Discrete Choice Experiments for Economic Research on Tobacco Regulation

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Tasks of Empirical Analysis in Economics

- "Evaluating the impacts of public policies, forecasting their effects in new environments, and predicting the effects of policies never tried are three central tasks of economics." (Heckman & Vytlacil, Econometrica, May 2005).
- Quasi-experimental methods focus on the first task: evaluating the impacts of public policies
  - Retrospective policy evaluation
  - Back-of-the-envelope forecasts of effects in new environments
  - Sometimes more formal forecasts.
- What about predicting effects of policies never tried?
  - Prospective policy evaluation
  - Lab and field experiments
  - Discrete choice experiments gather data on subjects' stated preferences, which can be used to predict the effects of policies in new environments and to predict the effects of policies never tried.

Stated preference methods

- **Stated preference (SP)** research *involves asking the same individuals to state their preferences in hypothetical (or virtual) markets.*
- ***DCEs** are an attribute-based approach to collect SP data. They involve presenting respondents with a sequence of hypothetical scenarios (choice sets) composed by two or more competing alternatives that vary along several attributes, one of which may be the price of the alternative or some approximation for it.*
  - Ryan et al., Using Discrete Choice Experiments to Value Health and Health Care, Springer 2008
- **Contingent valuation** asks respondents about their willingness to pay.
  - A dichotomous choice study -- Are you WTP $X? – is sometimes called a DCE.
- **Conjoint analysis** is a related broad set of techniques to elicit preferences. Use of the terms varies, but Louivre, et al. stress that only DCEs are linked to and consistent with economic demand theory.
  - Louivre, Flynn, and Carson, “Discrete Choice Experiments are Not Conjoint Analysis,” Journal of Choice Modelling, 3(3), pp 57-72.

DCEs are a well-established tool for causal inference in empirical microeconomics

- DCEs are commonly used in marketing research and economics
  - Marketing and pharmacoeconomic research use DCEs and conjoint analysis to provide predictions of consumer demand for new products or combinations of attributes.
- Examples of DCEs include economic studies of consumer demand in policy-relevant scenarios that are not yet observed in actual markets:
  - Kesternich, Heiss, McFadden, & Winter (*JHE* 2013) study consumer choices of Medicare Part D Rx insurance plans, before launch of Part D.
  - Blass, Lach, & Manski (*IER* 2010) study preferences for electricity reliability
  - Moshary, Shapiro, & Drango (NBER Working Paper 2023) study consumer preferences for firearms and the implications for regulation

Other Uses of DCEs in Economics

- DCEs also provide a way to test economic hypotheses that are hard to study with other approaches
  - Mas & Pallais (*AER* 2017) study workers' preferences for alternative work arrangements
  - Wiswall and Zafar (*QJE* 2018) study prospective workers' preferences for work flexibility, job stability, and high earnings growth potential.
  - Alex Chan (Stanford PhD dissertation, conditionally accepted at *AER*) used a discrete choice experiment to study patient discrimination against Black and Asian doctors.
- Environmental economics uses stated preference methods including contingent valuation and DCEs to estimate consumer willingness to pay for non-market goods like environmental quality.

Recent Tobacco Product DCEs in Economic Journals and at IHEA

Authors	Year	Journal
Buckell, Hensher, and Hess	2021	Health Economics
Buckell and Hess	2019	Journal of Health Economics
Guindon, Mentzakis, and Buckley	2024	Economics & Human Biology
Kenkel, Peng, Pesko, and Wang	2020	Health Economics
Kenkel et al.	2024	Annals of Public and Cooperative Economics
Kenkel, et al.	2025	Health Economics
Marti, Buckell, Maclean, and Sindelar	2019	Economic Inquiry
Farandy et al.	2025	IHEA: Tuesday 3:30 – 5 pm
Deng et al.	2025	IHEA: Tuesday 3:30 – 5 pm

DCE research: strengths and limitations

- Strengths
  - Strong internal validity: Experimental design identifies causal effects and overcomes challenges researchers face when using observational data.
  - Flexible & timely
  - Tightly linked to economic theory/useful for cost-benefit analysis
- Limitations
  - Important to follow good practices in DCE methodology
  - Important to tailor DCE to market/regulations under study
  - External validity – Is it valid to extrapolate results from experiment to predict results of real-world regulations?

