × *Christmas*	0.239	0.322	0.363	0.405	0.532
Barn × *RC*	-0.089	-0.043	-0.020	-0.000	0.035
Free-range × *RC*	-0.165	-0.113	-0.089	-0.066	-0.014
Organic × *RC*	0.059	0.105	0.134	0.160	0.216

bility intervals of the difference between MCMC draws of mean parameters in the hierarchical prior of seasonal and regime change egg labels relative to regular ones. It therefore illustrates whether coefficients are significantly different for the average household at the 95% credibility level. Similarly as inferred from Table 8 before, barn, free-range as well as organic eggs are on average significantly less appealing to consumers during Easter. During Christmas, battery and organic eggs are on average significantly more positively valued. Finally, the table illustrates that free-range eggs are slightly lower and organic eggs slightly higher valued on average after the policy shift.

Table 8 summarizes marginal posterior distributions of retail chain parameters as well. All distributions exhibit a large standard deviation, indicating heterogeneous preferences for the ten major retailers in Germany. In Section 4, we argue that it is crucial for our demand framework to recover negative parameter estimates for retail chains a household did not consider. The left panel of Figure 5 verifies that posterior mean estimates of retail chain parameters are indeed negative for those retailers where household was never observed to purchase eggs. The histogram

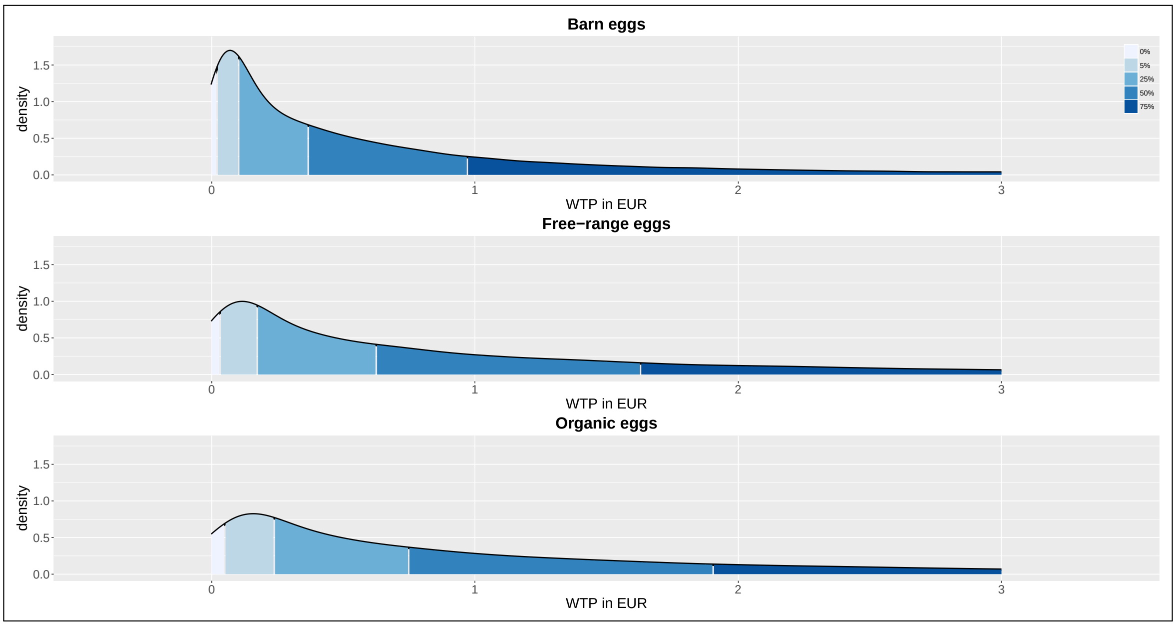
Figure 5: Retail chain parameter posterior mean estimates for the chains a household never purchased eggs from (left panel) and implied choice probabilities for egg alternatives offered by these chains at average prices in 2008 (right panel)



only includes posterior mean estimates of households who purchased at least twice in Retailer 1 that has been the baseline level in the estimation. In our setting, negative parameter estimates of retailers a household never purchased eggs from are only plausible once a household actually prefers the baseline, i.e. was observed to purchase in Retailer 1. The right panel of the figure indicates that the estimated chain coefficients are actually sufficiently large (in absolute terms) to essentially drop the respective egg alternatives from consumer's consideration, i.e., to translate into choice probabilities of approximately zero for the representative choice set in 2008.[32]

For the purpose of our analysis it is particularly relevant to analyze the distribution of WTP for different egg labels across households. We compute the posterior distribution of WTP for ten barn, free-range, and organic eggs compared to ten battery eggs according to Equation 4, based on draws from marginal posterior distributions as summarized in Table 8. Figure 6 displays the posterior distribution of WTP across households in the German population. We observe that the fraction of households that have no preference for the higher quality egg label, in other words the WTP equals zero, diminishes when we move from barn to organic eggs.

Figure 6: Posterior distribution of WTP for different egg categories compared to battery eggs



Note: We compare a pack of 10 eggs of the respective category to a pack of 10 battery eggs.

In addition, the mass center of the distribution moves farther away from zero. This is also reflected by the mean and median of each distribution as shown in Table 10. The mean (median) of the WTP distribution for barn eggs is 1.042 EUR (0.367 EUR). For free-range and organic eggs, 1.661 EUR (0.623 EUR) and 1.954 EUR (0.743 EUR) respectively. Table A.9 in Appendix A.5 contains a robustness check for the estimated WTP distributions shown in Figure 6 and Table 10 based on a model assuming limited information available to households at time of purchase. The comparison provides evidence that as we find differences between the two WTP

[32]More specifically, the plot shows choice probabilities of egg alternatives offered by those retailers a household never purchased eggs from based on respective individual posterior mean estimates in the full information choice set at average prices of year 2008. Similarly as in Section 6, we focus on package size ten alternatives and the representative choice set contains 39 product alternatives since Retailer 1 did not have battery nor organic eggs in its assortment in 2008.

distributions to be negligibly small, we do not bias demand estimates in our full information approach.

Table 10: Quantiles and first two moments of posterior distribution of WTP for different egg categories compared to battery eggs

Coefficients	Quantiles						
	5%	25%	50%	75%	95%	Mean	Stand. Dev.
Barn	0.018	0.101	0.367	0.966	3.733	1.042	3.608
Free-range	0.031	0.173	0.623	1.631	5.607	1.661	6.222
Organic	0.048	0.237	0.743	1.894	6.580	1.954	6.973

Indifferent households get harmed by banning battery eggs, since they are forced to buy more expensive eggs. Although prices for barn eggs drop after the ban, new equilibrium prices do not match those of battery eggs, which were cheaper. Thus, households with a WTP for barn eggs that is lower than the difference between former battery egg and new barn egg prices, $p^{new}_{Barn} - p^{old}_{Battery}$, also suffer due to the ban. In contrast, all households that have a higher WTP for barn eggs than $p^{new}_{Barn} - p^{old}_{Battery}$ benefit from the policy as long as $p^{new}_{Barn} \leq p^{old}_{Barn}$.

In order to assess which types of households are more likely to be positively or negatively affected by the ban, we investigate the relation between individual level WTP above battery eggs and households' demographics.[33] Table 11 depicts results from relating draws of individual level posterior WTP distributions on household's demographics in a second stage regression. In order to account for uncertainty in the first stage, we regress individual–level WTP on demographics for each of the 2000 MCMC draws. As a consequence, we estimate a distribution of regression coefficients reflecting the uncertainty in MCMC draws. The table shows the average effect (over draws) between WTP and demographics with the implied posterior standard deviation in parentheses. We check significance by investigating whether posterior credibility intervals of regression coefficients do not include zero for the 10, 5 and 1% significance levels.[34] While demographic variables such as household size, age, share of women, children or pet indicator are never significant, income and urban indicator are significant, in at least one specification at the 10% level. Overall, the fact that most demographic variables do not have a significant effect on WTP over battery eggs is also reflected in the low R squared of all three regressions. It means that observable consumer characteristics alone cannot explain differences in egg preferences, which additionally motivates more flexible specifications of unobserved heterogeneity in the

[33]We do not directly include demographic variables into our demand framework because of the change of variable we use to perform MCMC inference. On the transformed space, the convenient linear relation $\theta_i^* = \Delta_z' z_i + \bar{u}_i$ is likely miss-specified with $\bar{u}_i \sim N(0, V_{\theta^*})$ and z_i being the n_z vector of covariates for household i.

[34]We considered p-values associated with regression coefficients at every MCMC draw to account for second stage uncertainty. Average p-values (over MCMC draws) and corresponding standard deviations confirmed our results in Table 11.

demand model. Notably, income across all specifications is highly significant and an increase in the monthly net income per adult by 1000 EUR is associated with a higher WTP for barn eggs by 0.250 EUR on average. For free-range eggs the increase is around 0.683 EUR and for organic eggs about 0.868 EUR. In combination with evidence of Figure 3, the results in Table 11 therefore suggest that households in different income groups are not equally affected by the policy shift. For instance, as we further illustrate in Section 6, prices of remaining egg products typically fall after the policy intervention. As a result, banning the low-quality alternative redistributes welfare from households that do not value animal welfare to households that are willing to pay a premium for animal welfare. As the share of animal welfare-valuing households increases with higher income, this policy has a regressive impact on consumers.

Table 11: Relationship between WTP and demographics

Explanatory Variables	WTP above battery eggs for		
	Barn eggs	Free-range eggs	Organic eggs
Constant	0.500**	0.575	0.751*
	(0.214)	(0.421)	(0.476)
Household size	-0.031	-0.033	-0.031
	(0.037)	(0.076)	(0.085)
Income per adult in 1000 EUR	0.250***	0.683***	0.868***
	(0.066)	(0.142)	(0.153)
Urban dummy	0.089	0.227	0.330*
	(0.074)	(0.149)	(0.158)
Age of head of household	0.002	-0.000	-0.004
	(0.003)	(0.005)	(0.006)
Share of women in household	0.183	0.340	0.399
	(0.138)	(0.263)	(0.302)
Children in household	0.086	0.014	0.054
	(0.102)	(0.236)	(0.263)
Pet in household	-0.025	-0.117	-0.190
	(0.067)	(0.140)	(0.158)
Sample size	6961	6961	6961
R squared	0.005	0.009	0.011

Note: * 10% level, ** 5% level, *** 1% level.
Posterior standard deviation in parentheses.

6 Redistributive effects on consumer welfare and policy implications

In the previous section, we illustrate that the willingness-to-pay for animal welfare-differentiated eggs varies across German households. We expect that typical battery egg buyers are harmed by the ban on battery eggs as— everything else equal— we do not expect prices of the new minimum quality alternative, barn eggs, to fall below pre-ban battery egg prices. We theorize that consumer welfare for households preferring barn, free-range, and organic eggs may even rise due to the high-end price drop and the effect is determined by the equilibrium price changes of the animal welfare-differentiated egg products after the ban. We also show that higher income households have, on average, a greater willingness-to-pay for eggs that provide greater animal welfare. Thus, we conjecture that lower income groups exhibit higher welfare losses following a product ban for animal-welfare reasons than higher income groups. In order to quantify these effects, we introduce an explicit supply side model for the ten major retail chains in Germany. Our goal is to identify the isolated effect of higher minimum quality standards on prices and consumer welfare, and therefore we run the majority of counter-factuals without inducing the shift in egg tier preferences estimated in Section 5. This section is composed of two parts. The first part, 6.1, introduces the supply model and defines how we estimate changes in consumer welfare after a policy change. The second part, 6.2, quantifies equilibrium price reactions on the supply side and implied changes in consumer welfare followed by increasing minimum quality standards for different counter-factual settings. In addition, this section discusses policy implications and estimates the required cost reduction to protect low-income consumers that suffer, on average, the highest welfare losses following the introduction of higher minimum quality standards.

