Do Women Receive Slower Responses to Emails Than Men?

Chris Fleisch, Rob Foster, Todd Young

2017-December-18

Abstract

We conducted a email correspondence experiment to determine the extent to which response times differed based on whether the sender was male or female. Emails requesting additional information were sent to advertisers of commercial real estate and business services on Craigslist in eighty cities across the United States. Responses were collected and analyzed. We hypothesised that response times to emails sent by females would be slower than for emails sent by males. We did find that there was a very small difference, but in our experiment females received quicker responses. However, not all of our models show results that were practically or statistically significant.

Background

Recently, many news articles have been written about the different experiences men and women have in the workplace. One article, about a company run by two women, received a lot of attention and was featured on the NPR radio show *Wait Wait… Don't Tell Me*.[1] The two company founders created a startup featuring an online marketplace for eclectic art. As these women founders were trying to recruit outside developers and designers for their website, they noticed people were often very slow to respond to emails with some taking days to respond. The email responses were also sometimes condescending and disrespectful. That's when the two founders introduced a new made-up male cofounder "Keith Mann". As soon as Keith started sending emails, he was getting faster responses, addressed by his name, and was often asked if he needed anything else.

In another story, a man and a woman shared an inbox at work and the woman received slower responses to emails from clients.[2,3] The male coworker emailed a client from the shared inbox

---

1 https://www.fastcompany.com/40456604/these-women-entrepreneurs-created-a-fake-male-cofounder-to-dodge-startup-sexism

2 https://twitter.com/i/moments/839950218099576832

and observed the client was rude and ignored questions. He noticed he had been signing his emails using the woman's signature and not his own. When he switched back to using his own name, there was an immediate turnaround in the rude behavior of the client. The client started responding faster and transformed from a difficult client to a great one. Despite being the same person the whole time, the conversation changed when the email signature switched from a female's name to a male's name.

These two examples led us to the question: Do women receive slower responses to emails than men? Receiving slower responses just because of their sex would make for an unfair working environment that puts women at a disadvantage. In the second example, a woman would have had to deal with difficult clients on a daily basis, causing her to get less work done or take longer to deal with the same number of clients as the man. In the women's startup, they needed to get their site up and running as fast as possible. In the world of startups any delay could cost them a lot of business. These two examples received media attention and seemed an interesting topic to research. Were these two examples a symptom of a larger widespread problem? To find out we ran an experiment.

Hypothesis

Based on these anecdotes, we hypothesised that response times would be slower for emails sent from a female than from a male.

Experimental Design

Using Craigslist

Our focus was on workplace discrimination, and we needed to send emails to many businesses. In order get enough different businesses to email, we targeted ads posted on Craigslist. However, as you can see below in Figure 1, Craigslist ads span an enormous variety of products and services.

We expected heterogeneous treatment effects across product and service categories within Craigslist. For example, the motorcycles category might appeal more to men and the jewelry category might appeal more to women. We decided to focus on categories for which we did not anticipate a large category-specific difference in whether males or females would commonly be the target customer. The two categories within Craigslist that we targeted were Housing (Office & Commercial) and Services.

[3] https://medium.com/@nickyknacks/working-while-female-59a5de3ad266

Figure 1 - Craiglist Categories and Subcategories

Choosing Names

The choice of “Jessica” was the treatment and the choice of “Michael” was the control. We chose these names because of their popularity as first names for females and males, respectively, in the United States.[4,5] We used first names that were popular in the 1990s. We also chose Taylor, a popular surname in the US.

[4] Most common first names: https://www.ssa.gov/OACT/babynames/decades/names1990s.html
[5] Most common surnames: https://names.mongabay.com/most_common_surnames.htm

Email Accounts
Emails were sent from accounts with names based on the names ‘Jessica Taylor’ and ‘Michael Taylor’. Specifically, the we used the following email accounts for sending email requests:

michael.mikey.taylor@gmail.com
michaeltaylor200000@gmail.com
michael.cf.taylor@gmail.com

jessica.jt.taylor@gmail.com
jessicataylor100000@gmail.com
jessica.cf.taylor@gmail.com

We used separate email accounts to make the authors’ concurrent work more manageable. Note that these email account names were generally invisible to the subjects, because of the email anonymizer of Craigslist.

Each author was responsible for a Michael and a Jessica email account. The country was divided up into the West, Central, and East sections where each author targeted their ads. This was done to prevent the authors from responding to the same ads.

Email Message
Each ad would receive the following email and subject:

```
Subject: More info

Message:
Hi,
I am interested in [INSERT SERVICE/PRODUCT]. Would you please send me more
information?

Thank you,
[Michael/Jessica] Taylor
```

Interference Challenges
To assess the causal effect of our treatment (male/female) on the outcome (response time to an email), it was critical that we try to manage interference between subjects, and that we effectively randomly assign treatment. Managing interference was a challenge, and we had several cases of interference.

Many ads on Craigslist are duplicate posts. Posters post many copies of the same ad to increase the chances that their ad will be clicked. When choosing target ads, we were tried to avoid sending more than one email to these duplicate posts. We also saw many instances of large real estate companies that had posted ads for multiple properties or services across different cities, and we attempted to avoid these as well to manage interference. We chose to target cities with substantial populations that would support many active ads on craigslist. For example, in Orange County, CA on December 3, 2017, there were 607 ads for office space with a monthly rental rate between $600 and $900. On the same date, there were only 60 such ads in Boise, Idaho, and only 3 in Billings, Montana. For this reason, our choice of subjects was necessarily a function of the robustness of the market for office space and services in the cities.

We chose ads across a wide range of price points when pricing information was available in the post. Pricing information was mostly available for office space, but far less common for services. We also avoided ads that were clearly directed towards one sex or another. For example, in the *Services* category, ads for women's hairdresser were not considered.

Anonymization

Craigslist allows the ad poster to conduct anonymous correspondence with interested parties. Posters can choose to use this anonymous email address for responses or to use their own. Most posters use anonymous contact information, and we attempted to avoid using others. By posting to the craigslist-anonymized email address, we also took advantage of the anonymization to hide our own email address. Note that even when our email address was exposed, those addresses were from gmail accounts for Michael and Jessica, not the author's email accounts. This provided some reduction in risk of interference itself. In the pilot and experiment, we have a few instances of emailing directly to the ad poster, thus exposing our fake email accounts. In our analysis, we coded all emails with a binary indicator variable representing the anonymous status of the poster. We modified out python script to process these emails correctly.

