Take Home Challenge Writeup

July 1, 2015

1 Summary

Overall, there is no reason to believe that requiring guests to write a message of 140 or more characters to prospective hosts improves the Airbnb booking experience. Guests in the test group, who were required to do so, received replies and bookings as often and as quickly as the control group did. This remained true for either "contact me" or "book it" inquiries; in both cases, the effect of requiring longer messages was negligible. In light of this, it is my recommendation that the message requirement not be expanded and rather discontinued. There is no tangible benefit while serving as an additional hurdle to booking.

2 Analysis

2.1 Data

To study the effect of the message length requirement on booking experience, I was given an initial dataset of 10,000 booking requests made by guests to various listings in 2013. For each booking request, either the treatment was assigned, in which case the guest had to write a message of at least 140 characters, or the control was assigned, in which case the guest booked as normal. 9,094 unique guests made booking requests in the data set, of which 764 had multiple requests. 3,669 unique hosts received requests, of which 1,988 received multiple requests.

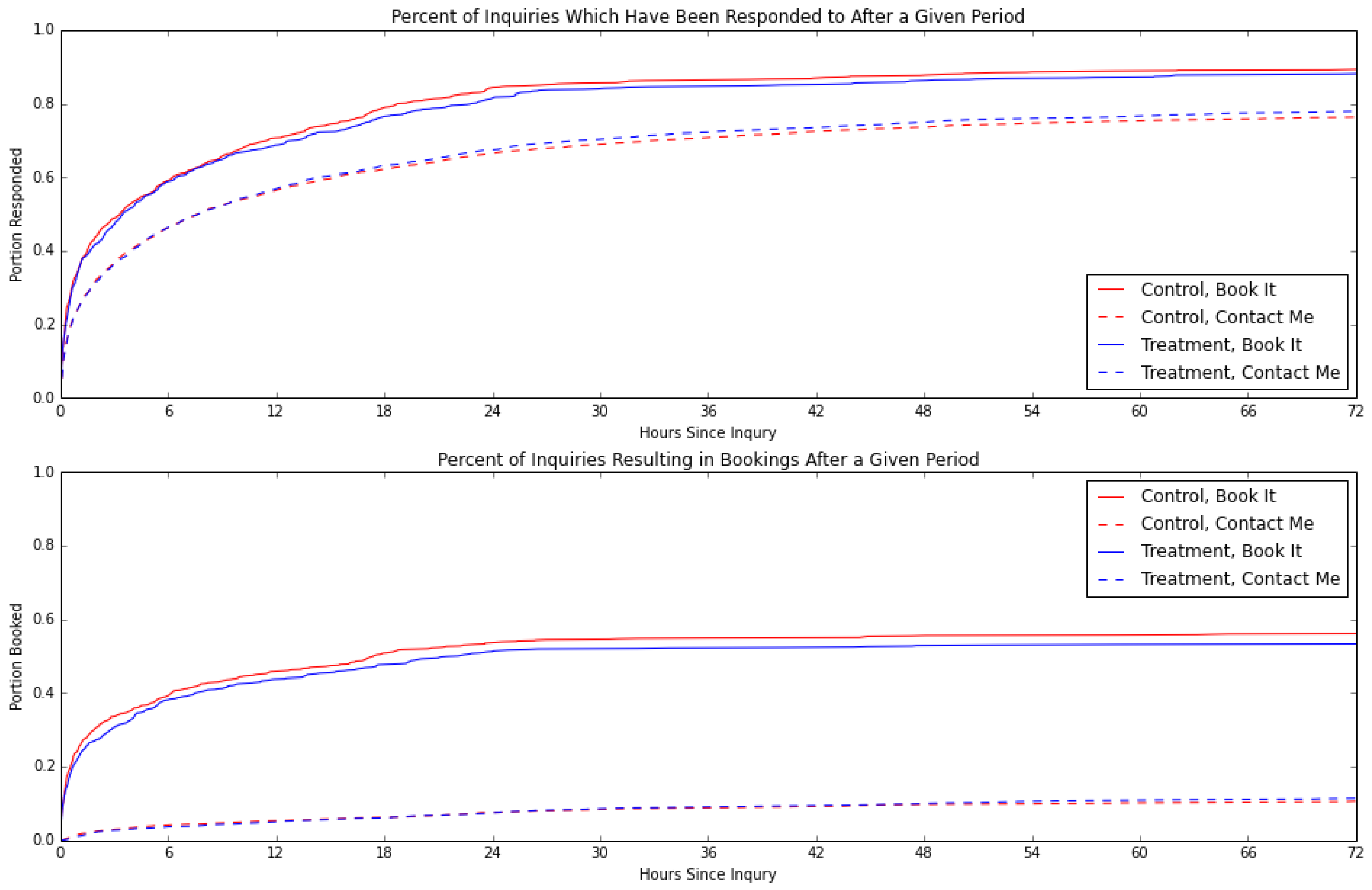
From this initial data set, I removed several small groups of observations.