6.1 Supply model

The supply model closely follows the established notation in the empirical industrial organization literature, as in Nevo (2001), and the structural marketing literature, as in Sudhir (2001). We assume M companies and L multi-product retail chains. Each retail chain l belongs to a company m and offers a set of quality-differentiated products. Each company maximizes its profits

$$\Pi_m = \sum_{j \in S_m} [p_j - c_j] \, s_j(p) D, \tag{7}$$

for $m = 1, \ldots, M$ where $s_j(p)$ equals the market share of product j, D denotes the market size and S_m is the set of products offered by retail chains belonging to company m.[35] Retail chains

[35] Since there are no prominent national brands for eggs in Germany and retail chains maintain relationships with a fragmented group of egg suppliers, we assume that egg suppliers have no pricing power on the upstream market. Otherwise we would have to explicitly model the vertical relation between retail chains and egg suppliers. We basically treat retailers' egg products like store brands where the empirical industrial organization literature assumes that these products are priced at marginal costs on the upstream market. See for instance "Scenario 2: the hybrid model" in Villas-Boas (2007) p. 364.

compete in a pure-strategy Nash-Betrand game with differentiated products. This leads to the following first-order conditions

$$s_j(p) + \sum_{k=1}^{J} \Omega(k,j)\,[p_k - c_k]\,\frac{\partial s_k}{\partial p_j} = 0, \tag{8}$$

for $j = 1, ..., J$ where Ω is a $(J \times J)$-matrix defining the product ownership structure from the perspective of the company with $\Omega(k,j) = 1$ if both product k and product j are offered by retail chains of the same company (and zero otherwise). Matrix notation allows for a more elegant representation of the first order conditions

$$s(p) + [\Omega * \Delta]\,(p - c) = 0, \tag{9}$$

where Δ denotes a matrix of partial demand derivatives with respect to price with $\Delta(k,j) = \frac{\partial s_j}{\partial p_k}$. The $*$ represents an element-by-element matrix multiplication. The vectors of market shares, prices, and marginal costs are represented by $s(p)$, p and c respectively.

In our setting, market share $s_j(p)$ is a function of households' preferences, as specified in Equation 2. As our model incorporates heterogeneous preferences, expected market shares are obtained by integrating over the distribution of households' preferences. We follow Pachali et al. (2018) and rely on a procedure defined as lower level model non smoothed (n.s.) to estimate the preference distribution representing the relevant population of German households. The implied estimate of posterior expected market share is given by

$$s_j(p) = \frac{1}{W}\sum_{i=1}^{N} w_i \int Pr\left\{j|p, \theta_h\right\} \delta(\theta_h|y_i, \phi)\delta(\phi|Y)d(\theta_h, \phi), \tag{10}$$

where $Y = (y_1', \ldots, y_i', \ldots, y_N')$ and $\{w_i\}$ are household-specific projection factors denoting the number of households in the population represented by each observation i in the sample and $W = \sum_{i=1}^{N} w_i$. The estimator in Equation 10 uses y_i both to inform the posterior of parameters in the hierarchical prior, $\delta(\phi|Y)$, as well as predicting new households' preferences based on individual level posteriors $\delta(\theta_h|y_i, \phi)$. Intuitively, this approach integrates over individual level posterior distributions and is not only less dependent on the functional form assumed in the first-stage model but also allows us to rely on projection factors to form a representative distribution of preferences from the posterior output of the model.[36]

We make the following two simplifying assumptions to reduce the complexity in our supply side model. First, since computing market equilibrium prices with several retailers and a high degree of preference heterogeneity is computationally burdensome, we restrict ourselves to use average prices and the market size recorded in 2008 in the off-season period.[37] Second, in order to ease comparability, we assume only packages of ten eggs are offered.[38]

As part of our policy evaluation, we seek to illustrate the redistributive effects of higher minimum quality standards on consumer welfare. We follow Small and Rosen (1981) and Train (2009) to calculate changes in expected consumer welfare for multinomial logit demand models. As specified in Equation 1, each household's indirect utility from choice alternative j can be separated into a deterministic part V_{ij} and non-deterministic part ε_{ij}. Small and Rosen (1981) derive the solution for the case that ε_{ij} is *iid* extreme value distributed and the price coefficient is constant with respect to income. We measure the change in consumer welfare as

$$\Delta E(CW_i) = \frac{1}{-\alpha_i}\left[ln\left(\sum_{j=1}^{J^{**}} e^{V_{ij}^{**}}\right) - ln\left(\sum_{j=1}^{J^{*}} e^{V_{ij}^{*}}\right)\right], \tag{11}$$

where $E(CW_i)$ is a function of preferences θ_i and the superscripts $*$ and $**$ refer to the status quo and to the counter-factual scenario respectively (in our case, before and after increasing the minimum quality standard for eggs). We approximate total changes in consumer welfare by taking the aggregate of Equation 11 evaluated at all draws from the preference distribution implied by lower level model n.s. with weights in order to extrapolate the total market size D observed in 2008, i.e.

$$\sum \Delta E(CW_r) := \sum_{r=1}^{R} g \cdot \Delta E(CW_r), \tag{12}$$

[36]One has to be aware that the composition of the sample used for estimation is not in conflict with the population, e.g. that it does not contain too many observations that have almost no weight in the population. This would distort pooling of information by shrinking individual estimates to a sample mean that is not representative of the population. We tested for this problem by re-estimating the model based on a sample that is representative for the German population of households, i.e. we created a modified sample by drawing from the $6,961$ observations with replacement in line with the projection factors. We concluded that the properties of the posterior distributions implied by the two samples are almost identical.

[37]Particularly, because with the exception of retailer 1, battery eggs were available everywhere in 2008.

[38]If a retail chain only offers a package of six eggs or both package sizes, we compute the average price per egg for a certain category and calculate the effective price for a package of ten eggs.

for $r = 1, \ldots, R$ and $g = D/R$.[39]

In order to illustrate the distributional effect, we also evaluate Equation 12 within the ten different income classes motivated in Section 3. We note that Equation 11 likely overestimates the absolute change in consumer welfare because it integrates over the idiosyncratic logit taste term distribution. As implied by any logit demand model, a consumer receives (in expectation) utility even from irrelevant products. By definition, we can increase consumer welfare by simply duplicating the existing products. On the other side, removing products will substantially decrease consumer welfare although almost identical products sold at comparable prices are still available. The relative differences across the different income groups, however, are correct as all groups lose the same amount of products (and thus the same number of logit error draws).

6.2 Counter-factual simulations

The supply model enables us to isolate equilibrium price reactions caused by a policy change and to identify the redistributive effects on consumer welfare.[40] As shown in Equation 9, equilibrium price reactions depend on retail chain-specific marginal costs and demand parameters. Since marginal costs are not observable, we extract retail chain-specific marginal costs by solving Equation 9 with given market prices in 2008. The ownership matrix Ω is specified according to the real ownership structure in the German retail landscape in 2008 with $M = 5$ and $L = 10$, i.e., the ten retail chains owned by five major retail companies.

Table 12 illustrates the resulting estimates of marginal costs (c), the average of prices in 2008 (p), margins ($p - c$) as well as estimates of market shares (s) for egg products offered at all retail chains. For all retail chains, margins increase as we move up from battery eggs to organic eggs. This pattern is reasonable as animal welfare-valuing households are often less price-sensitive and are willing to pay an extra premium for a promise of better animal welfare. We observe heterogeneity in marginal costs across retail chains. Likely reasons for these cost differences are e.g., retailer-specific quantity rebates or structural differences between farmers cooperating with retailers (i.e. full-line or premium supermarkets usually prefer cooperating with regional farmers whereas discounters more often cooperate with larger, supra-regional egg suppliers). However, some of the differences are very large, for example Retailer 2's marginal costs for organic eggs are 0.99 EUR compared to 2.14 EUR of Retailer 9. Reading these numbers, one should

[39]In the applications that follow below, we use $R = 100,000$ draws from the consumer preference distribution that is implied by lower level model n.s..

[40]For computing equilibrium prices we follow the advise in Morrow and Skerlos (2011) to use the mark-up version of the first-order conditions instead of the literal first-order conditions because the latter approach is not always ensured to deliver reliable results.

Table 12: Marginal costs, prices, margins and market shares

Retailer : Egg Product	c	p	$p-c$	s
Retailer 1: Free-range 10 units	0.85	1.51	0.65	5.80
Retailer 1: Barn 10 units	0.75	1.25	0.50	7.62
Retailer 2: Organic 10 units	0.99	2.44	1.45	2.43
Retailer 2: Free-range 10 units	0.70	1.51	0.81	5.73
Retailer 2: Barn 10 units	0.62	1.27	0.65	3.72
Retailer 2: Battery 10 units	0.49	0.92	0.44	3.09
Retailer 3: Organic 10 units	1.58	2.29	0.71	0.79
Retailer 3: Free-range 10 units	0.89	1.51	0.61	5.36
Retailer 3: Barn 10 units	0.69	1.26	0.57	8.05
Retailer 3: Battery 10 units	0.43	0.91	0.48	6.06
Retailer 4: Organic 10 units	1.53	2.43	0.90	0.63
Retailer 4: Free-range 10 units	0.88	1.58	0.70	2.05
Retailer 4: Barn 10 units	0.67	1.28	0.61	2.52
Retailer 4: Battery 10 units	0.32	0.90	0.57	8.36
Retailer 5: Organic 10 units	1.85	3.04	1.19	0.36
Retailer 5: Free-range 10 units	1.42	2.19	0.77	0.44
Retailer 5: Barn 10 units	1.33	1.98	0.65	0.14
Retailer 5: Battery 10 units	0.50	1.01	0.51	1.31
Retailer 6: Organic 10 units	1.92	2.54	0.62	0.23
Retailer 6: Free-range 10 units	1.16	1.52	0.37	0.79
Retailer 6: Barn 10 units	1.06	1.37	0.32	0.62
Retailer 6: Battery 10 units	0.63	0.90	0.27	3.41
Retailer 7: Organic 10 units	1.44	2.40	0.96	0.85
Retailer 7: Free-range 10 units	0.93	1.53	0.60	2.58
Retailer 7: Barn 10 units	0.81	1.25	0.43	2.59
Retailer 7: Battery 10 units	0.54	0.92	0.38	4.23
Retailer 8: Organic 10 units	1.98	2.98	1.00	0.35
Retailer 8: Free-range 10 units	1.28	1.95	0.67	1.12
Retailer 8: Barn 10 units	1.13	1.60	0.46	0.86
Retailer 8: Battery 10 units	0.71	1.05	0.33	2.40
Retailer 9: Organic 10 units	2.14	3.08	0.94	0.34
Retailer 9: Free-range 10 units	1.45	2.10	0.65	0.77
Retailer 9: Barn 10 units	1.31	1.85	0.54	0.21
Retailer 9: Battery 10 units	0.68	1.04	0.36	1.82
Retailer 10: Organic 10 units	1.97	2.82	0.85	0.05
Retailer 10: Free-range 10 units	1.39	2.08	0.69	0.15
Retailer 10: Barn 10 units	0.96	1.51	0.54	0.16
Retailer 10: Battery 10 units	0.63	1.06	0.43	0.25

take into account that they reflect retailers' economic opportunity costs rather than their pure accounting costs. Conditional on the estimated preference structure and market prices in 2008, the model predicts high costs for chains with particularly small market shares. Economically, it implies that such retailers are relatively inefficient at providing eggs in the marketplace. While we think that our marginal cost estimates are quite reasonable for the majority of retailer-product combinations, unrealistically large differences between retailers might also be caused by shortcomings or limitations of our demand and supply model. However, based on the robustness checks shown in Tables A.8 and A.10, we can at least rule out that the large differences are driven by the constraints and the full information approach we employ.