Randomization

The service or product name was inserted into the email, and the sender name (Michael or Jessica) was randomly assigned. Emails were sent in groups to minimize any time-of-day or day-of-week effects between treatment and control. We sent the *Jessica* and *Michael* emails within seconds of each other. Ads from *Services* or *Housing/Office & Commercial* were selected for assignment to *Jessica* or *Michael* based on the R script:

```
sample(c('Michael','Jessica'), size=2)
```

Or if a larger group was selected (this example for a group of 10 emails):

```
sample_list <- rep(0, 5)
sample_list <- append(sample_list, rep(1,5))
rand_sample <- sample(sample_list, 10)
rand_sample                           # prints out 0 for Michael or 1 for Jessica
```

The Pilot Study

A pilot study was conducted from November 2nd to November 9th. We sent out 185 emails across 33 different cities and received 105 responses, a 56.8% response rate as shown below in Table 1.

Total Observations in Table: 185

df_pilot$replied	df_pilot$female 0	1	Row Total
0	38	42	80
	0.409	0.457	0.432
1	55	50	105
	0.591	0.543	0.568
Column Total	93	92	185
	0.503	0.497	

Table 1 - Pilot Emails and Responses

The pilot was conducted to validate our method of sending out emails and collecting the data, and to work out any problems. During the pilot phase, the process of sending emails was rather laborious. In order to reveal the contact information for an ad, the experimenter had to solve a captcha puzzle to prove he was human. While not terribly difficult, it did slow us down.

For each email sent, we recorded the city, category, subcategory, price using the ‘label’ functionality built into Gmail. After sending email responses, we waited for replies until 11:00 AM on November 10th, and then we used a Gmail API-based python script to process the messages in the inboxes. The script generated the following fields and stored the data into a CSV file for each of the six email accounts:

1. Name (of sender)
2. To (Craigslist email)
3. From (Our gmail account)
4. Category
5. Subcategory
6. Reply Message (if existed)

7. Female ([0, 1] indicator)
8. Sent Message
9. Subject
10. Replied at (timestamp if existed)
11. Replied ([0, 1] indicator)
12. Sent at (timestamp)
13. Response time (calculated number of minutes from response time - sent time if exists)
14. Price
15. City
16. Pilot ([0, 1] indicator)
17. Anon_email ([0,1] indicating whether the sender's address was anonymous.

The pilot data from the six accounts were combined and analyzed in R.

Pilot Data Analysis

Survival Model and the Log-Rank Test

Response data is inherently incomplete as there is a high likelihood that some messages will not receive a response during the experiment. We only know the response time for messages that receive a response. For no-response messages, we do not know that there will never be a response - only that there has not been one yet. Data from processes like these, including mortality and fertility studies, are commonly analyzed using survival analysis. We used survival analysis to examine the expected duration of time until our outcome event occurred - until we got a response email.

The log-rank test is a test of the difference in Survival distributions for two samples. Using this test, we could determine whether there was a statistically different response time for Jessica and Michael.

Right-Censored Data

As we could not wait forever for all the email responses that might come, we had to end our experiment and accept that we would not get conclusive data for some subjects. For subjects who had not replied by the end of the experiment, the only data we had was that they had not yet replied. This type of data, in which samples have values up to a maximum value but not greater are called *right-censored data*. There is information in right-censored data, and the no-replies should not be considered to be never-replies, or NA values.

In Survival Analysis, it is common to assigned outcome values for these subjects. We assigned a *Replied at* time of the last day of the study for no-reply messages. For the Pilot, this time was: November 10, 2017 at 11:00 AM Eastern Time. (For the Experiment, the time was December 10, 2017 at 11:00 AM Eastern.)

Results
The survival curves for response time show a small difference in response times for male and female. The pilot results are shown below in Figure 2.

