Effect of feedlot images on demand for beef

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1. Introduction and motivation

Travelers of Interstate Highway 5 (I-5) pass a memorable landmark in California's Central Valley- the Harris Ranch feedlot. Located near the intersection of I-5 and California Route 198, it is readily visible from I-5 to motorists. It is also well-known for the pungent smell of thousands of cattle, usually noticeable for several miles.

For city-dwellers and other travelers unfamiliar with feedlots, the sight (and smell) may be shocking. An obvious speculation is that beef consumers may, upon viewing the conditions under which cattle are raised in their final weeks prior to slaughter, exhibit a reduced demand for beef.

2. Summary findings

We conducted a survey with approximately 400 MTurk subjects. We asked questions related to their level of beef consumption, as well as some demographic information. We then randomly assigned them into equally-sized groups, and asked them to view one of three one-minute videos: Control (who were presented with a video showing dams, canals, and agricultural irrigation), "Pastured" (who were presented with a video of cattle grazing in open range conditions), and "Feedlot" (who were presented with a video of cattle confined to a feedlot.) After viewing the videos, subjects answered a question about the video to verify compliance (i.e. that they'd viewed the full one-minute video), then were asked to rank the desirablity of different food types (including a beef item) for their next meal. They were also asked to predict how many servings of beef they would consume in the coming week.

While we anticipated the feedlot video would result in a decrease in demand for beef, we did not find that. However, we unexpectedly did see a significant effect on demand for beef among subject who viewed the pasture video. This effect was an increase among male subjects, but no real effect among female subjects.

3. Methods

3.1 Design

The objective of our study was to determine if viewing a cattle feedlot video causes reduction of consumer demand for beef. Subjects participating in the study were asked to take a survey (descibed in Section 3.3) that randomly showed one of three videos depicting cattle feedlots (treatment), irrigation systems (control), or cattle grazing in open pasture. This last video, originally intended as a "lower dose" treatment of cattle images, would ultimately show the greater effect.

3.2 Subjects

Subjects within the United States were recruited via Amazon Mechanical Turk. Overall, the study enrolled 405 subjects; 396 of whom ultimately passed the attention test, proving they had complied with treatment.

Note that we also translated the survey to Spanish and attempted several pilot tests in Ecuador and Argentina, and attempted a larger study in Mexico. However, MTurk response was so low (approximatly 12 responses in a week) that the hoped-for Spanish language study was abandoned.

3.3 Survey and Outcome Measures

Study participants were asked to take a survey (Copy available at https://berkeley.qualtrics.com/jfe/form/SV_dh8NxRde7ld3DtH). The first part of the survey asks for demographic information that we are interested in as co-variates. These include age, gender, geographical area (rural, suburbs, farm, city), and co-habiting pets. We initially suspected that geographical area is an important covariate to take into consideration because there may be varying levels of beef consumption depending on where the participant is located. For example, someone who lives in a more suburban area where beef may be less expensive might consume more beef at baseline compared to a person living in the city where beef is more expensive. Another possibility is that people who live on farms may have stronger feelings toward treatment of animals and cattle feedlots. Likewise, people who own pets may be more sympathetic to animals and have stronger reactions to animals living in poor conditions like those in the feedlot video.

Similarly, we included a question about pet ownership. While possibly having some correlation with economic status, we primarily viewed this as a proxy for general attitude towards anaimals.

After demographic data was collected (but before treatment, participants were then asked to estimate about how many times in the previous week they ate pork, dairy, eggs, fruit, beef, and vegetables. The purpose of this question is to obtain a baseline consumption level for various food groups. It also serves to identify any potential vegetarians that may be taking part in the study.

Participants were then shown one of three videos at random as control and two levels of treatment. The control video featured scenes agricultural irrigation (https://vimeo.com/263669422/cd376066a1 .) The "Pasture" video featured free-range cattle (https://vimeo.com/263669413/c0512edf5f .) The "Feedlot" Video (https://vimeo.com/263669431/04c7894ee4) featured cattle (in large numbers) confined to feedlots. To ensure compliance to the treatment videos, each video was embedded with digits that would appear and flash at certain time points during the video. Participants were then asked to enter the digits that appeared in the video. To ensure that subjects did not share the digits, each of the three videos was actually produced in two editions (with different digits.) Inspection of the data later indicated no evidence of "digit sharing" between subjects (in the very few cases in which digits were reported incorrectly, they were most commonly blank.)