Next, we use retail chain-specific cost estimates in Table 12 to simulate equilibrium prices after a ban on battery eggs.[41] The first three columns in Table 13 show market share-weighted average marginal costs ($\bar{c}$) for each egg label implied by Table 12, the across-retail chain market share-weighted average of prices in 2008 ($\bar{p}$) as well as the simulated market share-weighted average of adjusted prices ($\bar{p}'$) after increasing minimum quality standards.[42] We observe that prices of the remaining egg products fall according to our model, on average, after a ban on battery eggs. Thus, the ban definitely benefits some type of consumers: Households that already prefer barn, free-range and organic eggs over battery eggs under pre-ban prices face lower post-ban prices on average. As higher income households have, on average, a greater willingness to pay for hen welfare-differentiated eggs, we provide evidence of a regressive effect of the ban, where low-income households lose on average more than high-income households. From the policymaker's perspective, this is an unintended side effect of the ban, a point we further elaborate on at the end of the section.

According to Figure 6 in Section 5, a fraction of households are always indifferent between battery eggs, the old minimum quality standard, and barn eggs, the new minimum quality standard. Thus, in order to offset the regressive effects of setting barn eggs as the new minimum quality standard, new equilibrium prices of barn eggs must match the previous battery egg prices.
We estimate the marginal cost reduction for barn eggs needed to offset the regressive effect. This cost reduction can be motivated by policymakers actively intervening in a market and introducing a subsidy to soften the regressive effect. For more emerging industries other than the egg market, cost reductions could also naturally occur by economics of scale due to a narrower

[41] New equilibrium prices for the counter-factual scenarios are computed by solving the system of non-linear equations given by FOCs in Equation 9. We use the Gauss-Newton method. The maximum number of iterations is set to 200,000 and the tolerance level to 0.1^6. Convergence criteria are always achieved.

[42] From here on, we drop the adjective market share-weighted for better readability.

product assortment.[43]

Decision-makers and consumer protection agencies, such as the FTC, could use our approach to infer the necessary marginal cost reduction and compare it to the expected reduction in costs stated by industry experts. If the expected reduction in costs is close to the necessary cost reduction, the policy of increasing the minimum quality standard is unproblematic in terms of regressivity and consumer harm. Alternatively, a tailored subsidy can be proposed to soften the regressive effect if desired. At first glance, it might seem unrealistic to implement a subsidy for a consumer good but there are precedents in other markets. In 2016, the German government implemented a subsidy of 4,000 EUR for consumers buying an electric car to stimulate electric mobility.[44] In the EU, the largest share of budget is spent for subsidies in the agricultural sector. At the moment, the agricultural subsidies are mainly direct payments to farmers per eligible hectare and tied to specific conditions.[45] In principle, these agricultural subsidies could also be used in an entirely different way to regulate and stimulate certain production standards within a product category such as eggs or meat. There is actually already an indirect subsidy for consumer goods of basic need and cultural goods in Germany as consumers pay a reduced value added tax of 7% for some products such as food, books and public transport instead of the usual 19% value added tax. Likewise, another possible way to implement the subsidy would be to mandate a reduced value added tax and condition it on a certain production standard to reduce the regressive effect of a higher minimum quality standard. We use the term subsidy and marginal cost reduction interchangeably since a per-unit subsidy shifts the marginal cost curve downward. Let τ^* be the required subsidy to offset the regressive effect, then $T = \tau^* \hat{s}^*_{barn} D$ denotes the total expenditure for financing the subsidy if marginal costs were staying constant.[46] In this case, T can be interpreted as the implied cost to society of increasing the minimum quality standard without harming rather poor consumers.

The fourth column in Table 13 corresponds to the average equilibrium price vector $\bar{p}^*$ in the situation where barn eggs are subsidized. Accordingly, barn eggs would have to be subsidized by 0.32 EUR per package of ten eggs. Furthermore, we compute the change in industry profits $\sum \Delta\Pi_m$ and the change in consumer welfare $\sum \Delta E(CW_r)$ as well as the total expenditure for financing the subsidy given by T. Notably, average prices of free-range and organic eggs rise as a consequence of the subsidy.

[43] For example, if each quality label requires firms to invest in marketing and quality assurance management, which do not depend on the number of sales but on the number of offered quality tiers.

[44] See `https://www.bmwi.de/Redaktion/EN/Artikel/Industry/regulatory-environment-and-incentives-for-using-electr` `html`, accessed 26 June 2018.

[45] See `https://ec.europa.eu/agriculture/direct-support/direct-payments_en`, accessed 26 June 2018.

[46] $\hat{s}^*_{barn}$ denotes the sum of market shares for barn eggs across retail chains after imposing the subsidy τ^*.

The impact of retail market structure

In the remaining columns of the table, we vary the degree of retail competition by altering the product ownership matrix Ω to highlight the relevance of market structure in determining the outcomes. Besides the realistic benchmark case, we consider two other cases: A duopoly case with $M = 2$, in which all discounters are owned by one company and all full-line supermarkets are owned by another, and a monopoly case with $M = 1$. In the last case, we assume the whole retail market to be monopolized. The results show that margins for all types of eggs increase, on average, with a lower degree of retail competition.

In all three scenarios of competition, we observe that prices of the remaining egg products fall, on average, after a ban on battery eggs, suggesting that the regressive effect of the ban is evident across different scenarios of market structure.

Table 13: Optimal subsidy and welfare effects of product bans under different scenarios of competition

		Retail market structure								
		Ω^{real}			$\Omega^{Duopoly}$			$\Omega^{Monopoly}$		
Product	$\bar{c}$	$\bar{p}$	$\bar{p}'$	$\bar{p}^*$	$\bar{p}$	$\bar{p}'$	$\bar{p}^*$	$\bar{p}$	$\bar{p}'$	$\bar{p}^*$
Organic 10 units	1.39	2.52	2.47	2.59	2.86	2.79	2.98	3.77	3.61	4.43
Free-range 10 units	0.89	1.57	1.51	1.66	1.89	1.80	2.05	2.47	2.27	3.20
Barn 10 units	0.74	1.28	1.22	0.93	1.53	1.43	1.05	2.04	1.73	1.38
Battery 10 units	0.49	0.93			1.05			1.38		
τ^*				0.32			0.49			0.94
In million EUR:										
T				124.40			196.33			351.50
$\sum \Delta\Pi_m$			-17.85	4.51		-23.93	-13.95		-49.82	11.80
$\sum \Delta E(CW_r)$			-31.25	50.60		-30.90	71.96		11.03	64.52

Table 14: Market shares after product bans under different scenarios of competition

	Retail market structure								
	Ω^{real}			$\Omega^{Duopoly}$			$\Omega^{Monopoly}$		
Product	$\hat{s}$	$\hat{s}'$	$\hat{s}^*$	$\hat{s}$	$\hat{s}'$	$\hat{s}^*$	$\hat{s}$	$\hat{s}'$	$\hat{s}^*$
Organic 10 units	6.08	6.48	5.66	5.41	5.78	4.82	3.42	3.64	2.50
Free-range 10 units	24.75	30.14	16.53	20.44	25.29	11.62	14.35	17.18	4.50
Barn 10 units	26.93	48.88	67.40	24.10	46.00	69.48	16.21	37.55	65.05
Battery 10 units	30.61			32.19			28.05		
Outside good	11.63	14.50	10.41	17.87	22.92	14.09	37.97	41.63	27.94

The extent and direction of the price reactions depend on two factors: The degree of substitutability between products and market structure. A close substitute of the old minimum quality standard will usually exhibit a drop in equilibrium prices. Less competition between firms results in a steeper drop in prices for close substitute products. This is due to the trade-off between margin and quantity that becomes stronger in less competitive markets. As a consequence, the change in aggregate consumer welfare ΔCW after increasing the minimum quality standard is actually positive in the monopoly case. Thus, in this scenario, gains of barn, free-range and organic egg-preferring households outweigh losses of battery egg preferring consumers.

The market structure determines the optimal level of the subsidy τ^*. The less competitive the retail sector is, the higher the subsidy τ^* must be to offset the regressive effect of a higher minimum quality standard. This observation can be explained by the relationship between pass-through rates and pricing power. Typically, changes in costs are not fully transmitted to final prices unless firms have zero margins. With higher pricing power, i.e. higher margins, a smaller fraction of changes in costs is passed on to final consumers. Firms with more pricing power will tend to keep a higher portion of this subsidy/cost reduction to themselves.[47] By changing the market structure in our counter-factual scenarios, we give the retail chains more pricing power.

However, it should be noted that a marginal cost reduction for the new minimum quality standard also has some drawbacks. The first drawback is with respect to substitution patterns towards egg products that offer lower animal welfare. Table 14 illustrates an increase in market share of barn eggs as a consequence of lower barn egg prices and higher free-range and organic egg prices. As the subsidy reduces barn egg unit costs, they become more profitable and retail chains will try to divert more demand towards barn eggs, which explains these price reactions. This indicates that there is a negative cross-product cost pass-through rate. Second, if the marginal cost reduction is realized through a subsidy, it does not restore social welfare completely as the sum of producer and consumer surplus is only a fraction of total subsidy expenditure, i.e., there is a dead-weight loss. Finally, we note that a subsidy has a progressive policy implication as prices of the other higher quality egg labels rise in equilibrium.

Even higher minimum quality standards

In the next step, we successively increase the minimum quality standard until only organic eggs remain on the market. This scenario considers a possible future where only organic and sustainable products are allowed. Furthermore, we again determine the subsidy to offset the regressive effects. (Table 15 shows our findings.) As τ^* increases with a higher minimum quality standard, so does the extent of the regressive effect. If only organic eggs remain on the market, the majority of consumers lose surplus and only a minority benefits from the policy. Table 16 shows the impact on market shares under higher minimum quality standards. Similarly, as

[47]Further information on the relationship between pass-through and pricing power can be found in recent studies such as Weyl and Fabinger (2013), Fabra and Reguant (2014) and Kim and Cotterill (2008).