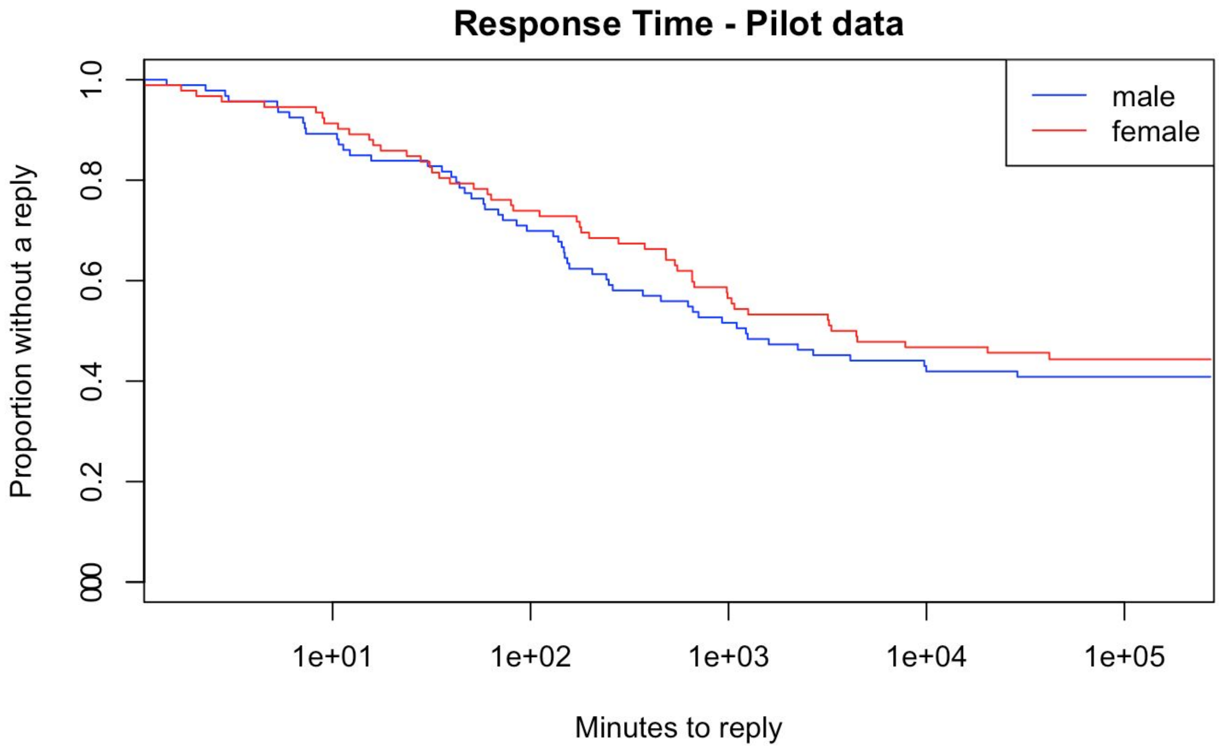

Figure 2 - Response Time Survival Curves for the Pilot Data

Using the survdiff function, we found that there was not a statistically significant difference between the two response times at the 5% level:

```
Call:
survdiff(formula = m.pilot.surv ~ df_pilot$female)
                   N Observed Expected (O-E)^2/E (O-E)^2/V
df_pilot$female=0 93       55     51.6     0.228     0.444
df_pilot$female=1 92       51     54.4     0.216     0.444

 Chisq= 0.4  on 1 degrees of freedom, p= 0.505
```

Table 2 - Pilot Difference in Response Times

To determine how many emails we would have to send to get to statistical significance given the pilot data, we duplicated the data until we attained statistical significance, and we determined that we needed to target a total of 800 emails for the full experiment.

Two problem areas were discovered in the pilot. The first being the aforementioned direct email versus the anonymized Craigslist email (e.g. sending to a company or individual's email like joe_smith@gmail.com). In the pilot, the non-anonymous direct emails ($n < 10$) received a 100% response rate. Therefore to not skew the experiment, we decided to only send to ads that showed an anonymized email.

The second problem was interference. With over 800 emails needing to be sent, the chance of an interference between treatment and control or double treatment / double control were higher. In the pilot, two interference emails were received even with our best attempts to not send to the same advertisers. One response was a unit that received a spillover of both a treatment and control email. The other was one that received two treatments. Both were from cities/ advertisements that were not previously emailed, but in the Office/Commercial category. This led us to believe that some national companies were advertising in different cities and even though the names, phone numbers and emails were different, these were collected and responded to from a central national office. These were the only interference responses received, but that does not mean more cases of interference did not occur. If receiving two emails from the same person, a typical response might be to only reply once and ignore the second or to ignore both.

The Experiment

Experimental Design

The things we learned in the pilot did not change the overall experimental design so we decided to use the pilot data in combination with the data from the full experiment. Our goal then was to send a total of 800 emails, leaving about 600 for the experiment. We sent emails from November 27th to December 4th to ads on Craigslist. During this time period, Craigslist no longer required the captcha puzzles in order to get the email address from the ads. This allowed us to send out more emails at a faster rate which ultimately helped us to reach our goal. Including the pilot data and this new data we were able to send a total of 810 emails. Response rates were over 50% for both the male and female senders as seen below in Table 3.

During the experiment two problems occured. First, another case of interference with dual treatment was observed. We decided to leave in all three known interference replies. Second, an auto-reply response email was received within a few seconds of our ad response. Appendix A shows the auto-reply message and an example of interference. A couple of other emails were received in less than five minutes, but it was difficult to ascertain whether they were auto-replies or just fast replies. We decided to exclude only the email that received the known auto-reply, leaving us with 809 emails for analysis.

```
Total Observations in Table:  809
             | df$female
  df$replied |         0 |         1 | Row Total |
-------------|-----------|-----------|-----------|
           0 |       196 |       167 |       363 |
             |     0.484 |     0.413 |     0.449 |
-------------|-----------|-----------|-----------|
           1 |       209 |       237 |       446 |
             |     0.516 |     0.587 |     0.551 |
-------------|-----------|-----------|-----------|
Column Total |       405 |       404 |       809 |
             |     0.501 |     0.499 |           |
-------------|-----------|-----------|-----------|
```

Table 3 - Full Experiment Emails and Responses

Data Collection / Censoring

The data were collected using the python script through the Gmail API and imported into R for analysis. For the pilot data used November 10 11:00 AM Eastern; for the experiment, we used December 10th 11:00 AM Eastern.

Subjects by Category

Approximately 61% of the emails were sent to the housing category and the rest were sent to the services category. In total, we sent emails to 80 different cities across the United States.

```
             | df$female
 df$category |         0 |         1 | Row Total |
-------------|-----------|-----------|-----------|
     housing |       249 |       248 |       497 |
             |     0.615 |     0.614 |     0.614 |
-------------|-----------|-----------|-----------|
    services |       156 |       156 |       312 |
             |     0.385 |     0.386 |     0.386 |
-------------|-----------|-----------|-----------|
Column Total |       405 |       405 |       809 |
             |     0.501 |     0.499 |           |
-------------|-----------|-----------|-----------|
```

Table 4 - Experiment Categorical Breakdown

Randomization Checks - Covariate Balance

To assess the validity of our random assignment, we conducted covariate balance checks on variables that should be randomly assigned: subcategory, price. Both of these checks show that randomization was effective and that the results were not drastically skewed in one direction. The results of this analysis is shown in Table 5 and Figures 3 & 4, below:

	Automotive	Beauty	Cell phone	Computer	Creative	Event
Michael	3	2	2	9	1	1
Jessica	8	0	1	4	7	0
	Farm/Garden	Financial	Household	Labor/hauling /moving	Legal	Lessons & Tutoring
Michael	10	4	63	21	0	6
Jessica	10	5	48	24	1	5
	Pet	Real Estate	Skilled Trade	Small Biz	Writing/editing / translation	(Other)
Michael	2	1	24	1	2	4
Jessica	5	1	33	3	0	1