After viewing the treatment, participants were asked questions about their preference for certain food items. We asked them to estimate how many times in the coming week they would eat a variety of food items. Because this question was identical to the pre-test question about previous week food consumptions, we were concerned about the "anchoring" effect the pre-treatment question might have on subjects. (i.e. the tendency to simply repeat the same answers given on the pre-treatmet questions). To combat this, we added, immediately post treatment, an addtional question in a different question format. We showed subjects images of various food items (hamburger, grilled chicken, eggs, grain, and fruit/vegetables) and asked to rank them by preference for their next meal. Only after this rank-ordering did the final question ask the participants to estimate how many times in the next week they expect to eat pork, dairy, eggs, fruit, beef, and vegetables. This gives two different fundamental analyses to perform and compare: First, to regress next week's anticipated beef consumption against last week's (and other co-variates) usintg OLS linear regression. And second, to use probit ordinal logistic regression to analyze the treatment impact on the ranked desirability of a beef item.

3.4 Randomization

The division of subjects into the three groups (Control, Pasture, and Feedlot) was done using Qualtrics survey flow mechanism. There were actually six videos- two for each group (differing only in the verification digits, as noted above.) Qualtrics survey flow provided the approximately equal random division of subjects between the six videos (and thus the three groups)

3.5 Data pipeline

The basic survey mechanism was Qualtrics. We presented the survey with the "Berkeley" headline removed.

Subject recruitment and payment was handled via Amazon Mechanical Turk. Due to the large numbers of participants (50 in some of our pilots, 400 in our main survey), we wrote Ruby scripts to access MTurk APIs and automatically approve (and in some cases bonus) subjects.

Qulatrics doesn't directly host videos; We tried two approaches: (1) include HTML5 video elements in the qualtrics survey, hosting the video .mp4 files on github.com, and (2) hosting videos on Vimeo. We used the former approach on pilots, and the latter on production. The Vimeo method required less bandwidth, but the github method was, unexpectedly, better at auto scaling videos for phones and tablets.

Due to the complexity of the the survey and reporting mechanisms, we implemented a "Robot" to take our Qualtrics survey. This was implemented using standard webapp QA tools ("Ruby/Watir"). It proved very useful, not only for finding and correcting errors in the survey and qualtrics API; it also enabled us to produce hundreds of responses with known distributions of random treatment effects. (These were based on our pilot results, but the generated data sets were much larger.) This lets us do an informal "End to end" review of the power of our entire data pipeline to identify effects.

Finally, we wrote scripts to pre-process the qualtrics output data. Initially these were command-line scripts which took the qualtrics-exported .csv file. A desire to have web access, and also not to distribute qualtrics API keys, led us to re-implement this as a ruby-on-rails application, hosted by a commercial IaaS provider (Heroku.) After using its web interface to distribute .csv files, it was recognized that REST URLs could be used to provide data directly into R's read.csv function, so the rails server was updated to provide that capability as well.

3.6 Internationalization

The qualtrics survey (and supporting text in Amazon Mechanical Turk) were translated into Spanish. At the time of this writing, data is being gathered in Mexico with the Spanish language version