Research on DCE External Validity

- In a narrative review of research, McFadden (2017) concludes that there is a "sharp reliability gradient"
  - "Forecasts that are comparable in accuracy to RP [revealed preference] forecasts can be obtained from well-designed SP studies for familiar, relatively simple goods that are similar to market goods purchased by consumers, particularly when calibration to market benchmarks can be used to correct experimental distortions. However, studies of unfamiliar, complex goods give erratic, unreliable forecasts."
- Penn and Hu (2018) conduct meta-analysis of "calibration factors" (CFs) which shows the ratio of willingness to pay estimated from SP data to the willingness to pay estimated from RP data.
  - About one quarter of the CFs are between 0.81 and 1.2 (close to 1 is good!)
  - Distribution of CFs is skewed right (=> SP over-estimates WTP).
  - Estimates for private goods are more reliable

Calibrating SP Estimates from DCEs

- "Revealed preference data have the advantage that they reflect actual choices…. However, RP data are limited to the choice situations and attributes of alternatives that currently exist or have existed historically. Often a researcher will want to examine people's responses in situations that do not currently exist…RP data are simply not available for these new situations."
- "Stated-preference data complement revealed-preference data…. The limitations of SP data are obvious: what people say they will do is often not the same as what they actually do. People might not know what they would do if a hypothetical situation were real. Or they might not be willing to say what they would do."
- By combining RP and SP data, "the advantages of each can be obtained while mitigating the limitations. The SP data provide the needed variation in attributes, while the RP data ground the predicted shares in reality." (Train, 2002, pp. 174-175).

Key stages in developing a DCE

- As used by Johnson et al, **Experimental Design = *the process of generating specific combinations of attributes and levels that respondents evaluate in choice questions*.** Experimental design should reflect:
  - **Research Objectives** refer to the object of choice for which preferences will be quantified, e.g. tobacco products.
  - **Attributes and Levels** are the features that comprise the research object, among which the survey will elicit trade-offs, **e.g. price, legality of sale, flavor**
  - **Choice Question Format** describes how a series of sets of alternatives from among all possible profiles will be presented to respondents.
  - **Analysis Requirements** for the intended model specification