Table 15: Higher minimum quality standards and negating the regressive effect

			New Minimum Quality Standard					
			Barn		Free-range		Organic	
Product	$\bar{c}$	$\bar{p}$	$\bar{p}'$	$\bar{p}^*$	$\bar{p}'$	$\bar{p}^*$	$\bar{p}'$	$\bar{p}^*$
Organic 10 units	1.39	2.52	2.47	2.59	2.33	2.66	1.96	0.93
Free-range 10 units	0.89	1.57	1.51	1.66	1.39	0.93		
Barn 10 units	0.74	1.28	1.22	0.93				
Battery 10 units	0.49	0.93						
τ^*				0.32		0.51		1.09
In million EUR:								
T				124.40		257.45		575.27
$\sum \Delta\Pi_m$			-17.85	4.51	-45.75	3.90	-128.29	29.94
$\sum \Delta E(CW_r)$			-31.25	50.60	-86.55	122.82	-323.25	125.09

Table 16: Market shares and higher minimum quality standards

		New Minimum Quality Standard					
		Barn		Free-range		Organic	
Product	$\hat{s}$	$\hat{s}'$	$\hat{s}^*$	$\hat{s}'$	$\hat{s}^*$	$\hat{s}'$	$\hat{s}^*$
Organic 10 units	6.08	6.48	5.66	8.21	4.21	49.02	91.70
Free-range 10 units	24.75	30.14	16.53	72.55	87.80		
Barn 10 units	26.93	48.88	67.40				
Battery 10 units	30.61						
Outside good	11.63	14.50	10.41	19.23	7.99	50.98	8.30

before, the subsidy incentives households to substitute higher animal welfare egg products for the new subsidized minimum quality alternative.

The economic mechanism driving these pricing reactions is also related to the literature studying pharmaceutical markets and the so-called brand-name price puzzle. In particular, the logic behind our observed pricing pattern is actually a reversed version of the brand-name price puzzle in the prescription drug market after patent expiry. The brand-name price puzzle states the (at first glance, odd) observation that after patent expiry and entry of generic products, price of the originally patented brand-name drug increases although competition intensified through losing the former monopoly awarded by the patent (e.g., Grabowski and Vernon, 1992; Frank and Salkever, 1992; Ching, 2010). The solution to the puzzle is that it reflects market segmentation. As a segment of price-sensitive consumers switches to generic drugs (which is perceived to have a lower quality), only price-insensitive consumers remain with the brand-name drug after patent expiry. This makes the brand-name drug manufacturer to raise price and optimize margin. This is the same logic as in our case of banning the low-quality tier product: Instead of observing entry, we observe exit of a lower quality tier product and firms lose one instruments for market segmentation. As a result, retailers lower prices of close substitutes to attract price-sensitive consumers. This pattern is also related to the research on private-label introduction in the food industry. Ward, Shimshack, Perloff, and Harris (2002) identify a similar pricing response of brand-name products following the private-label invasion in the U.S. food retail industry. Using grocery scanner data in thirty-two food and beverage industries, they find that brand-name firms' tend to rise prices and reduce promotional activities in response to private-label entry. Similar to our explanation of retailers' price responses after the ban of battery eggs, Ward et al. (2002) rationalize their empirical findings using the theory of product differentiation as developed in e.g, Perloff and Salop (1985).

Redistributive effect on different consumer segments

Finally, we further examine changes in consumer welfare across different consumer segments. Table 17 and 18 contain the effect on consumer welfare across ten different income groups of consumers. We report also the average income per adult for each consumer segment. Average income per adult increases as we move up from income group one to ten. These groups are the same as presented in our model-free evidence in Section 3.

Starting with the real mode of competition in Table 17, we observe that through the drop in prices for eggs that provide higher animal welfare ($p \rightarrow p'$), low-income groups exhibit a higher loss in consumer welfare than high-income groups. This observation is supported by our model-free evidence shown in Figure 3 in Section 3, which showed that the battery egg market share decreased from income group one to ten. Thus, low-income groups have a higher proportion of battery egg buyers who are negatively affected by this policy and a lower proportion of barn, free-range and organic egg buyers who benefit. The effect on consumer welfare is therefore regressive.

However, as we lower the degree of competition in the retail sector, the welfare losses due to banning battery eggs decrease in tendency across all consumer segments. In case of a monopolized retail sector, we observe aggregate consumer welfare increases within all consumer groups, except for the lowest income-group. This result is explained by the steeper price reactions following the rise of the minimum quality standard in cases where retail chains have more pricing power.

Our model shows the subsidy τ^* is able to offset this regressive effect. In fact, lower income groups would benefit the most. As the subsidy leads to higher prices for the remaining higher quality eggs, higher-income groups benefit less. The effect of combining the ban with a subsidy is then progressive.

The consumer welfare effects of a future scenario of further increasing the minimum quality standards can be observed in Table 18. As the new minimum quality standard is further increased to free-range eggs or even to organic eggs, a larger share of households within each income-group is negatively affected. Notably, the difference in consumer welfare losses between the lowest and the highest income group increases with an even more restricted minimum quality standard. Thus, the regressive effect becomes even stronger.

Interestingly, in case of mandating organic eggs as the minimum quality standard in combination with a subsidy, the policy is still regressive as higher income groups benefit more from the subsidy because they have a higher proportion of consumers that actually value organic eggs over battery eggs.

Table 17: Consumer welfare effects across different income groups and retail market structure

		Retail market structure					
		Ω^{real}		$\Omega^{Duopoly}$		$\Omega^{Monopoly}$	
		$p \to p'$	$p \to p^*$	$p \to p'$	$p \to p^*$	$p \to p'$	$p \to p^*$
Income group	Avg. Income	$\sum \Delta E(CW_r)$ in million EUR					
1	503.44	-5.49	6.69	-5.61	9.71	-0.39	9.75
2	711.46	-4.83	6.63	-4.79	9.67	0.56	9.34
3	858.61	-4.45	6.94	-4.61	9.81	0.31	9.83
4	988.95	-3.45	5.97	-3.40	8.59	1.17	8.35
5	1115.20	-3.13	5.70	-3.10	7.99	1.26	7.74
6	1260.83	-2.73	5.38	-2.61	7.63	1.71	7.02
7	1418.63	-2.82	4.58	-2.82	6.41	1.39	5.06
8	1627.28	-1.87	3.90	-1.75	5.49	1.90	4.12
9	1923.78	-1.48	2.72	-1.29	3.84	1.64	2.25
10	2950.51	-1.01	2.10	-0.93	2.83	1.49	1.06
Overall	1225.75	-31.25	50.60	-30.90	71.96	11.03	64.52

Table 18: Consumer welfare effects across different income groups and higher minimum quality standards

		New Minimum Quality Standard					
		Barn		Free-range		Organic	
		$p \to p'$	$p \to p^*$	$p \to p'$	$p \to p^*$	$p \to p'$	$p \to p^*$
Income group	Avg. Income	$\sum \Delta E(CW_r)$ in million EUR					
1	503.44	-5.49	6.69	-13.28	12.86	-40.36	9.34
2	711.46	-4.83	6.63	-12.16	14.32	-42.18	10.95
3	858.61	-4.45	6.94	-11.95	13.27	-39.65	9.31
4	988.95	-3.45	5.97	-9.72	12.98	-34.61	12.42
5	1115.20	-3.13	5.70	-9.05	13.45	-36.15	11.80
6	1260.83	-2.73	5.38	-8.33	13.67	-33.55	13.67
7	1418.63	-2.82	4.58	-8.02	12.99	-32.72	13.83
8	1627.28	-1.87	3.90	-6.20	11.94	-27.40	14.84
9	1923.78	-1.48	2.72	-4.52	9.53	-20.61	14.45
10	2950.51	-1.01	2.10	-3.30	7.82	-16.03	14.48
Overall	1225.75	-31.25	50.60	-86.55	122.82	-323.25	125.09

Robustness checks

As our benchmark analysis already involves costly computation of several scenarios, we re-run our counter-factuals for a subset of scenarios while altering our key assumptions in two dimensions: Choice sets and stability of egg preferences.

Our demand framework assumes that households have complete information about the egg products offered by the ten retailers. As a robustness check, we also model demand that assumes limited information available to households at time of purchase. Section A.5 in the Appendix summarizes the results after limiting the egg product alternatives in a given choice occasion to the eggs offered in the retail chain of purchase. Notably, in terms of estimating the WTP for different egg quality tiers, the results do not change. This alternative assumption has, however, an even stronger impact on our supply model. With the limited choice set assumption, retail chains are effectively local monopolies and, as a consequence, systematically achieve higher margins, which turns most of the marginal cost estimates to be negative in Table A.10 in the Appendix. The cost estimates from our original approach in Table 12 are therefore more realistic and support our assumption of including retail competition in the demand and supply model. While the level of cost estimates and margins seem unrealistic with this alternative assumption, the overall direction of the equilibrium price effects after the ban is similar as in our original model. In particular, barn, free-range, and organic egg prices fall after the ban of battery eggs. The price reactions, however, are more extreme after the ban if retail firms are local monopolies resulting in an increase in aggregate consumer welfare after the ban of battery eggs. This is explained by the observation that high-income households gain, on average, more consumer welfare than low-income households lose (See A.13). Thus, the regressive impact of the policy shift remains under this different assumption.

In our demand estimation in Section 5, we control for a possible shift in egg preferences after the policy change. As another robustness check, we rerun the counter-factual simulations where we subsequently increase the minimum standards with the difference that banning battery eggs induces the shift in preferences as estimated in Section 5. In Appendix A.6.1, we show the equivalents to Table 15, 16 and 18 under this different assumption. The main insight from this robustness check is that our price reactions and regressive effect do not qualitatively change but the overall loss in consumer welfare is lower as the ban on battery eggs increases consumers' valuations for organic eggs on average under this assumption. Thus, more consumers benefit here from the fall in organic egg prices compared to our original model.

Redistributive effect on retailer profits

Our study focuses on consumer welfare implications of higher minimum quality standards. Another interesting aspect is how the ban affects retailer profits. In particular, we examine whether retail chains with a higher-income or lower-income customer base are differently affected. Table 19 shows how profits change across retail chains. All retail chains up to the dashed line are discounters and the rest are full-line supermarkets. As expected, we observe that the average income per customer is in tendency higher for full-line supermarkets than for discounters. When the minimum quality standard increases, competition among retailers for the price-sensitive consumer segment amplifies. Retailers with relative cost efficiency gains that are able to further drop prices of closest substitutes potentially benefit in the long-term equilibrium after a ban. This becomes evident when reconsidering Table 12 that compares marginal cost estimates for different quality tiers across retailers. According to Table 19, profits at Retailer 1 and 2 improve after banning battery eggs. At the same time, these two retailers have low marginal costs for above battery quality tiers and thus relative cost efficiency gains. On the other side, it is costly to offer higher quality eggs for Retailer 6, 5, 8, 9 and 10 that all together lose profits after increasing minimum quality standards according to Table 19. The fact that Retailer 3 and 4 exhibit the highest loss in profits, while being cost efficient, is because these two retail chains had the lowest marginal costs for battery eggs that got banned.

The system of subsidies maintains heterogeneity in retailer profits. Given the same unit-subsidy for each retailer, chains with lower marginal costs for higher quality tiers (i.e. more efficiency) are able to further attract price-sensitive consumer. In summary, these results indicate that minimum quality regulations tend to benefit firms that are more cost efficient on the new quality floor.