4 Analysis

We preprocess the data as follows

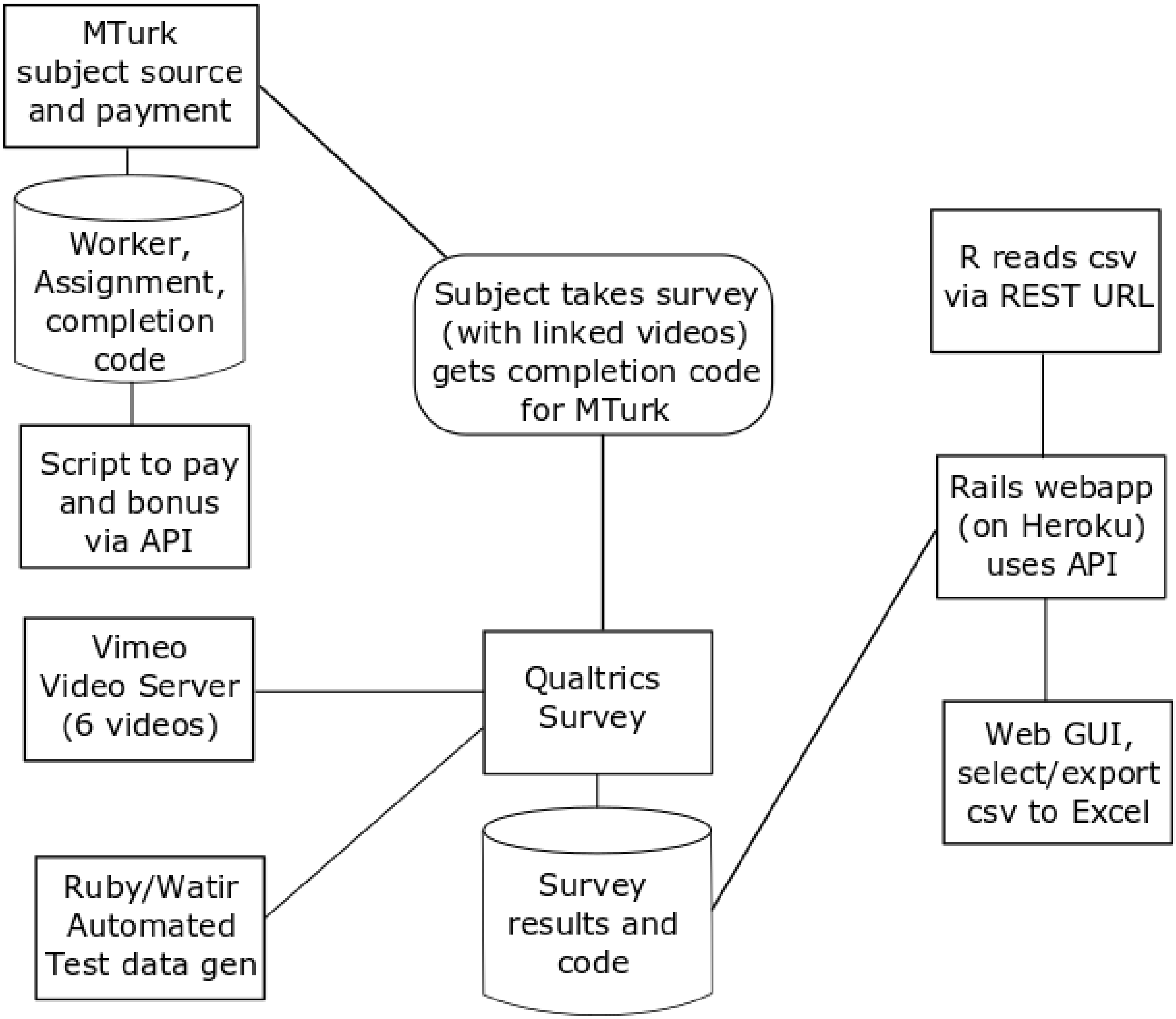


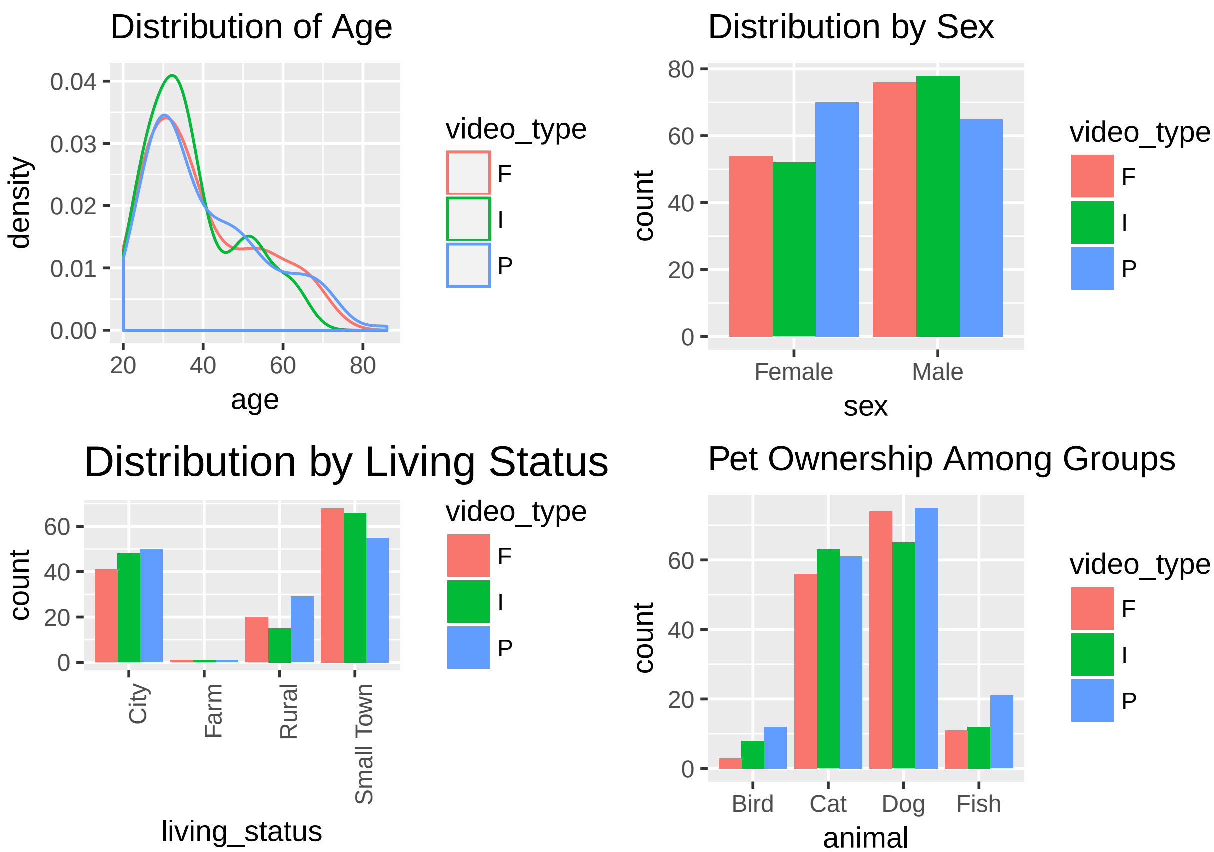
Figure 1: Data pipeline

```r
df = read.csv("https://thawing-shore-85209.herokuapp.com/get_csv/MainRunUS")
#rename some columns
column_names = c("mturkcode", "age", "sex", "living_status", "has_dog", "has_cat", "has_bird", "has_fish",
                 "veg_last_week", "fruit_last_week", "dairy_last_week", "eggs_last_week", "beef_last_week",
                 "pork_last_week", "hamburger_rank", "chicken_rank", "eggs_rank", "grain_rank",
                 "fruit_veg_rank", "veg_next_week", "fruit_next_week", "dairy_next_week", "eggs_next_week",
                 "beef_next_week", "pork_next_week", "video_type", "attention_check")
colnames(df) <- column_names

#Remove anyone failing attention check
df <- df[df$attention_check == "true",]

df <- droplevels(df)


#df$has_dog <- df$has_dog == 'Dog'
#df$has_cat <- df$has_cat == 'Cat'
#df$has_bird <- df$has_bird == 'Bird'
#df$has_fish <- df$has_fish == 'Fish'
df$has_dog <- as.integer(df$has_dog != '')
df$has_cat <- as.integer(df$has_cat != '')
df$has_bird <- as.integer(df$has_bird != '')
df$has_fish <- as.integer(df$has_fish != '')



#column for number of pets
df$num_pets <- df$has_dog + df$has_cat + df$has_bird + df$has_fish


# pre_ is weekly consumption before they watch the video
# post_ is weekly plan for next week
```

4.1 Baseline Characteristics

We plot various baseline characteristics that were collected such as age, sex, living status, and pet ownership.

```
## Using video_type as id variables
```



Examining the plots, there does not appear to be any systematic imbalance between baseline characteristics that would suggest poor randomization. There appears to be more females and fish owners in the pasture group, but it is likely that this observation is due to random variation. To know for sure, we will need to perform some statistical testing.