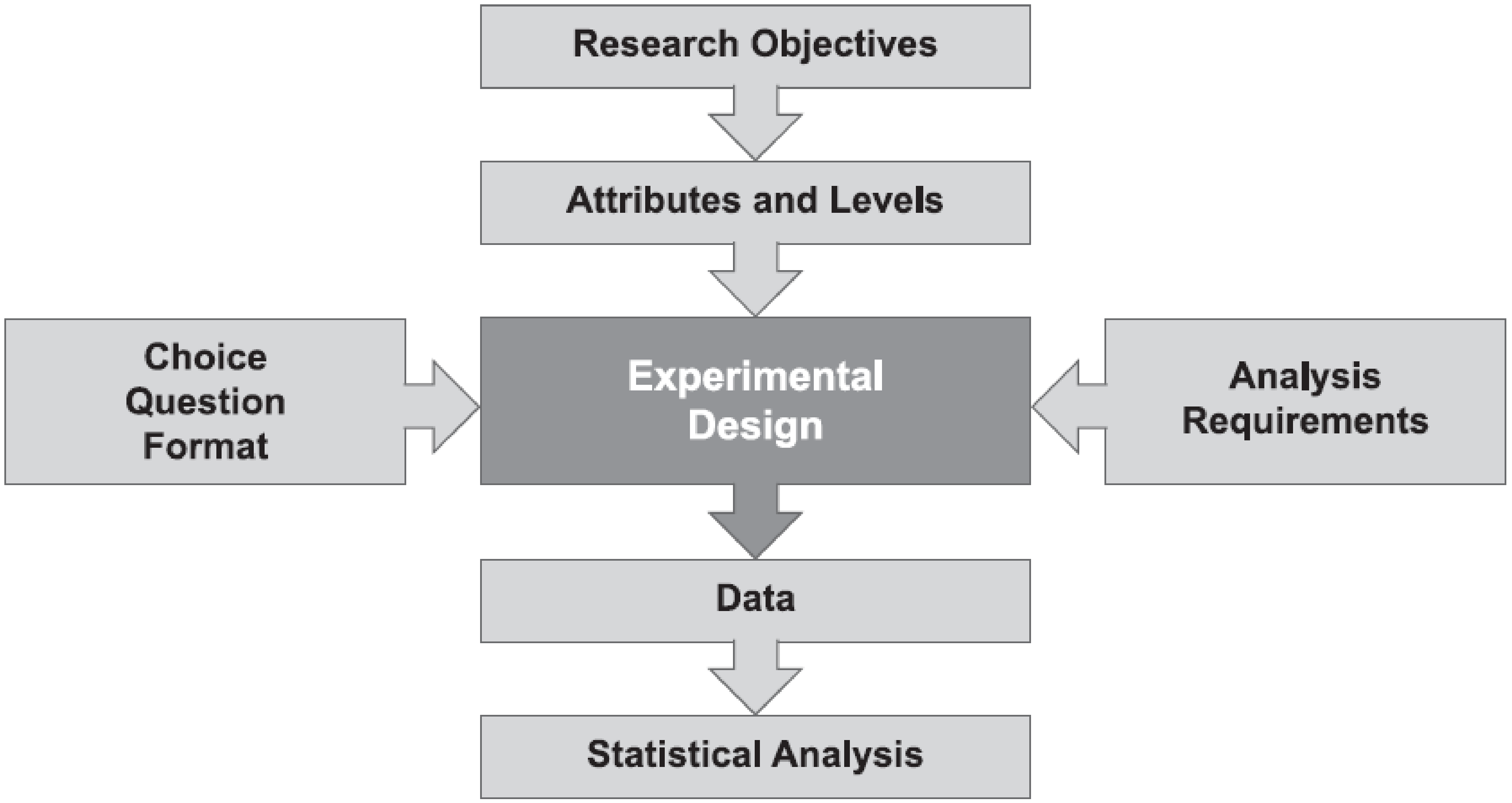

Fig. 1 – Key stages for developing a discrete-choice experiment.

Source: Johnson, Lancsar, Marhall, et al. (Value in Health, 2013), Constructing Experimental Designs for Discrete-Choice Experiments: Report of the ISPOR Conjoint Analysis Experimental Design Good Research Practices Task Force.

Examples: Cornell DCEs

- Method: collect and analyze primary data from online DCEs
- In Fall 2021 we completed **Round 1** of the DCEs: Australia, China, Indonesia, Japan, Sweden, UK, US; in January 2023 we added Malaysia
  - Hypothetical choices between cigarettes, e-cigarettes (Japan: heated tobacco), quitting
  - Attributes: price, flavor, nicotine (Australia: Rx), health messages
- **Round 2**: DCEs of illegal markets
  - April 2022: US proposed prohibition of menthol
  - January – February 2023: Australian e-cigarette Rx requirement
China e-cigarette flavor ban
- **Round 3**: research collaborations with
  - Alan Farandy and colleagues, Indonesian Development Foundation
  - Asena Caner and colleagues, TOBB University of Economics and Technology, Ankara, Türkiye

Türkiye DCE: Product Attributes and Levels

OPTIONS

ATTRIBUTE

	Packaged Cigarette	Roll Your Own (RYO)	E-Cig or HTP	Quit
Price	0,5 P P (actual price paid) 2P	30 TL	20 TL 40 TL 80 TL	-
Sale Type	Legal with banderole	Illegally sold	Legal with banderole Illegally sold Strictly Banned	-
Flavor	Tobacco only Menthol available	Tobacco	Tobacco only Variety of Flavors	-