Table 19: Firm's profit effects across different retailers and higher minimum quality standards

		New Minimum Quality Standard					
		Barn		Free-range		Organic	
		$p \to p'$	$p \to p^*$	$p \to p'$	$p \to p^*$	$p \to p'$	$p \to p^*$
	Avg. Income of Customers	$\Delta\Pi_l$ in million EUR					
Retailer 1	1158.32	4.46	7.55	2.24	11.90	-44.51	-44.51
Retailer 2	1377.65	0.92	4.18	-0.81	8.48	3.78	61.18
Retailer 3	1173.03	-4.11	1.57	-14.80	-4.78	-31.10	-2.69
Retailer 6	1050.01	-2.93	-2.09	-3.44	-0.60	-6.49	-2.17
Retailer 7	1122.25	-1.36	0.76	-2.78	2.20	-3.87	21.14
Retailer 4	1323.03	-6.29	-1.93	-14.18	-6.40	-29.00	-0.16
Retailer 5	1188.11	-2.81	-2.25	-3.32	-2.18	-4.44	-0.69
Retailer 8	1463.09	-2.46	-1.19	-4.05	-1.96	-6.33	-0.24
Retailer 9	1408.54	-3.02	-2.17	-3.81	-2.25	-5.18	-1.67
Retailer 10	1216.12	-0.25	0.08	-0.80	-0.52	-1.14	-0.26
Overall	1224.25	-17.85	4.51	-45.75	3.90	-128.29	29.94

Note: Retail chains up to the dashed line are discounters and the rest are full-line supermarkets.

We note that Retailer 1 is somehow special as it does not have battery nor organic eggs in its assortment. Therefore, it especially benefits from the ban of battery eggs as its competitors lose a low-cost product. Similarly, if organic eggs are the new quality standard, this retail chain loses all its profits because of the "everything else equal"-assumption of the counter-factual.

7 Conclusion

In this paper, we empirically examine the redistributive effects of higher minimum quality standards on consumer welfare. As animal welfare is a form of product quality, we use German household purchase data on eggs to answer this question. More specifically, we study the impact of the EU's ban on battery eggs, the previous minimum quality standard, on household egg purchases and evaluate its redistributive effect on consumer welfare. In our main analysis, we estimate a hierarchical Bayesian multinomial logit model with flexible mixture of normals first-stage priors to account for consumer heterogeneity.

The results show substantial heterogeneity in preferences across households for animal welfare-differentiated eggs. Our structural model makes it possible to isolate the price effect of mandating higher minimum quality standards. Prices of the remaining higher quality eggs typically fall after increasing the minimum quality standard. This means that consumer welfare is essentially redistributed from households that do not value animal welfare to households that are willing to pay a premium for animal welfare. As higher-income households are willing to pay, on average, more for eggs that provide better animal welfare, this provides evidence of a regressive impact of higher minimum quality standards on households in Germany. Our findings suggest that equilibrium price reactions on the supply side are a major driver for the regressive impact of higher minimum quality standards.

Using counter-factual studies, we show how consumer protection agencies can estimate the necessary reduction in marginal costs of the new minimum quality standard needed to offset the regressive effect. As the market structure is less competitive, the marginal cost reduction must be higher. This cost reduction can be either achieved by implementing a subsidy or by other factors that effectively lower the marginal costs of production such as unexploited economics of scale that are triggered by the higher demand for the new minimum quality standard. We emphasize, however, that cost reductions due to economics of scale are not likely to occur in rather mature industries such as the egg market. So more generally, if the expected reduction in costs is close to the necessary cost reduction, the policy of increasing the minimum quality standard is less likely to harm low-income households.

Finally, we examine hypothetical future scenarios by successively increasing the minimum quality standard until only organic eggs remain on the market. The regressive effect becomes larger as we increase the new minimum quality standard. Our model finds that the costs of the compensating subsidy increase with higher minimum quality standard levels.

The insights generated in this study are not limited to the egg market but should sensitize policymakers to the possible regressive effects of increasing minimum quality standards in general. Ideally, policymakers should assess equilibrium price effects and expected reduction in marginal costs before mandating a higher quality floor on products as it is done in merger cases.

Although we provide several robustness checks and additional counter-factuals to verify our main findings, our model is not without limitations. For example, we do not include smaller package sizes in our counter-factuals as this would further increase the computational burden for each of the many scenarios we simulate and would make it even more difficult to extract marginal costs for all product alternatives at different package sizes. Furthermore, we also do not explicitly model the vertical relation between retail chains and egg suppliers. We do not have information about strong prominent brands of egg suppliers and have reason to believe that egg suppliers do not have much pricing power in the upstream market. This becomes especially evident when following the ban of battery eggs in 2010 while retail prices of barn eggs did not increase at the same time, even though market shares of barn eggs almost doubled. Finally, as we study only fresh egg purchases at discounters and supermarkets, we cannot generalize our insights to egg purchases at farmer's markets and indirect egg consumption in the food processing industry.

Going forward, future research could extend our analysis to markets with asymmetric information on quality (i.e. quality that is not observed by everyone) and markets with externalities. Furthermore, another study could focus on the long-term consequences of the product ban on farmers in the upstream market. In particular, it would be interesting to better understand whether and how shocks on the upstream market are transmitted to retail prices.

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A Appendix

A.1 Imputing prices of non-chosen alternatives

A common feature of homescan consumer panel data is that we only observe prices of purchased products. In the US, Nielsen homescan data can be linked to Nielsen retail scanner data (at least for several chains).[48] Thus, prices for non-chosen alternatives within a product category

[48]Researchers from US departments can obtain US Nielsen data from the Kilts Center. See `https://research.chicagobooth.edu`

at certain retailers are observed and can be matched to households' shopping trips. See for instance Erdem et al. (2008) as an example of studies that match homescan consumer data with retail scanner data. For Germany and many other countries, however, typically only consumer panel data sets are available. Studies estimating demand based only on homescan consumer panel data, therefore, have to impute prices of non-chosen alternatives. Dubois et al. (2018), for instance, aggregate 1,800 unique product codes (UPCs) of potato chips in the UK to 37 brand-package size combinations using mean transaction prices. Seiler (2013) relies on the national pricing policy of UK supermarket chains in order to construct weekly price series for each brand-package size-supermarket chain in the UK detergent market.

The main differentiation for egg products in German retail chains is on the hen welfare dimension (battery, barn, free-range, organic) and the package size. Brands do not play an important role in the German egg market. Most retail chains have only one type of brand in their assortment, which is often a private label. In contrast to other product categories such as detergents, coffee, soft drinks or chocolate, there is no national brand that is available at several retail chains. We are also not aware of any company that advertises in the German egg market. For this reason we define a product as an egg-hen welfare category of specific package size offered at one of the ten major retail chains.

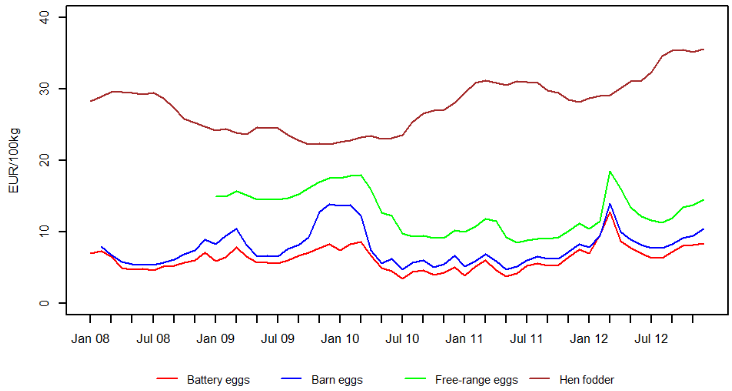
The strategy to impute prices of non-chosen alternatives is as follows:

1. Compute the weekly median price for each egg type category-package size combination at each retail chain based on all households' egg purchases
2. Fill in empty weeks for each egg type category-package size at each retail chain with the last egg product price. This is reasonable since fresh egg pricing by the vast majority of German retail chains follows a national pricing policy combined with an everyday low price (EDLP) strategy instead of the high-low pricing strategy.

A.2 Strength of potential instruments

Figure A.1 shows variation in monthly hen fodder prices as well as wholesale prices of battery, barn and free-range eggs from the agricultural commodities exchange in Germany. We emphasize, however, that prices shown in the graph do not reflect retail chains' actual paid wholesale prices, which are unobservable as they are negotiated directly between individual retailers and egg suppliers on a retailer-specific basis. In this sense, wholesale prices from the agricultural commodity exchange can be seen as the "best" proxy available for retailers' actual paid wholesale prices. In the following, we explore the strength of these variables as instruments by regressing monthly retail egg prices on potential cost shifters and several other control factors.

Figure A.1: Potential cost shifters: Monthly average wholesale prices for hen fodder as well as battery, barn and free-range eggs



Source: MEG - Marktinfo Eier & Geflügel and AMI- Agrarmarkt Informations-GmbH

Equation 13 shows our model for p_{glt}, the retail price of egg product g in chain l at month t

$$p_{glt} = p_0 + \rho_g \mathbf{1}\{g \neq Battery\} + \delta \mathbf{1}\{units_g = 6\} + \lambda_l \mathbf{1}\{l \neq 1\} + d^X \mathbf{1}\{t = Christmas\} + d^E \mathbf{1}\{t = Easter\} + d^{RC} \mathbf{1}\{t > RC\} + \kappa \tilde{c}_t + \eta \tilde{p}_{gt} + \varepsilon_{glt}, \quad (13)$$

where $g \in \{Battery, Barn, Free\text{-}range\}$ and $l \in \{1, \ldots, 10\}$.[49] The coefficient λ_l captures the retail chain fixed effect of retailer l. We set battery eggs as well as chain 1 as the baseline levels of the respective egg label and retail dummies. Therefore, the intercept p_0 represents the price of ten units of battery eggs in chain 1 in the off-season period that is implied by the model. We also include dummy variables for the Christmas and Easter period as well as a control for the policy shift. κ and η are the coefficients of interest and represent the effect of hen fodder and wholesale prices from the agricultural commodities exchange on retail egg prices respectively.

Table A.1 shows coefficient estimates from an OLS regression based on the model in Equation 13. The estimates confirm our descriptive analysis in Section 3. In addition, we can see that most full-line supermarkets (such as chains 5, 8, 9, 10) set significantly higher prices than discounters (such as chain 1), after controlling for egg tier quality. We also find that prices

[49] Recall that our regression does not include prices of organic eggs since we do not have access to corresponding wholesale prices. The time period covered in this regression is January 2009 till December 2012 as we have complete data of wholesale prices for battery, barn and free-range eggs available for this period.

significantly fall after the policy shift, in line with Figure 2 in Section 3. Regarding the impact of potential cost shifters, we find that both hen fodder prices as well as wholesale prices do not significantly affect egg prices set by retailers. In other words, our results show that short-term variation in potential cost shifters is not directly transmitted to retail egg prices. Based on this observation, we conclude that the potential cost shifters we observe are weak instruments. A possible explanation for this finding could be long-term contracts between egg suppliers and retailers such that cost shocks are only passed-on if they are substantial enough and persistent. Furthermore, the wholesale prices we use here are from the agricultural commodities exchange in Germany and do not necessarily reflect retailers' actual paid wholesale prices.

Table A.1: OLS regression of retail egg prices on potential cost shifters and other controls

Explanatory Variable	Estimate	Standard Error
Intercept	1.001***	0.049
Barn	0.314***	0.017
Free-range	0.662***	0.021
Package size six	-0.307***	0.008
Chain 2	0.004	0.020
Chain 3	-0.121***	0.021
Chain 4	0.093***	0.018
Chain 5	0.346***	0.018
Chain 6	0.071***	0.018
Chain 7	0.029***	0.019
Chain 8	0.306***	0.018
Chain 9	0.254***	0.018
Chain 10	0.265***	0.018
Christmas	0.004	0.013
Easter	-0.002	0.013
Regime change	-0.093***	0.014
Hen fodder price in EUR/100kg	-0.002	0.002
Wholesale price in EUR/100kg	-0.001	0.002

Sample size: 1601, R squared: 0.777.
Note: * 10% level, ** 5% level, *** 1% level.