To test for distribution similarity in age, we cannot use a typical KS test since we have more than two groups. Instead, we perform an Anderson-Darling k-Sample test to assess for similar distributions.

```
age_P <- df$age[df$video_type == "P"]
age_I <- df$age[df$video_type == "I"]
age_F <- df$age[df$video_type == "F"]

ad.test(age_P, age_I, age_F)
```

```
##
##
##  Anderson-Darling k-sample test.
##
## Number of samples:  3
## Sample sizes:  135, 130, 130
## Number of ties: 342
```

```
##
## Mean of  Anderson-Darling  Criterion: 2
## Standard deviation of  Anderson-Darling  Criterion: 1.0702
##
## T.AD = ( Anderson-Darling  Criterion - mean)/sigma
##
## Null Hypothesis: All samples come from a common population.
##
##               AD   T.AD  asympt. P-value
## version 1: 2.319 0.2982          0.2897
## version 2: 2.290 0.2703          0.2983
```

From the test results, there is no significant evidence that suggests the distribution of age are significantly different between treatment groups.

Next, we perform a chi-square test to determine co-variate balance for sex. Based on the output, we find no evidence of significant imbalance.

```
chisq.test(df$sex, df$video_type)
```

```
##
##  Pearson's Chi-squared test
##
## data:  df$sex and df$video_type
## X-squared = 4.4803, df = 2, p-value = 0.1064
```

Next, we check for balance in living status and find no significant imbalance among the treatment groups. Since chi-square may be unreliable due to the low count in the 'farm' category for living status, we also perform a Fisher's exact test which yielded the same conclusion.

```
chisq.test(df$living_status, df$video_type)
```

```
## Warning in chisq.test(df$living_status, df$video_type): Chi-squared
## approximation may be incorrect
```

```
##
##  Pearson's Chi-squared test
##
## data:  df$living_status and df$video_type
## X-squared = 7.0537, df = 6, p-value = 0.3159
```

```
fisher.test(df$living_status, df$video_type, alternative = 'two.sided')
```

```
##
##  Fisher's Exact Test for Count Data
##
## data:  df$living_status and df$video_type
## p-value = 0.2381
## alternative hypothesis: two.sided
```

Finally, we check for balance in pet owners and find no evidence of significant imbalance.

```r
chisq.test(pets_melt$variable, pets_melt$video_type)
```

```
##
##  Pearson's Chi-squared test
##
## data:  pets_melt$variable and pets_melt$video_type
## X-squared = 8.3017, df = 6, p-value = 0.2168
```

Overall, the baseline characteristics were well balanced between each treatment group. We found no evidence that would suggest a significant imbalance or poor randomization.

4.2 Video Effects on Planned Future Beef Consumption

```r
df$sex <-relevel(df$sex, ref = "Male")
df$video_type <-relevel(df$video_type, ref = "I")
df$vegetarian <- (df$beef_last_week == 0) & (df$pork_last_week == 0)
df$standardized_beef_last_week <- scale(df$beef_last_week)
df$standardized_beef_next_week <- scale(df$beef_next_week)

# naive model
mod.naive <- lm(standardized_beef_next_week ~ standardized_beef_last_week + factor(video_type), data = df)

# try a simple regression; set male and Irrigation video as reference levels for those factors
model1 = lm( beef_next_week ~ beef_last_week*vegetarian + factor(sex) + factor(video_type) + factor(sex)*facto

# Now try it with standarized beef scores
model2 = lm( standardized_beef_next_week ~ standardized_beef_last_week*vegetarian + factor(sex) + factor(video

# pets added
mod.pets <- lm(standardized_beef_next_week ~ standardized_beef_last_week + has_dog + factor(video_type) + has_
```

We evaluated three models using our data:

1. A Naive model regressing anticipated beef consumption on only the video type and previous beef consumption.

$$standardized\_beef\_last\_week = \beta_0 + \beta_1 * feedlot + \beta_2 * pasture$$

2. A Covariate model regressing anticipated beef consumption on video type, previous beef consumption, vegetarian status, sex, interactions between vegetarian status and previous beef consumption, and interactions between sex and video type

$$standardized\_beef\_last\_week = \beta_0 + \beta_1 * feedlot + \beta_2 * pasture + \beta_3 * vegetarian + \beta_4 * female$$

$$+\beta_5 * standardized\_beef\_last\_week * vegetarian + \beta_6 * female * feedlot + \beta_7 * female * pasture$$

3. A "With Dog" model regressing anticipated beef consumption on video type, previous beef consumption, dog ownership, and interactions between dog ownership and video type

$$standardized\_beef\_last\_week = \beta_0 + \beta_1 * feedlot + \beta_2 * pasture + \beta_3 * has\_dog + \beta_4 * has\_dog * feedlot + \beta_5 * has\_dog * pasture$$

Beef consumption for the previous week and anticipated beef consumption for the following week were standardized. Results are shown in Table 1.

The Naive model suggests that feedlot videos reduce anticiapted beef consumption by an average of 0.053 standard deviations; however, this does not appear to be significant. As expected, beef consumption in the previous week is highly predictive of anticipated beef consumption.

After controlling for some covariates such as sex and vegetarian status, contrary to our expectation, we did not find that the feedlot video caused a significant increase in demand for beef. Rather, we found that the pasture video caused an **increase** in demand for beef, but only among male subjects.

We see the most interesting results in the model controlling for dog ownership. Among non-dog owners the feedlot video reduced anticipated beef consumption by about 0.203 standard deviations; however, taking dog-ownership into account, this effect is essentially reversed with an increase in anticipated beef consumption by 0.275 standard deviations due to the interaction effect between dog ownership and the feedlot video. One possible explanation for this is that dog owners may have an increased demand for beef in order to provide food for their dogs.

```
labs = c("Naive", "Covariates", "With Dog")
stargazer(mod.naive, model2, mod.pets, type="latex", header=FALSE, no.space=TRUE, column.labels = labs,
          title = "Video Effects on Anticipated Beef Consumption")
```

4.3 Video Effects on Future Food Preferences

We examined the effects of the videos on future food preferences by exploring rank data provided for hamburgers where users ranked their preference for hamburgers as their next meal on a 1-5 scale (lower is better). Table 2 shows the probit ordinal logistic regression of Beef-item (actually a hamburger) desirability rank regressed on the same predictors as above. We see a corroboration of the results. Pasture video decreases rank [i.e. increases desirablity] for Males viewing the pasture video. In this regression we did not, however achieve statistical significance. An *ad hoc* resampling experiment (e.g. doubling or tripling out data) suggests we'd need about 1,000 subjects - rather than our 400 - to achieve statistical significance.

```
df$hamburger_rank_as_factor = factor(df$hamburger_rank, ordered=TRUE)
levels(df$hamburger_rank_as_factor) = levels=c("Hamburger most preferred", "Hamburger second choice", "Hamburg


#Let's do some more releveling, for consistency with the rest of the paper
df$sex <-relevel(df$sex, ref = "Male")
df$video_type <-relevel(df$video_type, ref = "I")
df$vegetarian <- (df$beef_last_week == 0) & (df$pork_last_week == 0)

#double data
df_double = rbind(df, df)
```