Türkiye DCE Choice Task Screen

	Option 1	Option 2	Option 3	Option 4
	 (Packed Cigarettes)	 (Roll Your Own)	 (E-cigarette or a heated tobacco product)	None
PRICE	3 Levels	1 Level	3 Levels	
SALE TYPE	1 Level	1 Level	3 Levels	I will quit smoking cigarettes and not use e-cigarettes.
FLAVOR	2 Levels	1 Level	2 Levels	
Please select one option.	O	O	O	O

Choice of levels

- Depends on research question
    - E-cigarette manufacturer might want to know if consumers prefer mint flavor over menthol flavor.
    - Health economist (and maybe also manufacturer) might want to test economic model that predicts consumers care about e-cig health effects, or effectiveness of e-cigs for smoking cessation
- **Türkiye DCE** (and other Cornell DCEs) use levels to correspond to regulatory policies that already vary across countries or are under consideration: price, flavor, nicotine, **health messages**, legality
    - Policies affect the **availability** of flavors and nicotine levels
    - Policies can mandate health messages on warning labels but cannot mandate how consumers react to those messages.

Other DCEs of tobacco product choices have used different approaches to define levels

- Example study by Buckell et al.: Subjects presented with choice between products with specific flavors, life year losses
  - Ex: regular cigarette, fruit flavored e-cig, sweet-flavored e-cig
  - Some subjects, e.g. menthol smokers, unhappy with all the alternatives
  - Subjects can opt out (“none of the above”) but interpretation is ambiguous: do they plan to quit, or to get their preferred product somewhere else?
- Choice task is not a realistic description of choices presented in real markets
  - Also not a realistic description of how regulations would change real markets
- Study’s model does provide estimates of the Δ utility from flavors, so model can predict choices in status quo markets and under alternative regulatory regimes
- Study’s model also provides estimates of the Δ utility per life-year lost
  - Regulations can influence but can’t exactly determine consumers’ perceptions of life-year loss

Option 1: Tobacco Cigarette	Option 2: Tobacco Cigarette
 • Flavor: **Tobacco** • Nicotine level: **High** • Die earlier: **10 Years** • Price: **$4.99**	 • Flavor: **Tobacco** • Nicotine level: **High** • Die earlier: **10 years** • Price: **$13.99**
Option 3: E-cigarette	**Option 4: E-cigarette**
 • Flavor: **Fruit** • Nicotine level: **High** • Die earlier: **2 Years** • Price: **$13.99**	 • Flavor: **Sweet** • Nicotine level: **High** • Die earlier: **Unknown** • Price: **$4.99**

Source: Buckell, Marti, & Sindelar (2019, Tobacco Control)

Also note: Option 1 dominates Option 2.

Table 1
Discrete Choice Experiment (DCE) Attributes and Levels

	Cigarettes[a]	Vape pen
Less harmful to health than cigarettes		Yes [left blank]
Effective for helping people quit		Effective Not effective Unknown
Nicotine strength	12 mg per stick	None (0 mg) Low (1-12 mg) Medium (13-17 mg) High (18 mg or higher)
Flavor	Tobacco[b] Menthol[b]	Tobacco Menthol Fruit/candy/sweet/other flavors
Price	Price per pack[b]	Starter Kit: $30[c] Refill Price: $3 $5 $7

Source: Shang et al, Tobacco Regulatory Science 2020.

These attributes can not be directly manipulated by regulatory policy

Not a realistic description of product availability in markets; for example, consumers never see only high nicotine products or only fruit/candy flavored products

Identification in DCEs

- Random assignment of attributes => clean identification of the causal effects of the attribute on product choice.
- But the DCE needs to be carefully designed to allow for identification of every parameter of interest with enough degrees of freedom.
    - Review of health care literature found: *some studies had one or more effects that were perfectly confounded with other effects, meaning that the effects could not be independently identified….* (Johnson et al. 2013)
- Simple example: suppose choice set is between #1 a Tx that has no pain and a risk of heart attack vs #2 a Tx with mild pain and a risk of infection.
    - If subjects choose #2, is it because they found mild pain acceptable, or because they wanted to avoid the side-effect risk of a heart attack?
    - For identification, DCE needs to include more alternatives in the choice set: #3 no pain & infection risk, and #4 mild pain & heart attack risk