Table 5 - Services Subcategory Breakdown

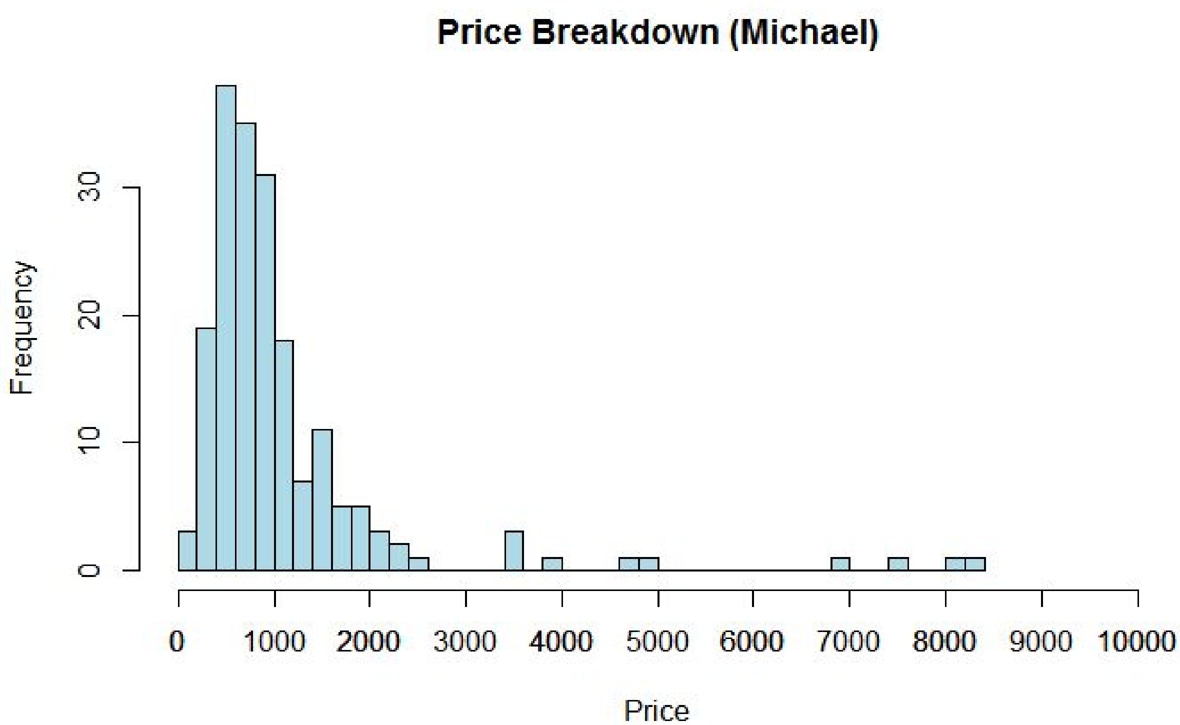

Figure 3 - Price Breakdown for Michael

Figure 4 - Price Breakdown for Jessica

Experimental Results

Response Rate
As viewed in Table 3 (above), we sent a total of 810 emails and received 446 responses, for a total response rate of 55.1 percent. The male response rate was 51.6 percent with the female response rate higher at 58.5 percent.

Response Times
Response times for Jessica, Michael, and the two combined have similar distributions (see Figures 5-7, below). Note: the actual data used in the survival analysis include the right-censored no-replies to the end of the experiment window.