Table 1: Video Effects on Anticipated Beef Consumption

	Dependent variable:		
	standardized_beef_next_week		
	Naive	Covariates	With Dog
	(1)	(2)	(3)
standardized_beef_last_week	0.844***	0.833***	0.845***
	(0.027)	(0.030)	(0.027)
vegetarian		−0.003	
		(0.090)	
factor(sex)Female		−0.065	
		(0.095)	
has_dog			−0.098
			(0.094)
factor(video_type)F	−0.053	−0.011	−0.203**
	(0.067)	(0.086)	(0.098)
factor(video_type)P	0.061	0.178**	−0.039
	(0.066)	(0.089)	(0.096)
standardized_beef_last_week:vegetarian			
factor(sex)Female:factor(video_type)F		−0.098	
		(0.134)	
factor(sex)Female:factor(video_type)P		−0.211	
		(0.132)	
has_dog:factor(video_type)F			0.275**
			(0.133)
has_dog:factor(video_type)P			0.189
			(0.132)
Constant	−0.003	0.023	0.045
	(0.047)	(0.061)	(0.066)
Observations	395	395	395
R^2	0.714	0.723	0.718
Adjusted R^2	0.712	0.718	0.714
Residual Std. Error	0.536 (df = 391)	0.531 (df = 387)	0.535 (df = 388)
F Statistic	326.087*** (df = 3; 391)	144.520*** (df = 7; 387)	165.049*** (df = 6; 388)
Note:			*p<0.1; **p<0.05; ***p<0.01

```r
#triple data
df_triple = rbind(df, df, df)

#Try with standardized beef (makes more in the case of rank, since we're not comparing actual quantity beef la
df$standardized_beef_last_week <- scale(df$beef_last_week)
mk2 = polr(hamburger_rank_as_factor ~ beef_last_week*vegetarian + sex*video_type, method="logistic", data=df,
```

```
## Warning in polr(hamburger_rank_as_factor ~ beef_last_week * vegetarian + :
## design appears to be rank-deficient, so dropping some coefs
```

```r
#double data
mk_double = polr(hamburger_rank_as_factor ~ beef_last_week*vegetarian + sex*video_type, method="logistic", dat
```

```
## Warning in polr(hamburger_rank_as_factor ~ beef_last_week * vegetarian + :
## design appears to be rank-deficient, so dropping some coefs
```

```r
#triple data
mk_triple = polr(hamburger_rank_as_factor ~ beef_last_week*vegetarian + sex*video_type, method="logistic", dat
```

```
## Warning in polr(hamburger_rank_as_factor ~ beef_last_week * vegetarian + :
## design appears to be rank-deficient, so dropping some coefs
```

```r
#coeftest(mk2)
```

```r
labs2 = c("Normal", "Double", "Triple")
stargazer(mk2, mk_double, mk_triple, type="latex", header=FALSE, no.space=FALSE, column.labels = labs2,
          title = "Video Effects on Hamburger Ranking")
```

5. Conclusions and Directions for Further Investigations

Contrary to expectations, the feedlot video didn't have statistically significant effect in reducing demand for beef. To the contrary, the pasture video showed an increased demand. We also saw a curious effect from dog ownership, which might suggest further study. Another interesting question for future research is whether video effects persist. Since we only measured demand for beef right after the video, there is a possibility that any effect that the videos might have had disappear in a relatively short time frame.

6. Appendix: Notes on mehods

6.1 Qualtrics

We used qualtrics for presenting our survey (with videos hosted initially on github, ultimamtely on vimeo, as Qualtrics does not support direct hosting of videos.) In additon to our survey and treatment items, we used qualtrics to generate a random code for each subject, which the subject later entered into Amazon Mechanical Turk for completion verification.

One of our team members [AB] translated one of our pilot surveys and our final survey into Spanish.

Table 2: Video Effects on Hamburger Ranking

	Dependent variable:		
	hamburger_rank_as_factor		
	Normal	Double	Triple
	(1)	(2)	(3)
beef_last_week	-0.366^{***}	-0.366^{***}	-0.366^{***}
	(0.060)	(0.042)	(0.034)
vegetarian	1.265^{***}	1.265^{***}	1.265^{***}
	(0.351)	(0.248)	(0.203)
sexFemale	0.698^{**}	0.698^{***}	0.698^{***}
	(0.334)	(0.236)	(0.193)
video_typeF	0.043	0.043	0.043
	(0.301)	(0.213)	(0.174)
video_typeP	-0.394	-0.394^{*}	-0.394^{**}
	(0.318)	(0.225)	(0.184)
sexFemale:video_typeF	0.065	0.064	0.065
	(0.477)	(0.337)	(0.275)
sexFemale:video_typeP	0.342	0.342	0.342
	(0.468)	(0.331)	(0.270)
Observations	395	790	1,185
Note:	*p<0.1; **p<0.05; ***p<0.01		

6.2 Amazon Mechanical Turk

We used Amazon Mechanical Turk to source (and reward) our subjects. We did a series of pilots in Canada (to avoid contaminating our eventual US-pool of workers with our pilot surveys.)