Intended model specification

A critical issue in all discrete choice models is the specification of the "representative" (i.e. estimated) utility function $V(X_{in}, \beta)$, that relates the observed attributes of the alternatives to the utility U_{in} derived from alternative i. It is common to assume linear-*in*-parameters function as shown in Equation 1.6.

$$V_{in} = \text{ASC}_i + \beta_1 x_{i1} + \ldots + \beta_K x_{iK} \tag{1.6}$$

where there are $k = 1, 2, \ldots, K$ attributes (possibly including price) with generic coefficients (to be estimated) β_k across alternatives.[7] An alternative-specific constant (ASC_i) captures the mean effect of the unobserved factors in the error terms for each of the alternatives.[8]

Source: Ryan et al., Using Discrete Choice Experiments to Value Health and Health Care

Intended model specification continued

- **Linear in parameters** model
  - β_K parameters capture the **main effects** of each attribute on utility, i.e. if attributes continuous, the marginal utility of the attribute level.
  - **Interaction effects** when marginal utility of one attribute depends upon the level of one or more other attributes.
- **Non-linear main effects**: when the marginal utility of attribute K depends on the level of attribute K
  - Only two levels: linear marginal utility
  - Three levels: generally suffice to identify non-linearities (Ryan et al.)
- **Discrete levels:** estimate Δ utility instead of marginal utility

Türkiye DCE example specification

- Linear main effects, no interaction effects
  - We estimate marginal utility of price = - marginal utility of income
    - Three price levels so we could estimate non-linearities
    - For most consumers, changes in tobacco product prices are small relative to income => marginal utility of income approximately constant in range
  - We estimate Δ utility for different levels of legality
  - We estimate Δ utility for different levels of flavor availability
- Sub-sample analysis allows are parameters to vary across age sub-groups

Empirical analysis of DCE data

- Cross-tabulations
  - If balanced, orthogonal design, cross-tabs provide unbiased estimates of the differences in choices across different attribute levels
- Linear probability models
  - OLS is a marginal effect generator: *The upshot of this discussion is that while a nonlinear model may fit the CEF [conditional expectation function] for LDVs [limited dependent variables] more closely than a linear model, when it comes to marginal effects, this probably matters little. This optimistic conclusion is not a theorem, but…it seems to be fairly robustly true*. (Angrist & Pischke Mostly Harmless Econometrics 2009, p. 107)
- Logit or probit models of 0-1 choices
- Conditional logit model of multinomial choices
- **Structural models of utility function**

		All		Ages 18-30		
		Mean	**Std.Dev.**	**Mean**	**Std.Dev.**	**M**
ASC (Base: Quit)						
Cigarette	**Estimate**	5.572 ***	3.356 ***	4.943 ***	3.057 ***	6
	(SE)	(0.275)	(0.265)	(0.303)	(0.290)	(
RYO	**Estimate**	2.906 ***	4.147 ***	2.386 ***	2.914 ***	2
	(SE)	(0.352)	(0.232)	(0.318)	(0.283)	(
Vape	**Estimate**	2.326 ***	3.662 ***	2.885 ***	2.257 ***	2
	(SE)	(0.495)	(0.424)	(0.332)	(0.392)	(
Price	**Estimate**	-0.033 ***	0.040 ***	-0.022 ***	0.027 ***	-
	(SE)	(0.003)	(0.003)	(0.003)	(0.003)	(
Legal status of vapes (Base: Legal with banderole)						
Illegally Sold	**Estimate**	-0.767 ***	1.057 **	-0.407 ***	0.720 ***	-
	(SE)	(0.199)	(0.468)	(0.167)	(0.257)	(
Strictly Banned	**Estimate**	-1.038 ***	1.123 ***	-0.615 ***	0.865 **	-
	(SE)	(0.197)	(0.288)	(0.190)	(0.422)	(
Flavor availability (Base: Tobacco only)						
Menthol cigarettes	**Estimate**	-0.523 ***	1.326 ***	-0.091	0.834 ***	-
	(SE)	(0.113)	(0.245)	(0.129)	(0.209)	(
Vape in various flavors	**Estimate**	-0.148	0.916 ***	-0.193	1.141 ***	-
	(SE)	(0.119)	(0.207)	(0.198)	(0.347)	(
N		13452		5136		