- I removed one guest who made a booking request to the same listing twice, once receiving the control and once the treatment. Since it was only one observation and it would be hard to disentangle the effect of multiple booking requests for the same listing, I excluded it.
- A group of 730 booking requests were nominally assigned to the treatment group, but did not actually write 140 character messages. Since they didn't truly receive the treatment while presumably receiving some sort of intervention, I excluded them from the dataset.
- 44 of the booking requests were made as "instant bookings", which were booked automatically when requested. Since this clearly precludes the message length having any effect, I also removed these from the dataset.

All together this left a cohort of 9,233 bookings, since several of the above groups overlapped. This final data set does include a group of 112 bookings where the timestamps indicate that the booking inquiry/request preceded the first reply from the host. This is impossible, but the differences were always less than two minutes. I left them in since these small discrepancies seemed indicative of a consistently small mismeasurement. These inquiries were likely replied to quickly, which happened often in the data, but the recored time was off by a few minutes.

2.2 Results

Looking at the basic statistics within the remaining data, there is no cause to think the treatment makes a difference for booking. For the treatment group, 86.1% of requests received a reply, as oppose to 85.3% in the control group; however, only 21.0% in the treatment group ultimately received a booking, while 21.2% in the control group did. These differences are minor to the point of likely being insignificant. The time the to reply or booking is also similar in both groups, as is seen in the chart below.



This graph shows that at each point in the first three days after a booking inquiry, the portion of guests who have been responded to or booked is no higher for the treatment than the control groups, irrespective of whether they submitted a “contact me” or “book it” inquiry. This pattern holds after this three day window as well.

The experiment set up, where any person is equally likely to be in the treatment as the control group, should dictate, in theory, that this kind of basic statistic is all that is needed. For a large enough sample size, the two groups will be pretty much identical, and any differences between them should just be due to the treatment.

However, in practice, one should verify that besides the treatment, the two groups are extremely similar. We see this here. The number making "contact me" as opposed to "book it" contacts differs by less than 1%. The number making queries on weekends differs by less than .1%. The requests were made in different months and hours of the day in nearly the same portions. At a glance, the test and control group seem very similar besides the message requirement.

Finally though, to be doubly sure and perform a rigorous statistical test, I fit a few regressions. The idea with regression is that rather than compare the outcome across one other variable, as I've done above, it compares it to across all variables at the same time. This helps ensure that one variable's effect isn't accidentally ascribed to another variable. I performed four regressions; the first two were logistic regressions which predict the probability of ever getting a reply or booking, and the last two were linear regressions predicting the log time until this reply or booking occurred, assuming it did. Dealing with the log time rather than actual time is largely a mathematical convenience; it ensures that negative times aren't predicted. In these regressions, I included the treatment, the sort of inquiry, and the time of day/week/year of the inquiry as variables. Though a number of these variables had very meaningful effects, for no regression was the effect of the treatment, even when combined with the sort of inquiry, statistically significant. This indicates that the treatment effect is either nonexistent, or too small to measure.

3 Conclusion

Based on these results, we can say pretty strongly conclude that forcing guests to write an 140 character message doesn't improve their odds of getting booked. This combined with the message requirement dictating more work to make an inquiry is a good reason to do away with it. However, we should keep in mind that ones chances of getting booked given an inquiry isn't the only measure of success Airbnb should be concerned with. For instance, it's within the realm of reason that the additional requirement to request a booking would dissuade some guests from initiating contact in the first place. This data set is inadequate to measure whether this is occurring, but it should certainly be a concern; fewer booking requests ultimately mean fewer bookings and less business.

4 Further Work

This analysis is a relatively simple one, and deeper examination could be done. To start with, the regression model could be improved, culling variables that aren't meaningful and including interactions that are. More flexible regressions, such as generalized additive models, might be used. As well, one might leverage the repeated occurrence of certain guests and hosts in the data to mitigate unseen variables via self control methods. However, nothing in the data or problem suggests this is necessary; its unlikely these analyses would yield a different conclusion. If this topic is still of interest, a more important extension would be to examine the treatment's effect on the rate at which guests make inquiries, though this would require different data.

If you're reading this as a pdf, my appologies for some of the code being cut off. I made it originally as an ipython notebook, and all of the options to turn it into a pdf seem to result in some amount of loss.

In [8]:
```
# imports; may not end up using all of these
import pandas as pd, numpy as np, numpy.linalg as nplin, matplotlib.py
    scipy as sp, scipy.stats as spstat, sklearn as sk, datetime as dt,
    statsmodels.api as sm, statsmodels.formula.api as smf
from __future__ import division
from datetime import datetime, time
from pandas.tseries.offsets import DateOffset
from orthogonal_poly import *   # replicates the poly command in R
%matplotlib inline
```

Do some basic data cleaning

I start with reading in and merging the two data sets

In [16]:
```
# read in the two data sets and merge them into one, matching the id_u
assign = pd.read_csv("takehome_assignments.csv",header=0)
contacts = pd.read_csv("takehome_contacts.csv",header=0)

# I normally avoid concatenating two tables just by row number (its be
# However, that is unavoidable in this case, since id_guest doesn't un
# and the row numbers appear to match
data = pd.concat([assign,contacts],1)

# Check to make sure that I got the matching I wanted
print "id_user and id_guest are mismatched %d times" % (sum(data.id_gu
```

```
id_user and id_guest are mismatched 0 times
```