6.3 Production of Treatment and Control Videos

These videos were shot on three separate feeld trips to California's central valley or coast (South of Half Moon Bay) on February 17, 24, and March 3, 2018. A Nikon 5300 and several Cannon ELPH-series cameras were used.

Sound was was collected onsite during video shoots, with some animal sounds collected from public domain web sources, such as:

https://home.nps.gov/yell/learn/photosmultimedia/soundlibrary.htm

Some sounds were self-produced by one team member.

Sound was edited and mixed using the Audacity tool.

Videos were stabilized, edited and rendered using the KDENLive tool.

Inkscape was used to draw the flashing digit overlays used to assess subject attention to the video.

Video hosting: After trying to host .mp4 and .webm files on both the vimeo streaming service and on github, the ultimate decision was to use vimeo for greater assurance that different browsers could view them. (Note, however, that github hosting of the videos gave a better auto-scaling for phones and tablets. Our pilots showed us that our mturk workers were all using laptop/desktop, so that advantage was moot. This file lists the URLs of the 6 final videos. File names are encoded: Initial F for feedlot, I for irrigation (control), and P for pasture video. Second and third letters in the file name encode the "attention-digits" flashed during the video.

6.4 Support Scripts

Files:

generate_digits_for_qualtrics_drill_down.rb This generates a 1000-line long set of exhaustive combinations of values for the qualtrics survey drill-down used after each video to ask subjects to record up to three digits seen during the video. (For attention verification)

drill_down.csv The file produced by the ruby script above

key.csv A sample output file for the "payoff.rb" script, giving more detail on the meaning of each column of the output.

payoff.rb Script to pull the results of a selected survey over from qualtrics, and do some pre-processing, deleting extraneous columns and calculating a few columns (e.g. checking for proper response on the attention-digits drill-down). It also connects to mturk API to approve HIT assignments if attention-digits are correct.

response_generator.rb A Ruby/Watir web QA script. This is a robot to run an arbitrary number of simulated users taking the survey. It takes about 20 sec. per survey (but multiple copies may be run in parallel). Ruby/Watir is built on top of the Selenium infrastructure and drives chrome/chromium browsers.

robot_small.mp4 A short demo of a preliminary version of response_generator running

5.5 Web application

We wrote a ruby-on-rails web applcation to serve the results of our various experimental runs. (https://thawing-shore-85209.herokuapp.com). This had a simple GUI to permit real-time access of qualtrics APIs to create and download data in CSV format. (Rather than use Qualtircs gui-based csv downloader.)

The rails application permitted helpful pre-processing of the csv file. It also permitted real time monitoring of the jobs status without needing to reveal qualtrics API keys.

Finally, a REST/API was added, which permitted us to use read.csv("URL") in our analytic scripts, which eliminated the need to transfer around .csv data files to team members. (example: our main run data: https://thawing-shore-85209.herokuapp.com/get_csv/MainRunUS)

6.6 Pilots and data runs

Pilot 1: 10 subjects, two batches of 5

Verified Qualtrics/Mturk, batch "private" visibility, "Canada" qualification

Pilot 2: 50 subjects, one batch

Video served from github Tried "Raffle of gift cards" mechanism; failed (c5 bidders total) "Robot user" test (on qualtrics; bypassed Mturk) 400 simulated subjects, with simulated treatment effect Run with ruby/watir web robot software QA tool Corrected issues with survey, scripts, verified "Power" of tool chain

Pilot 3: 20 subjects, one batch

Validate final version of survey; video served from Vimeo

Main Run/US:

Final version of survey; shortened videos to 1 min; new attention test 400 responses in c30 min.; Review and export results with web tool

Pilots in Ecuador, Argentina

Both Abandoned Spanish translation of final version of survey No responses in either

Attempted run in Mexico

Few responses (only 11), sme in English, some in Spanish Unlikely to provide enough data for analysis