Türkiye DCE: Predicted Market Shares

	Cigarettes	*RYO*	*Vapes*	*Quit*
Scenario 1: Baseline + Double vape price	52.39 ↑	27.35 ↑	10.84 ↓	9.42 ↑
Scenario 2: Baseline + Vapes legally available	48.56 ↓	25.08 ↓	19.43 ↑	6.93 ↓
Scenario 3: Baseline + Vapes legally available + Double vape price	50.50	26.82 ↑	13.75 ↓	8.93 ↑
Scenario 4: Baseline + Vapes strictly banned	51.44 ↑	26.16 ↑	14.55 ↓	7.85 ↑
Scenario 5: Baseline + Vapes strictly banned+ Double vape price	53.80 ↑	27.79 ↑	8.61 ↓	9.79 ↑
Baseline Scenario: Cigarettes legal, RYO under-the-counter, vapes under-the-counter, only tobacco flavor for cigarettes and RYO, various flavors for vapes (prices: current average prices for all product options)	50.96	25.77	15.57	7.71

Estimating Willingness to Pay

- Because α_i is the marginal utility of income, WTP for attribute is $\frac{\beta_i}{\alpha}$
- Because β_i is lognormal, with α fixed, WTP is lognormally distributed.
  - Alternative approach (not reported) is to estimate model in WTP space: specify convenient distributions for WTPs
- Note: WTP for an attribute ≠ Compensating Variation
  - Small & Rosen (1981 *Econometrica*) "log-sum" expression for CV weights the utility associated with each alternative by the probability of selecting that alternative
- We assume SP choices are free from behavioral biases and estimate CVs w.r.t. experienced utility.
  - SP quit rate > RP quit rate, possibly reflecting behavioral biases in decision utility

Willingness to Pay Estimates for Illegally Sold and Banned Vapers

	All	Ages 18–30	Ages 31–45	Ages 46–6
Legal status (Base: Legal with Banderole)				
Illegally Sold	-23.31	-18.81	-10.08	-69.19
(illegal retail/ under-the-counter)	**-37%**	**-30%**	**-16%**	**-110%**
Strictly Banned	-31.53	-28.38	-18.03	-109.84
(illegal street)	**-50%**	**-45%**	**-29%**	**-174%**

In each legal status category, the first figure is the WTP estimate in Turkish liras, while the second one shows the estimate as a % of average price of a pack of cigarettes (63 TL/pack) at the time of the survey

Menthol DCE: Predicted Market Shares

Policy Scenario	Menthol Cigs	Menthol-flavored E-cigs	Non-menthol Cigs	Tabacco-flavored E-cigs	Quit Attempt
Status quo					
1. Status quo legality & prices	0.455	0.253	0.065	0.066	0.162
Illegal Retail Market for Menthol Cigs					
6. 50% lower price for illegal products	0.420	0.274	0.077	0.072	0.156
7. No price change	0.330	0.306	0.085	0.082	0.197
8. 50% higher price for illegal products	0.270	0.328	0.093	0.088	0.221
Illegal Street Market for Menthol Cigs					
12. 50% lower price for illegal products	0.372	0.294	0.084	0.078	0.172
13. No price change	0.290	0.322	0.092	0.087	0.210
14. 50% higher price for illegal products	0.236	0.342	0.099	0.093	0.231

Source: Kenkel, et al., (2025). “Understanding the Demand-side of an Illegal Market: The Case of Menthol Cigarettes,” Health Economics.

Re-capping

- DCEs allow researchers to collect data on consumers' stated preferences in realistic market-like situations not yet observed.
  - Experimental design provides strong internal validity
  - Research suggests DCEs for familiar goods purchased in private markets yield reliable predictions, which can be enhanced by calibrating with RP data
- DCEs have and can explore the impact of regulations that:
  - Increase product prices
  - Provide information (or misinformation!) to consumers about product risks
  - Change availability of desirable attributes like flavors
  - Lead to illegal markets for prohibited products