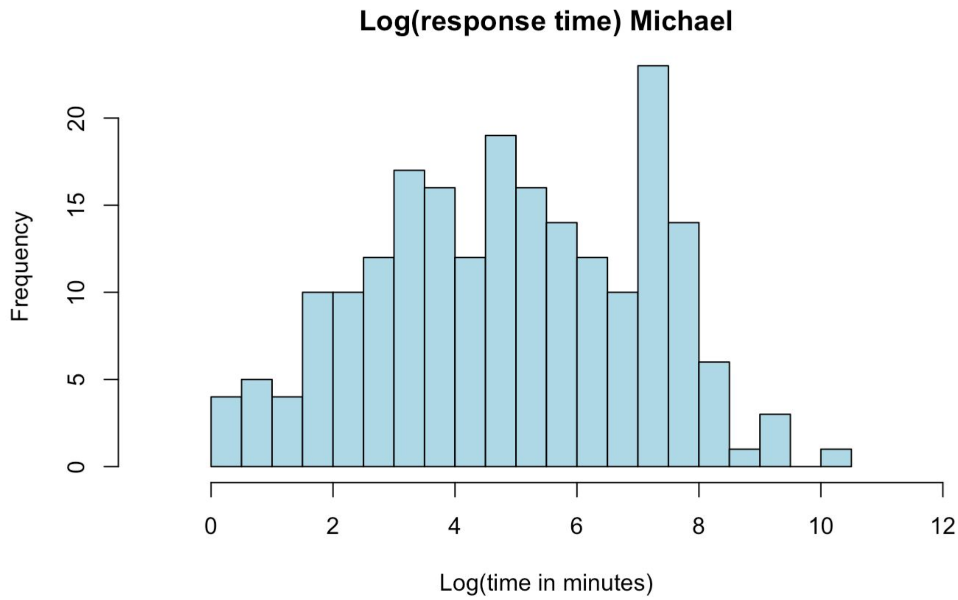

Figure 5 - Response Times for Michael

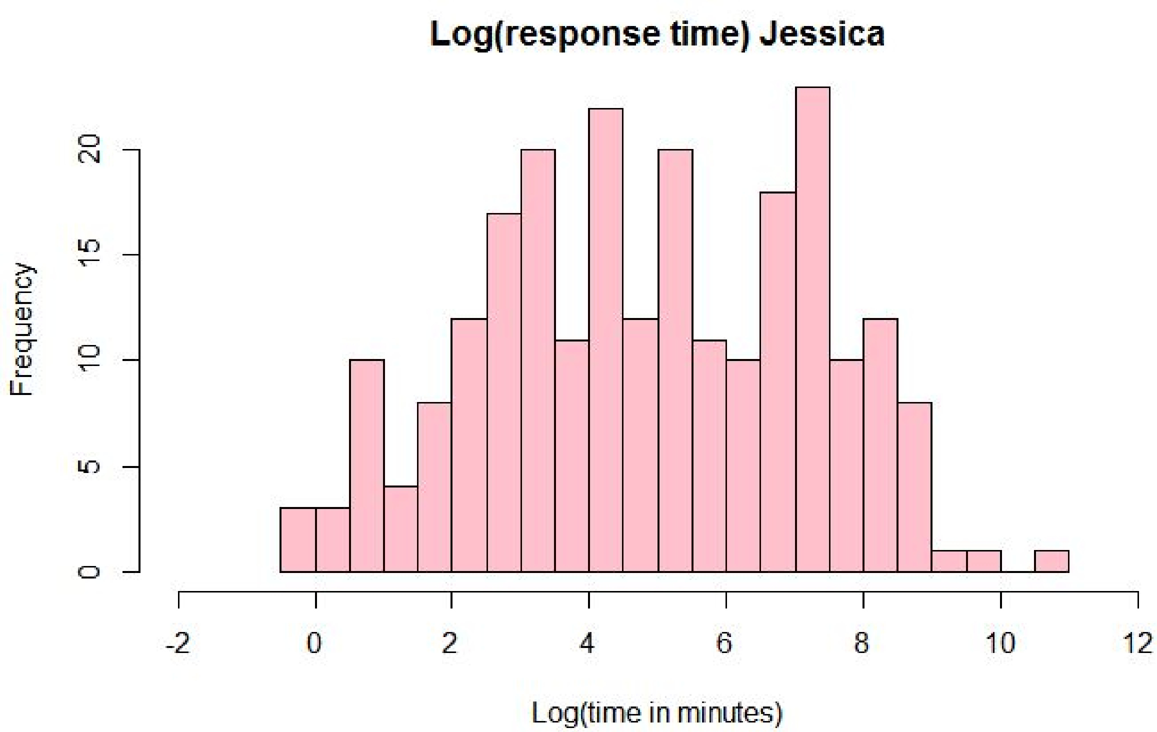

Figure 6 - Response Times for Jessica

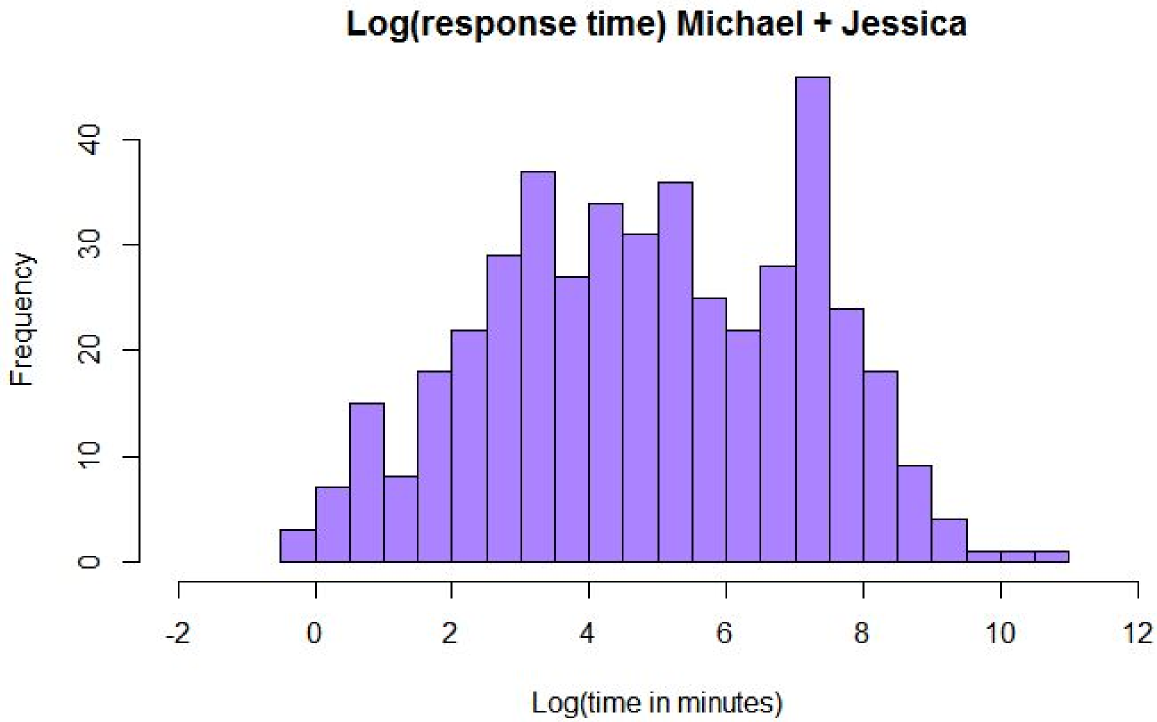

Figure 7 - Response Times for Michael + Jessica

We did not find a significant difference in response time between the male and female emails that we sent out. Using the log-rank survival test with all of our data we see the difference is not statistically significant at the 5% level (p=0.056)

```
Call:

survdiff(formula = m.all.surv ~ df$female)

              N Observed Expected (O-E)^2/E (O-E)^2/V
df$female=0 405      209      229      1.77      3.65
df$female=1 404      237      217      1.88      3.65

Chisq= 3.7  on 1 degrees of freedom, p= 0.056
```

Table 6 - Full Experiment Difference in Response Times

Survival Curves
The response time survival curve (see Figure 8) shows that the female receives more and quicker responses than males. *This is the opposite of what we found in the pilot!*