A.3 MCMC sampler and prior settings

Parameters in the hierarchical prior from Equation 5 can be separated between k_c constrained and k_{uc} unconstrained coefficients for each household i (conditional on component membership $\text{ind}_i = s$)

$$\theta_i^* = \begin{pmatrix} \theta_i^{*c} \\ \theta_i^{*uc} \end{pmatrix} \sim N\left(\begin{pmatrix} \mu_{c_s}^* \\ \Gamma'_s \mu_{c_s}^* + z_s \end{pmatrix}, \begin{pmatrix} V_s^* & V_s^* \Gamma_s \\ \Gamma'_s (V_s^*)' & \Gamma'_s V_s^* \Gamma_s + \Sigma_s \end{pmatrix}\right), \quad (14)$$

where
$\theta_i^{*c} = \left(\alpha_i^*, \gamma_{i,Barn}^*, \ldots, \gamma_{i,Organic}^*, \tilde{\gamma}_{i,Barn}^*, \ldots, \tilde{\gamma}_{i,Organic}^*, \bar{\tilde{\gamma}}_{i,Barn}^*, \ldots, \bar{\tilde{\gamma}}_{i,Organic}^*, \gamma_{i,Barn}^{RC^*}, \ldots, \gamma_{i,Organic}^{RC^*}, \beta_i^*\right)'$
and $\theta_i^{*uc} = \left(\gamma_{i,Battery}^*, \tilde{\gamma}_{i,Battery}^*, \bar{\tilde{\gamma}}_{i,Battery}^*, \hat{\psi}_{i,2}^*, \ldots, \hat{\psi}_{i,10}^*\right)'$ here. The set of parameters $\left\{(z_s, \Gamma_s, \Sigma_s), (\mu_{c_s}^*, V_s^*)\right\}$ is characterized through two multivariate regression equations conditional on N_s household parameters, $\{\Theta_s^{*uc}, \Theta_s^{*c}\}$, clustered into each of the S components

$$\Theta_s^{*uc} = \Theta_{z_s}^{*c}\Gamma_{z_s} + U$$
$$\Theta_s^{*c} = \iota(\mu_{c_s}^*)' + U_{V_s^*}, \tag{15}$$

with $vec(U') := u \sim N(0, I_{N_s} \otimes \Sigma_s)$, $U_{V_s^*} := u_{V_s^*} \sim N(0, I_{N_s} \otimes V_s^*)$, (Γ_{z_s}, Σ_s) being a $(k_c+1 \times k_{uc})$ coefficient matrix with the intercept vector z_s included in the first row as well as the $(k_{uc} \times k_{uc})$ variance-covariance matrix of unconstrained coefficients respectively and $(\mu_{c_s}^*, V_s^*)$ are the k_c-size mean vector as well as $(k_c \times k_c)$ variance-covariance matrix of constrained coefficients respectively. ι denotes a $(N_s \times 1)$-vector of 1's.

The MCMC we apply here is a standard "Gibbs"-style sampler with an RW-Metropolis step to draw individual level parameters $\{\theta_i^*\}$ similar to the one described in Rossi et al. (2005). The modification is a two-stage update of the parameters entering the hierarchical prior. More specifically, the sampler draws from the following conditionals in each iteration (omitting subjective prior parameters for simplicity)

1. $\theta_i^*|(\mu_{c_{\text{ind}_i}}^*, V_{\text{ind}_i}^*), (\Gamma_{z_{\text{ind}_i}}, \Sigma_{\text{ind}_i}), y_i, \ i = 1, \ldots, N$
2. $\{\Gamma_{z_s}, \Sigma_s\} \,|\, \{\Theta_s^{*uc}, \Theta_s^{*c}\}, \{\text{ind}_i\}$
3. $\left\{\mu_{c_s}^*, V_s^*\right\} |\{\Theta_s^{*c}\}, \{\text{ind}_i\}$

This approach allows us to specify subjective priors of unconstrained and constrained coefficients separately from each other. This is necessary as the two represent distinct distributions on the retransformed θ-space. We use the natural conjugate prior to perform step 2 and the conditionally conjugate prior to perform step 3 of the MCMC sampler. More specifically,

$$p(\Gamma_{z_s}, \Sigma_s) = p(\Gamma_{z_s}|\Sigma_s)p(\Sigma_s),$$
$$vec(\Gamma_{z_s})|\Sigma_s \sim N(\bar{\gamma}_z, \Sigma \otimes A_{\Gamma_z}^{-1})$$
$$\Sigma_s \sim IW(\nu_\Sigma, \bar{\Sigma}) \text{ and}$$
$$p(\mu_{c_s}^*, V_s^*) = p(\mu_{c_s}^*)p(V_s^*), \tag{16}$$
$$\mu_{c_s}^* \sim N(\bar{\mu}_c^*, A_{\mu_c^*}^{-1})$$
$$V_s^* \sim IW(\nu_{V^*}, \bar{V}^*)$$

Explicit posteriors associated with these priors can be found in Pachali et al. (2018). The conditionally conjugate prior implies that mean and variance-covariance matrix are a priori independent which allows it to affect $\mu^*_{c_s}$ more explicitly through $A^{-1}_{\mu^*_c}$. We use standard weakly informative subjective priors for the parameters entering the hierarchical prior of unconstrained coefficients, $\bar{\gamma}_z,\ A_{\Gamma_z},\ \nu_\Sigma,\ \bar{\Sigma}$. Note that these priors mainly affect posterior inference of θ^{*uc}_i. We use "informative" specifications for the parameters entering the hierarchical prior of constrained coefficients, mainly affecting posterior inference of θ^{*c}_i. More specifically, $\bar{\mu}^*_c = \begin{pmatrix} 0 & \dots & 0 \end{pmatrix}'$ and $A_{\mu^*_c} = \text{diag}\begin{pmatrix} 1/4 & 1/2 & 1/2 & 1 & 1/2 & 1/2 & 1 & 1/2 & 1/2 & 1 & 1/2 & 1/2 & 1 & 1/4 \end{pmatrix}$ for all mixture models. The specification of $A_{\mu^*_c}$ seems informative or restrictive at first glance. There are two reasons we believe this is a reasonable prior for our data. First of all, this prior is set on the log-transformed space and standard specifications would imply an unreliably high prior variance of θ^{*c}_i. Second, we have several households included in the sample who are extreme in the sense of only purchasing a specific type of egg label (like organic or battery), no matter how prices evolve. For instance, the individual level likelihood of households who buy only battery eggs would be maximized by setting $\alpha^*_i \to \infty$, and $\gamma^*_{i,Barn} = \cdots = \gamma^*_{i,Organic} \to -\infty$, which translates to an infinite price sensitivity and complete indifference between quality differences. These extremes are ideally shrunk towards more reliable estimates in a hierarchical model. The functional form of our log-normal prior, however, puts additional prior support to these kinds of extreme outliers if its variance is large enough. We do not find this plausible, however, as it implies that such households would suffer from almost infinite losses after banning battery eggs. We therefore restrict $A_{\mu^*_c}$ to make such extreme posterior outcomes less likely through the prior. The subjective priors entering the Inverted Wishart prior for V^*_s are similar as in Allenby et al. (2014), implying $\nu_{V^*} = 30(40, 50, 60)$ as well as $\bar{V}^* = c^* \nu_{V^*} I_{k_c}$ with $c^* = 0.25(0.05, 0.025, 0.015)$ for mixture models with $S = 1(5, 10, 15)$ components respectively where I_{k_c} is the identity matrix of dimension $k_c \times k_c$.

A.4 Posterior inference in the unconstrained model

In Section 4 we argue that the constraints we impose in the hierarchical are critically important for posterior estimates and the economic reliability of implied counter-factual analyses. This Appendix documents posterior inference in the unconstrained model to highlight this line of argumentation.[50] First of all, Table A.2 shows that the unconstrained model outperforms the

[50]We estimate the unconstrained model using standard weakly informative priors as documented in, e.g. Rossi et al. (2005).

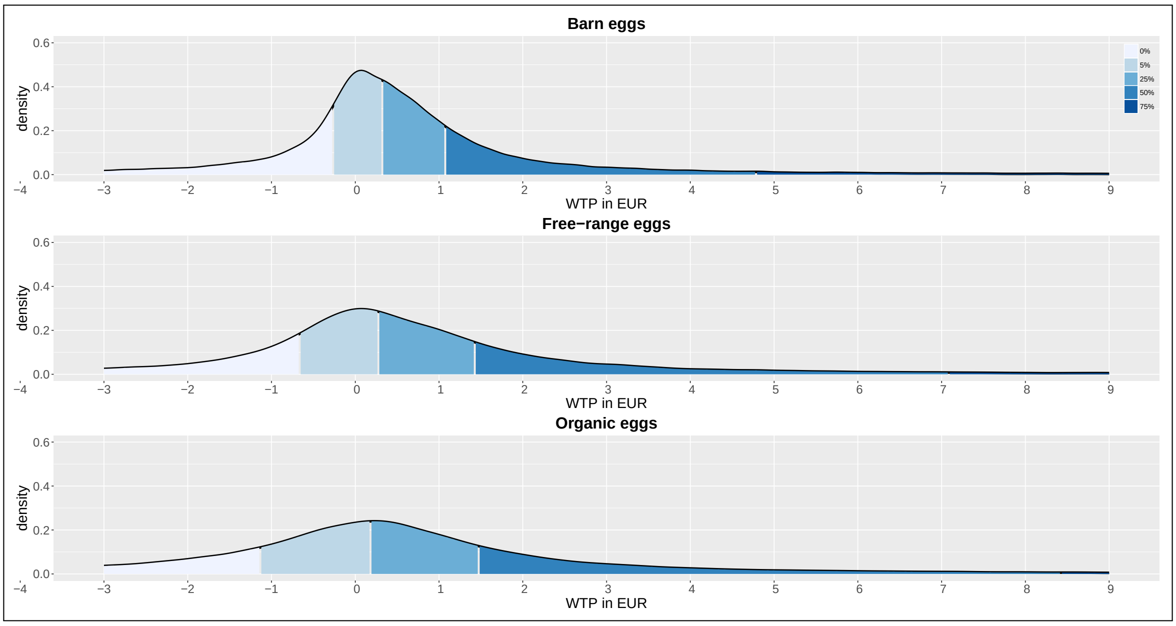
model imposing constraints— as illustrated in Table 7— based on the Newton Raftery estimator of the log marginal likelihood.

Table A.2: Log marginal likelihood in the unconstrained model

One normal component	-511467.8

However, Figure A.2 and Table A.3 show that inference based on the (standard) unconstrained model lacks economic rationality: The model characterizes a large fraction of household with a negative WTP for eggs providing higher animal welfare. Furthermore, it predicts that households have, on average, the lowest WTP for organic eggs as compared to barn and free-range eggs.

Figure A.2: Posterior distribution of WTP for different egg categories compared to battery eggs in the unconstrained model



Note: We compare a pack of 10 eggs of the respective category to a pack of 10 battery eggs.