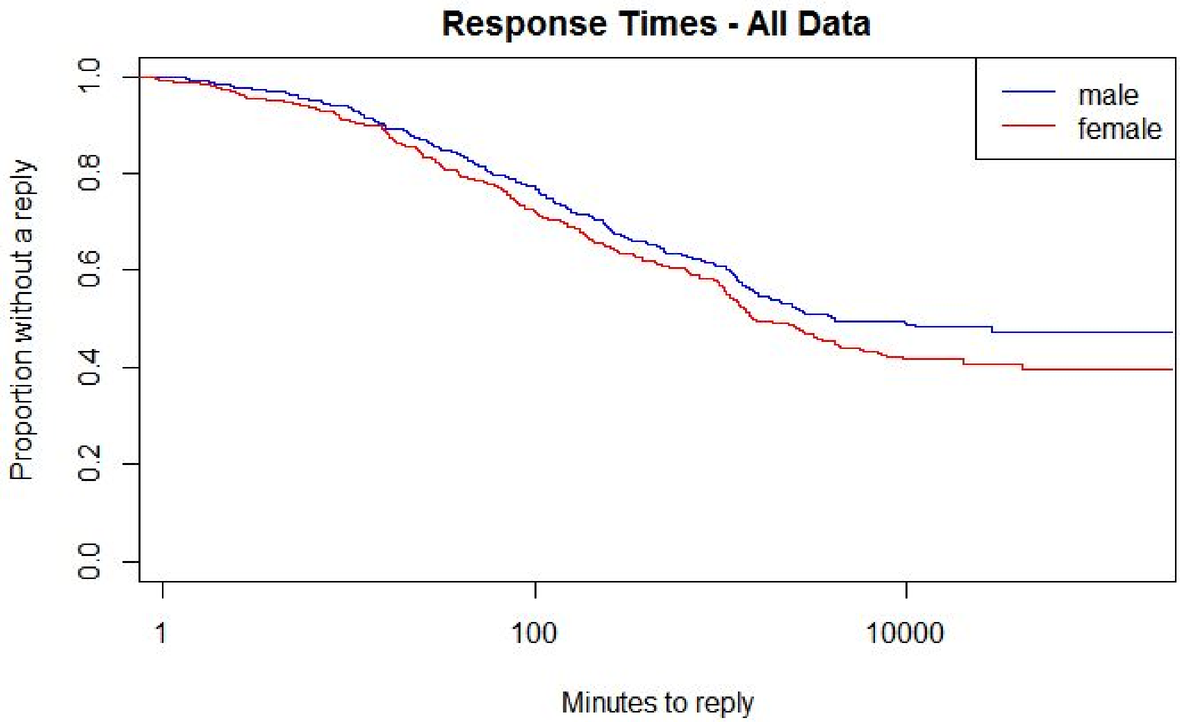

Figure 8 - Full Experiment Response Times

Hypothesis Testing
Our hypothesis was that Jessica would receive replies to emails at a slower rate than the Michael. The results, while not statistically significant at $p < 0.05$, show the opposite.

Average Treatment Effect for Response Time
We also use a survival regression parametric (accelerated failure time) model using a lognormal distribution. This allows us to estimate a logarithm of the ratio of response times. In this case we're interested in if the estimate is positive indicating a slower response time or negative showing a faster response time. The partial results for the model are below in Table 7 below.

Survival regression (lognormal dist))

	Dependent variable:				
	m.all.surv				
	(1)	(2)	(3)	(4)	(5)
female	-0.664*	-0.671*	-0.667*	-0.743*	-0.750**
	(0.381)	(0.381)	(0.381)	(0.382)	(0.361)
anon_email	3.481*	3.115	3.203	3.180	3.667*
	(2.074)	(2.070)	(2.078)	(2.054)	(2.018)
pilot	0.440	0.631	0.715	0.710	0.555
	(0.453)	(0.455)	(0.493)	(0.493)	(0.861)
categoryservices		1.286***	1.358**	-0.870	-1.527
		(0.402)	(0.635)	(2.350)	(2.242)
price_factorlow			0.623	0.617	0.214
			(0.566)	(0.559)	(0.600)
price_factorno_price			0.306	0.302	0.313
			(0.691)	(0.684)	(0.815)

Table 7 - Average Treatment Effect for Response Time

This table is truncated, the full table is available in final_exp.Rmd

Column (1) regresses female onto the response time survival object. We get a negative estimate indicating that female treatment was responded to faster than male treatment. Column (2) adds in fixed effects for the category. Column (3) adds in fixed effects for high (>=$1000), low (<$1000), or no price. Column (4) adds in fixed effects for subcategory and column (5) adds in fixed effects for city. As we add in the fixed effects our estimate for female becomes significant using this model at the p<.05 level. Using this model we can estimate the effect of being female on response time has a negative effect meaning that response times are lower for the female.

Randomization Inference for Response Time

We used randomization inference to check our result against the sharp null hypothesis that there is no difference between treatment and control. In Figure 9, below, the actual average treatment effect (the red line) is a negative value indicating that female got quicker response from male (minus number of minutes) not at a significant level of p = 0.05493.

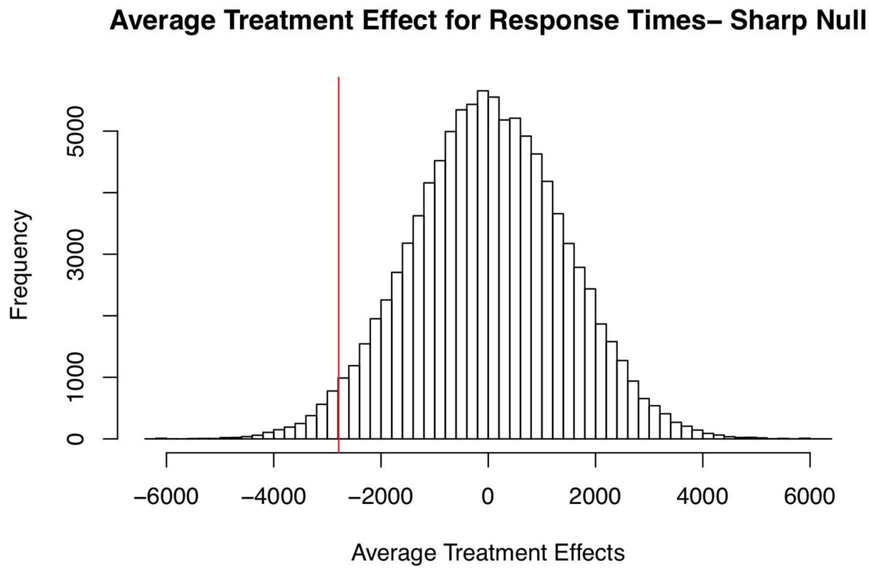

Figure 9 - Average Treatment Effect for Response Time

Average Treatment Effect for Response/No-Response

We also looked to see see if the number of responses was different between a male and female (Table 8). Using a regression model we estimate that the female name received 8% more responses than the male name and it was statistically significant at the p<.05 level. Note this is the vertical distance between the rightmost values of the survival curves shown in Figure 8.

	Dependent variable:				
	replied				
	(1)	(2)	(3)	(4)	(5)
female	0.071**	0.071**	0.071**	0.079**	0.080**
	(0.035)	(0.034)	(0.034)	(0.035)	(0.035)
anon_email	-0.442***	-0.391***	-0.392***	-0.394***	-0.421***
	(0.034)	(0.036)	(0.039)	(0.040)	(0.083)
pilot	0.017	-0.010	-0.023	-0.029	-0.070
	(0.042)	(0.042)	(0.045)	(0.046)	(0.088)
categoryservices		-0.174***	-0.198***	0.176	0.174
		(0.036)	(0.058)	(0.187)	(0.223)
price_factorlow			-0.055	-0.056	-0.035
			(0.052)	(0.052)	(0.059)
price_factorno_price			-0.006	-0.003	0.002
			(0.063)	(0.064)	(0.082)

Table 8 - Average Treatment Effect for Response/No-Response

This table is truncated, the full table is available in final_exp.Rmd

Column (1) regresses female onto the replied indicator. We get an estimate of 0.071 or about 7.1% more replies for female. We also control for the pilot data and the anonymous emails. The pilot fixed effect has no significance, but the anonymous emails show a significant decrease in responses and are highly significant. However, we only had 6 non-anonymous emails in our data. Column (2) adds in fixed effects for the category. Column (3) adds in fixed effects for price: high (>=$1000), low (<$1000), or no price. Column (4) adds in fixed effects for subcategory and column (5) adds in fixed effects for city. As we add in the fixed effects our estimate for female increases slightly to 8.0% at the $p < .05$ level. In our data we saw that the female name received 25 more responses while sending out 405 emails. We do not see this effect having much practical use either since we do not anticipate anyone sending out hundreds of emails like we did in a short amount of time. However, over time people do send out thousands of emails and this may have more of an effect over longer periods.

Randomization Inference for Response/No-Response

For the number of responses, randomization inference was used again. Figure 10 shows the histogram and data indicating an average treatment effect of 0.0705 at a p-value of 0.0461 (statistically significant). This means there is a 7.05% better chance that the treatment, Jessica would receive a response than the control, Michael.

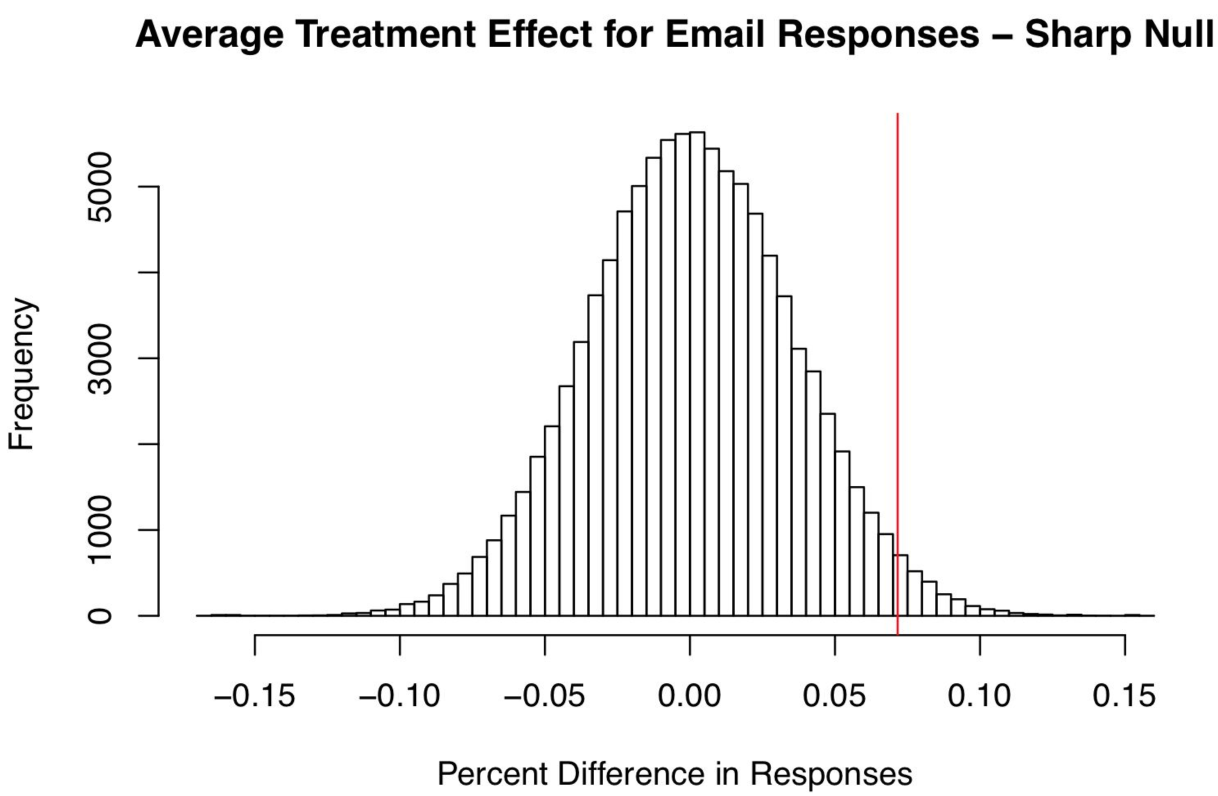

Figure 10 - Average Treatment Effect for Email Responses

Discussion

There were a number of choices we made in our experimental design to make the experiment viable in a short time period. We chose not to vary the text of the email beyond the product name and the sender name. This leaves our analysis less robust to text effects. Further, by choosing a single name for male senders and a single name for female senders, we may also have unmitigated name effects. These effects are discussed in more detail below.

Text Effects

We chose to make the message generic and not to address it to a specific name in the post. This simplicity might have made the messages appear unauthentic. Further, we did not vary the substantial text of the message itself beyond the product/service name and the sender name.