Table A.3: Quantiles and first two moments of posterior distribution of WTP for different egg categories compared to battery eggs in the unconstrained model

Coefficients	Quantiles						
	5%	25%	50%	75%	95%	Mean	Stand. Dev.
Barn	-3.844	-0.257	0.317	1.075	4.782	0.994	228.851
Free-range	-6.084	-0.668	0.278	1.433	7.078	0.912	227.524
Organic	-8.018	-1.143	0.185	1.484	8.415	0.725	307.831

As we argue in Section 4, these findings are implausible because the perceived ordering of the quality tiers as well as the price coefficients are not economically identified in the unconstrained model. With real market data, researchers often lack the experimental variation in prices that one needs to identify such ordering. As a consequence, the marginal posterior distribution of the price coefficient has about 18% support in the positive domain as shown in Figure A.3. This is particularly problematic for computing counter-factual prices because it would be optimal to charge infinitely high prices and only keep consumers with weakly positive price coefficients in the market. Similarly, implying more structure in the demand model through the rationality assumption helps us to estimate preferences for the different quality tiers.

Figure A.3: Marginal posterior distribution of the price coefficient in the unconstrained model

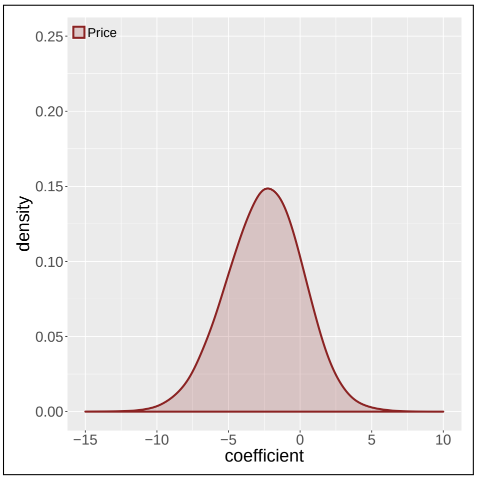


Table A.4 illustrates the choice pattern of household 19— a typical example of households with positive price valuation and odd coefficients for quality tiers. This household provided $T = 99$ observations and chose the cheapest, lowest quality alternative in the vast majority of purchase incidents.

Table A.4: Number of purchases of different egg products observed for household 19

	Battery	Barn	Outside	Free-range	Organic
Purchases	59	32	4	3	1

Table A.5 illustrates why the inferences in the standard model lacks economic rationality. The table compares quantiles of individual level posterior distributions of household 19 for the price and quality tier coefficients implied by the unconstrained and constrained model. It is apparent that the unconstrained model misleadingly rationalizes the choice pattern by estimating large valuations of poor quality tiers such as battery and barn eggs as well as low valuations for higher quality tiers such as free-range and organic eggs.

Table A.5: Comparison of individual level posterior distributions of household 19 implied by the unconstrained and constrained model

Quantiles	Unconstrained					Constrained				
	Price	Battery	Barn	Free-range	Organic	Price	Battery	Barn	Free-range	Organic
5%	-0.8	1.9	-0.4	-2.8	-5.4	-6.6	-3.6	-3.3	-3.3	-3.0
25%	0.4	3.3	0.8	-1.7	-3.7	-6.0	-2.6	-2.4	-2.4	-2.1
50%	1.2	4.3	1.5	-0.9	-2.6	-5.5	-2.0	-1.8	-1.7	-1.4
75%	1.9	5.2	2.3	-0.2	-1.7	-5.1	-1.3	-1.2	-1.1	-0.8
95%	3.0	6.7	3.5	1.0	-0.4	-4.5	-0.3	-0.1	-0.1	0.2
Mean	1.2	4.3	1.5	-0.9	-2.7	-5.5	-2.0	-1.8	-1.7	-1.4
Stand. Dev.	1.1	1.5	1.2	1.2	1.5	0.6	1.0	1.0	1.0	1.0

The price coefficient is unidentified for this household and positive on average. In the constrained model, on the other hand, ordinal constraints identify price sensibility of this household. Furthermore, the model characterizes this household being relatively indifferent between quality tiers, which is more convincing from an economic viewpoint.

Table A.6: Own- and cross-price elasticities for egg products in a subset of retail chains in the unconstrained model

Product	Retailer	Elasticity							
Organic 10 units	Retailer 6	-2.21	0.13	0.03	0.09	0.03	0.04	0.02	0.01
Free-range 10 units	Retailer 6	0.07	-3.10	0.12	0.21	0.04	0.15	0.05	0.03
Barn 10 units	Retailer 6	0.02	0.12	-2.89	0.38	0.01	0.03	0.07	0.06
Battery 10 units	Retailer 6	0.02	0.07	0.13	-2.01	0.00	0.01	0.04	0.20
Organic 10 units	Retailer 7	0.01	0.02	0.00	0.00	-1.33	0.22	0.07	0.04
Free-range 10 units	Retailer 7	0.01	0.04	0.01	0.01	0.12	-1.67	0.19	0.10
Barn 10 units	Retailer 7	0.00	0.02	0.02	0.04	0.04	0.21	-2.10	0.36
Battery 10 units	Retailer 7	0.00	0.01	0.02	0.17	0.02	0.10	0.35	-1.76

Note: Cell entry j, k, where j indexes rows and k indexes columns, gives the percentage change in market share for product j for a one percent change in the price of product k.

Table A.7: Own- and cross-price elasticities for egg products in a subset of retail chains in the constrained model

Product	Retailer	Elasticity							
Organic 10 units	Retailer 6	-4.60	0.24	0.09	0.12	0.24	0.07	0.03	0.02
Free-range 10 units	Retailer 6	0.11	-4.95	0.28	0.34	0.05	0.21	0.09	0.05
Barn 10 units	Retailer 6	0.06	0.39	-5.77	0.71	0.02	0.08	0.18	0.11
Battery 10 units	Retailer 6	0.02	0.14	0.20	-3.65	0.01	0.02	0.08	0.42
Organic 10 units	Retailer 7	0.07	0.03	0.01	0.01	-3.44	0.49	0.14	0.06
Free-range 10 units	Retailer 7	0.01	0.06	0.02	0.02	0.25	-3.67	0.50	0.22
Barn 10 units	Retailer 7	0.01	0.03	0.05	0.07	0.08	0.60	-4.71	0.76
Battery 10 units	Retailer 7	0.00	0.02	0.02	0.33	0.03	0.22	0.65	-3.52

Note: Cell entry j, k, where j indexes rows and k indexes columns, gives the percentage change in market share for product j for a one percent change in the price of product k.

Table A.6 and Table A.7 show that implied elasticities are considerably different in the unconstrained and constrained model as well. Finally, Table A.8 illustrates retailer-specific marginal cost estimates implied by the unconstrained model. Compared to estimates based on the constrained model in Table 12, the majority of cost estimates seem odd and clearly lack face validity.

Table A.8: Marginal costs, prices, margins and market shares in the unconstrained model

Retailer : Egg Product	c	p	$p - c$	s
Retailer 1: Free-range 10 units	0.24	1.51	1.27	5.40
Retailer 1: Barn 10 units	0.20	1.25	1.05	8.13
Retailer 2: Organic 10 units	-2.66	2.44	5.09	2.53
Retailer 2: Free-range 10 units	-0.21	1.51	1.73	5.57
Retailer 2: Barn 10 units	-0.04	1.27	1.31	3.93
Retailer 2: Battery 10 units	0.05	0.92	0.87	2.79
Retailer 3: Organic 10 units	1.20	2.29	1.09	0.58
Retailer 3: Free-range 10 units	0.36	1.51	1.14	5.42
Retailer 3: Barn 10 units	0.15	1.26	1.10	8.60
Retailer 3: Battery 10 units	0.01	0.91	0.90	5.78
Retailer 4: Organic 10 units	0.31	2.43	2.11	0.61
Retailer 4: Free-range 10 units	0.19	1.58	1.39	1.99
Retailer 4: Barn 10 units	0.09	1.28	1.19	2.67
Retailer 4: Battery 10 units	-0.19	0.90	1.09	8.04
Retailer 5: Organic 10 units	9.99	3.04	-6.95	0.50
Retailer 5: Free-range 10 units	7.42	2.19	-5.22	0.57
Retailer 5: Barn 10 units	4.72	1.98	-2.74	0.39
Retailer 5: Battery 10 units	0.08	1.01	0.93	0.96
Retailer 6: Organic 10 units	1.25	2.54	1.28	0.20
Retailer 6: Free-range 10 units	0.93	1.52	0.59	0.66
Retailer 6: Barn 10 units	0.77	1.37	0.60	0.76
Retailer 6: Battery 10 units	0.41	0.90	0.49	3.32
Retailer 7: Organic 10 units	0.84	2.40	1.56	0.82
Retailer 7: Free-range 10 units	0.32	1.53	1.20	2.42
Retailer 7: Barn 10 units	0.35	1.25	0.90	2.73
Retailer 7: Battery 10 units	0.16	0.92	0.76	3.89
Retailer 8: Organic 10 units	-109.58	2.98	112.56	0.40
Retailer 8: Free-range 10 units	-0.15	1.95	2.10	1.01
Retailer 8: Barn 10 units	0.49	1.60	1.11	1.06
Retailer 8: Battery 10 units	0.28	1.05	0.77	2.16
Retailer 9: Organic 10 units	65.26	3.08	-62.18	0.41
Retailer 9: Free-range 10 units	-2.68	2.10	4.78	0.86
Retailer 9: Barn 10 units	-3.36	1.85	5.21	0.44
Retailer 9: Battery 10 units	0.37	1.04	0.66	1.90
Retailer 10: Organic 10 units	-28.54	2.82	31.36	0.04
Retailer 10: Free-range 10 units	-7.96	2.08	10.04	0.18
Retailer 10: Barn 10 units	0.04	1.51	1.46	0.17
Retailer 10: Battery 10 units	0.15	1.06	0.91	0.26

A.5 Alternative specification of consumer choice set

Our demand framework assumes that households have complete information about the egg products offered by the ten retailers. We argue that individual-specific retail chain preference parameters included in the demand model attenuate the likely bias in egg preference estimates caused by the full information assumption. In this part, we employ the different implications of the full information model as specified in Section 4 as well as a more parsimonious model that assumes limited information available to households at time of purchase. The latter essentially limits the egg product alternatives in a given choice occasion to the eggs offered in the retail chain of purchase. This approach effectively reduces the danger of including product alternatives from a different retailer a household did not consider at the time of purchase. It is therefore probably a more robust approach to estimate household-specific preference coefficients. The main drawback of this approach, however, is that it does not make it possible to infer individual preferences for the retail chains included in the sample, which we argue is crucial for the counter-factual analysis and the policy analysis we perform in Section 6.

We start with a robustness check of the egg preference estimates by comparing the WTP heterogeneity distributions implied by the full information model as specified in Section 4 and the model assuming limited information.

Table A.9: Posterior distribution of WTP for different egg categories compared to battery eggs implied by the model with limited information

Coefficients	Quantiles						
	5%	25%	50%	75%	95%	Mean	Stand. Dev.
Barn	0.013	0.081	0.329	0.911	3.878	1.084	4.087
Free-range	0.027	0.154	0.589	1.530	5.634	1.633	5.607
Organic	0.048	0.233	0.732	1.830	6.668	1.924	6.048

Table A.9 summarizes the posterior distribution of households' WTP implied by the model with limited information and is directly comparable to Table 10, its counterpart assuming full information.[51] The quantiles of the posterior distribution of WTP seem compatible with Table 10 and we do not find a systematic bias caused by the full information model.