We cannot be sure that the text itself did not impact our results. However, the number of replies were high and similar for both Michael and Jessica. Further, since the same messages were sent to both treatment and control groups the effects should be uniform across both groups. For these reasons, we do not believe that there was a significant message effect.

Name Effects

We chose a single name for each sex - Michael for male, and Jessica for female. We chose these names based on their similar popularity in the 1990s. We thought that these names would make it obvious to the person reading our emails what the sex of the person they were responding was. If the person receiving our emails did not grow up in the U.S. or is not familiar with the tradition of naming boys Michael and girls Jessica then it's possible our treatment would not have the desired effect.

Our choice of using a single name for each sex leaves our analysis open to the possibility that there were name effects that drove the response rates and times. With more time, it would be better to include a set of several names for females and a separate set for males and randomly assign those within the male/female assignment. This would allow us to identify names that resulted in different outcomes beyond their male/female group. For example, it is possible that Jessica is simply a more interesting or younger-sounding name than is Michael and that this difference in appeal of the name drove differences in outcomes.

To investigate this post-experiment, we looked at the popularity of the two names over time, as is shown in the Figure 11[6]. The median year for Michael being the most popular male name was around 1978. For Jessica, this year was 1988. We decided that it is possible that Michael could have been perceived to be older than Jessica, as the name Michael has been popular over a wider time period than has Jessica. Using the graph to gauge which might be the average perceived age of a Michael or a Jessica, a Michael may be thought of as being ten years older than a Jessica.

[6] This graph is based on the data: https://www.ssa.gov/OACT/babynames/top5names.html

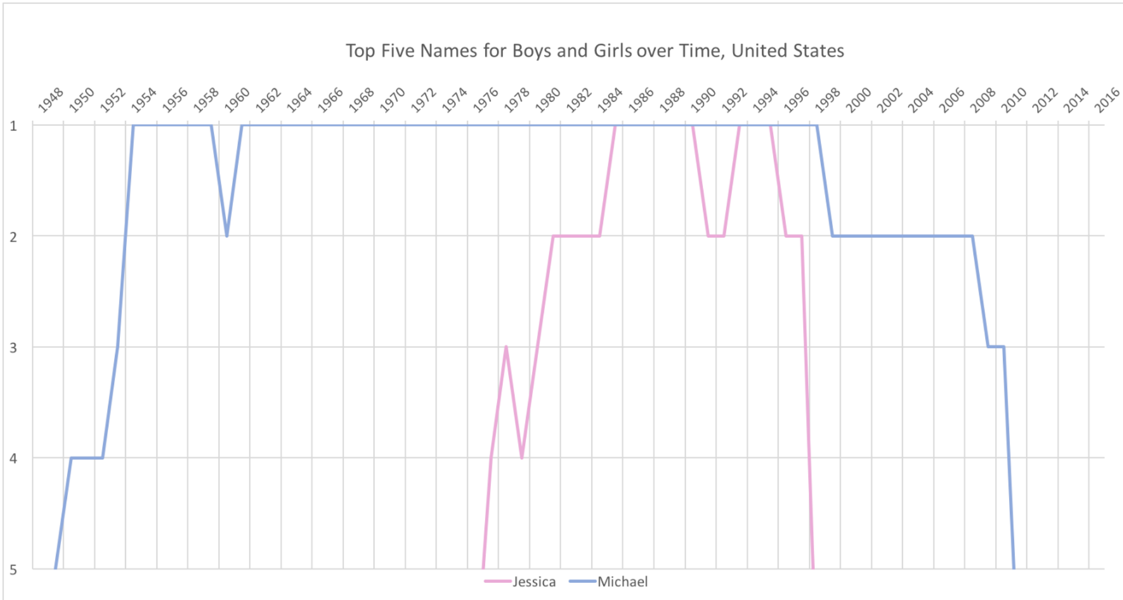

Figure 11 - Popularity of *Michael* and *Jessica* Over Time

Conclusion

Anecdotal evidence led us to believe that a woman would receive slower responses to emails than a man. However, in our experiment, support for this hypothesis was mixed. Using a simple log-rank test based on gender we found no statistically significant difference in response times. However, using a survival regression model and taking into account other fixed effects (price level, subcategory, and city, we found a statistically significant *negative* effect. This model showed that a *woman received responses faster than a man*.

Regression analysis also supported the case that females receive more overall responses than men - by about 8% in our experiment. The random inference also shows that we have statistical significance for response rate differences. All of the statistical significance is just under $p < .05$.

This experiment does not provide evidence that a woman would receive slower responses in a general business setting. Our experiment, and thus the generalizable conclusions about the causal relationship between gender and response time, was limited to two product/service categories on Craigslist. We see this experiment as a stepping stone for further experiments in this area.

Due to time constraints our experiment was focused on only two specific categories on Craigslist that targeted businesses. This oversampling allowed us to send quickly emails to hundreds of different businesses, and it allowed us to measure the causal effect of interest. We cannot surmise whether this effect would be seen outside of Craigslist or even in other Craigslist categories. We envision a larger study over a longer period of time that uses businesses from sources other than Craigslist that would help to add evidence to our research.

We also acknowledge the possibility that there are other things affecting the outcome of our experiment including text and name effects. A factorial experiment with many more names and text variations would help to reduce these possible effects. This would be more practical only with an automated system, which might preclude the use of craigslist, depending on the captcha settings at the time of the experiment.

Appendix A

Non-Compliance Example

Email to Jessica with 8-second response time. This email was removed as the auto-response was not considered to be a valid response.

Subject: Auto Response: More info

From **craigslist 6402137313** <qb9fw-6402137313@hous.craigslist.org>

I am currently no longer using this email address please use:

leemondarryl@gmail.com

Thank you

Interference Example

craigslist 6387085769 *<7xpqr-6387085769@hous.craigslist.org>*
to : de45e37c545a35

Hi Jessica,

Are you looking for multiple offices? I notice you were also interested in our Ontario location.

If so I can help you find the best locations for your needs and can also give you a better deal.

Feel free to contact me directly at (949)672-8090.

Best Regards,

Giselle Rubi