Next, we use the model with limited information to compute counter-factual outcomes that are comparable with the results obtained in Section 6.2. Technically, the limited information model requires a modified estimator of the household preference distribution. In this model, every artificially generated household —in the form of a draw from the posterior predictive population distribution— will shop a single chain without considering alternatives offered by other retailers. We use the number of egg purchases in the ten retail chains observed for every household in the sample and construct empirical probabilities of chain visits for each household. These probabilities randomly determine the chain visited by each draw of the preference distribution. I.e., our estimator of the preference distribution is appended by an indicator for the specific

[51]Prior specifications were the same for both models.

retail chain every "household" (in the form of a draw) considers in the choice set. This will treat retailers as monopolists every time households purchase eggs. Consequently, the model assumes that a customer would never leave the retailer and purchase at a different chain once entered, regardless of how high prices for the egg alternatives might become in the counter-factual. Table A.10 shows retailer-specific marginal cost estimates implied by the model treating retailers as monopolists.[52] Compared to the results in Table 12, retailers in this scenario systematically achieve higher margins, which turns most of economic cost estimates to be negative. This is a direct consequence of the higher market power that retailers take advantage of: In this model, every retailer determines egg prices based on the anticipated preference structure of its customers only, without considering competitive pressure.

Table A.11 uses retailer-specific cost estimates in Table A.10 to simulate equilibrium prices after a ban on battery eggs. Since computations are based on observed market prices in 2008 and we do not manipulate the ownership matrix here, we compare results with the first four columns of Table 13. The reason retailer market share-weighted average of prices in 2008, $\bar{p}$, slightly differ in both tables is because market shares are not observed but inferred from two different demand specifications. Differences in $\bar{p}$ are very small and market share forecasts at the observed prices in 2008 are similar between the two models. Comparing simulated average equilibrium prices after the ban on battery eggs, $\bar{p}'$, we see a similar pattern as with the model assuming full information in Table 13: We observe that prices of the remaining egg products fall, on average, after the ban on battery eggs based on the model with limited information as well. This shows robustness of our main finding regarding the regressive effect of the ban on battery eggs (see Table A.13).

With regard to the subsidy, we find that, as before, average prices of free-range and organic eggs rise as a consequence of subsidizing barn eggs producers. Therefore, the subsidy has a progressive policy implication based on the model with limited information as well (see Table A.13). However, the level of the required subsidy turns out to be 1.27 EUR per package of ten eggs, which is more than three times as much as with the model assuming full information. The reason is that retailers have more pricing power in the model with limited information, which we find to increase the required subsidy in Section 6.2.

Table A.12 confirms the negative aspect of the subsidy in the sense that substitution patterns towards egg products providing lower animal welfare are incentivized through the subsidy.

[52] We note that the specification of ownership matrix Ω does not affect results in the limited information model.

Table A.10: Marginal costs, prices, margins and market shares for a setting treating retailers as monopolists in each trip

Retailer : Egg Product	c	p	$p - c$	s
Retailer 1: Free-range 10 units	-3.09	1.51	4.60	6.09
Retailer 1: Barn 10 units	-3.28	1.25	4.53	8.56
Retailer 2: Organic 10 units	-2.29	2.44	4.72	2.15
Retailer 2: Free-range 10 units	-2.50	1.51	4.02	5.12
Retailer 2: Barn 10 units	-2.61	1.27	3.88	3.47
Retailer 2: Battery 10 units	-2.87	0.92	3.79	3.09
Retailer 3: Organic 10 units	-2.73	2.29	5.02	0.60
Retailer 3: Free-range 10 units	-3.50	1.51	5.01	4.14
Retailer 3: Barn 10 units	-3.79	1.26	5.04	6.72
Retailer 3: Battery 10 units	-4.07	0.91	4.98	5.75
Retailer 4: Organic 10 units	-1.93	2.43	4.36	0.72
Retailer 4: Free-range 10 units	-2.55	1.58	4.13	2.42
Retailer 4: Barn 10 units	-2.87	1.28	4.15	2.82
Retailer 4: Battery 10 units	-3.34	0.90	4.24	8.53
Retailer 5: Organic 10 units	1.01	3.04	2.02	0.45
Retailer 5: Free-range 10 units	0.70	2.19	1.50	0.58
Retailer 5: Barn 10 units	0.57	1.98	1.41	0.15
Retailer 5: Battery 10 units	-0.39	1.01	1.40	1.30
Retailer 6: Organic 10 units	-0.19	2.54	2.73	0.27
Retailer 6: Free-range 10 units	-1.14	1.52	2.66	0.91
Retailer 6: Barn 10 units	-1.33	1.37	2.70	0.72
Retailer 6: Battery 10 units	-1.88	0.90	2.77	3.45
Retailer 7: Organic 10 units	-2.87	2.40	5.27	0.68
Retailer 7: Free-range 10 units	-3.42	1.53	4.94	2.32
Retailer 7: Barn 10 units	-3.66	1.25	4.91	2.45
Retailer 7: Battery 10 units	-4.02	0.92	4.94	4.26
Retailer 8: Organic 10 units	-0.14	2.98	3.12	0.47
Retailer 8: Free-range 10 units	-0.58	1.95	2.53	1.22
Retailer 8: Barn 10 units	-0.86	1.60	2.46	1.01
Retailer 8: Battery 10 units	-1.49	1.05	2.54	2.43
Retailer 9: Organic 10 units	1.00	3.08	2.08	0.46
Retailer 9: Free-range 10 units	0.51	2.10	1.60	1.01
Retailer 9: Barn 10 units	0.22	1.85	1.62	0.37
Retailer 9: Battery 10 units	-0.56	1.04	1.60	2.60
Retailer 10: Organic 10 units	0.90	2.82	1.92	0.06
Retailer 10: Free-range 10 units	0.20	2.08	1.87	0.18
Retailer 10: Barn 10 units	-0.35	1.51	1.86	0.24
Retailer 10: Battery 10 units	-0.70	1.06	1.76	0.35

Table A.11: Optimal subsidy and welfare effects for a setting treating retailers as monopolists in each trip

Product	$\bar{c}$	$\bar{p}$	$\bar{p}'$	$\bar{p}^*$
Organic 10 units	-1.55	2.57	2.40	3.19
Free-range 10 units	-2.54	1.59	1.46	2.37
Barn 10 units	-3.07	1.29	1.16	0.93
Battery 10 units	-2.84	0.93		
τ^*				1.27
In million EUR:				
T				578.53
$\sum \Delta\Pi_m$			-81.13	427.30
$\sum \Delta E(CW_r)$			8.30	5.45

Table A.12: Market shares after product bans for a setting treating retailers as monopolists in each trip

Product	$\hat{s}$	$\hat{s}'$	$\hat{s}^*$
Organic 10 units	5.87	6.45	3.97
Free-range 10 units	23.99	30.12	6.09
Barn 10 units	26.53	51.53	78.68
Battery 10 units	31.76		
Outside good	11.86	11.90	11.26

Table A.13: Consumer welfare effects across different income groups for a setting treating retailers as monopolists in each trip

		$p \to p'$	$p \to p^*$
Income group	Avg. Income	$\sum \Delta E(CW_r)$ in million EUR	
1	501.42	-0.56	4.60
2	710.69	-0.14	2.04
3	858.38	-0.02	3.88
4	988.36	0.93	2.36
5	1114.98	0.58	0.50
6	1260.96	1.48	0.53
7	1418.83	1.13	-0.88
8	1626.02	1.86	-1.88
9	1922.58	1.53	-2.86
10	2969.06	1.53	-2.84
Overall	1224.11	8.30	5.45

A.6 Additional Tables

Table A.14: Net monthly income per household: Original coding

Label	Income range
5	below 750 EUR
7	750 up to 1000 EUR
9	1000 up to 1250 EUR
10	1250 up to 1500 EUR
11	1500 up to 1750 EUR
12	1750 up to 2000 EUR
13	2000 up to 2250 EUR
14	2250 up to 2500 EUR
15	2500 up to 2750 EUR
16	2750 up to 3000 EUR
18	3000 up to 3500 EUR
19	3500 up to 4000 EUR
20	4000 EUR and above

A.6.1 Counterfactual calculations including preference shift after regime change

Table A.15: Higher minimum quality standards and negating the regressive effect for a setting with regime change in egg preferences after banning battery eggs

			New Minimum Quality Standard					
			Barn		Free-range		Organic	
Product	$\bar{c}$	$\bar{p}$	$\bar{p}'$	$\bar{p}^*$	$\bar{p}'$	$\bar{p}^*$	$\bar{p}'$	$\bar{p}^*$
Organic 10 units	1.39	2.52	2.30	2.46	2.19	2.52	1.95	0.93
Free-range 10 units	0.89	1.57	1.51	1.66	1.38	0.93		
Barn 10 units	0.74	1.28	1.22	0.93				
Battery 10 units	0.49	0.93						
τ^*				0.31		0.50		1.09
In million EUR:								
T				119.24		249.01		578.26
$\sum \Delta\Pi_m$			-19.51	2.69	-48.14	1.04	-127.11	31.98
$\sum \Delta E(CW_r)$			-22.26	53.82	-73.28	121.69	-283.02	167.94

Table A.16: Market shares and higher minimum quality standards for a setting with regime change in egg preferences after banning battery eggs

		New Minimum Quality Standard					
		Barn		Free-range		Organic	
Product	$\hat{s}$	$\hat{s}'$	$\hat{s}^*$	$\hat{s}'$	$\hat{s}^*$	$\hat{s}'$	$\hat{s}^*$
Organic 10 units	6.08	9.20	7.53	11.61	5.55	50.10	92.02
Free-range 10 units	24.75	27.73	15.74	69.11	86.01		
Barn 10 units	26.93	48.48	66.04				
Battery 10 units	30.61						
Outside good	11.63	14.59	10.69	19.28	8.44	49.90	7.98

Table A.17: Consumer welfare effects across different income groups and higher minimum quality standards for a setting with regime change in egg preferences after banning battery eggs

		New Minimum Quality Standard					
		Barn		Free-range		Organic	
		$p \to p'$	$p \to p^*$	$p \to p'$	$p \to p^*$	$p \to p'$	$p \to p^*$
Income group	Avg. Income	$\sum \Delta E(CW_r)$ in million EUR					
1	503.44	-4.83	6.89	-12.18	12.75	-36.78	13.62
2	711.46	-3.95	7.03	-10.90	14.06	-37.14	16.29
3	858.61	-3.73	6.93	-10.64	13.25	-35.25	13.89
4	988.95	-2.63	6.17	-8.49	13.02	-31.09	16.73
5	1115.20	-2.15	6.11	-7.66	13.37	-31.32	16.68
6	1260.83	-1.77	5.67	-6.82	13.36	-28.83	18.49
7	1418.63	-1.82	4.92	-6.48	12.76	-28.16	18.45
8	1627.28	-0.96	4.16	-4.79	11.87	-23.35	19.40
9	1923.78	-0.53	3.19	-3.33	9.54	-17.87	17.25
10	2950.51	0.11	2.75	-1.98	7.72	-13.23	17.15
Overall	1225.75	-22.26	53.82	-73.28	121.69	-283.02	167.94