Deal with same guest & listing combo appearing multiple times

In [17]:
```
# Drop the redundant id_user column
data.drop('id_user',axis=1,inplace=True)

# Index the data set by the three ids, and see if there are any duppli
# One would presume that if a guest contacts a host twice, that might
data.set_index(keys=["id_guest","id_host","id_listing"],inplace=True)
dups = data.index.get_duplicates()
data.loc[dups]
```

Out[17]:

			ab	ts_interaction_first	ts_reply_a
id_guest	**id_host**	**id_listing**			
358f8e36-f99a-42d8-82e6-0b0577910900	**cb0b0e8b-061c-4bf6-9e5a-db806ffaa3d3**	**e723dcab-3a75-4f72-97b9-daf264e604cf**	control	2013-01-07 20:08:25	2013-01-0 20:06:46.0
		e723dcab-3a75-4f72-97b9-daf264e604cf	treatment	2013-01-03 10:36:47	2013-01-0 14:53:52.0

There is only one case of a duplicated request, so I'm just going to drop the duplicate and the original. One might just keep the contact_me observation which occured first and drop the book_it observation which occured second, but it doesn't make much difference either way

In [18]:
```
# drop it like it's hot
data.drop(dups,axis=0,inplace=True)
```

Convert the time stamps from strings to a datetime value

Now, I'm going to clean up these dates. I want the time of the first contact, and then the time lags from that to the other time variables.

In [19]:
```
# first, replace each string variable with a date time variable
timevars = ["ts_interaction_first","ts_reply_at_first","ts_accepted_at
for tv in timevars:
    data[tv] = pd.to_datetime(data[tv])

# Calculate lags from first interaction:
for tv in timevars[1:]:
    data[tv + '_lag'] = data[tv] - data.ts_interaction_first

# Sense checks. Do the time variables follow the proper order?
for i in range(len(timevars)):
    for j in range(i+1,len(timevars)):
        tv1, tv2 = timevars[i],timevars[j]
        print "%s preceeded %s %d times" % (tv1,tv2,sum(np.logical_and
```

```
ts_interaction_first preceeded ts_reply_at_first 154 times
ts_interaction_first preceeded ts_accepted_at_first 109 times
ts_interaction_first preceeded ts_booking_at 87 times
ts_reply_at_first preceeded ts_accepted_at_first 0 times
ts_reply_at_first preceeded ts_booking_at 0 times
ts_accepted_at_first preceeded ts_booking_at 0 times
```

It seems that sometimes there are issues with the first interaction preceeding the follow ups (which should be impossible)

In [20]:
```
# Lets take a look at a few examples
tv1,tv2 = 'ts_interaction_first', 'ts_reply_at_first'
data.loc[np.logical_and(pd.notnull(data[tv2]),data[tv1]>data[tv2])].he
```

Out[20]:

			ab	ts_interaction_first	ts_reply
id_guest	**id_host**	**id_listing**			
30abce0e-e105-41b0-b31a-0673efa0cd26	**a8b671c7-4bdf-4896-b42f-2ba1b1a93adf**	**6e59bc7e-8084-4ff4-a1b2-21399a6b8829**	treatment	2013-02-11 09:51:06	2013-02 09:49:2
0de89a34-2978-4bbf-b60a-f6607affa804	**f50d600e-b995-4313-aa7b-a5ac605bf5e0**	**5051a4f0-d301-48f3-81fc-093c8550570b**	treatment	2013-03-08 05:36:44	2013-03 05:36:3
14f79f2c-cd59-4f28-bb92-0c9b0100479d	**f5539bb0-8edf-4135-b753-0daaa650d6dc**	**c9bba49e-525d-4762-9daa-a687d4fd7cc3**	control	2013-03-10 21:23:13	2013-03 21:22:5
ef1a48d7-e2f0-4820-b54c-4e8b0860ccc6	**a73083f8-89c8-4d3a-b079-f8b00f57c71e**	**4348c9ec-6f7c-4301-a159-a771b4c5cbbc**	treatment	2013-03-15 17:17:17	2013-03 17:16:1
9d155939-c4c1-4fad-9328-ddc853034ecb	**dd6affae-f76d-40dd-a31f-aaee70334e8d**	**b94f0316-2f10-4f62-b2e7-58e095f612d8**	control	2013-03-19 16:24:31	2013-03 16:22:5

These negative lags seem to generally be only a matter of a minute or two, and may just be a small bug, especially for 'instant_booked'

In [21]:
```
# How many negative lags are more than two minutes?
print 'Negative lags exceeding 2 minutes happened %d times' % sum(data

# Looking at the not 'instant_booked', which are of more interest anyw
# compared to a small positive lag?
not_instant = data['dim_contact_channel']!='instant_booked'
print '\nExcluding instant booked:'
for j in range(1,len(timevars)):
    lag = data[timevars[j]+'_lag']
    neg_lags = sum(np.logical_and(not_instant,lag<0))
    pos_lags = sum(np.logical_and(not_instant,np.logical_and(lag>=np.t
    print '%s had %d lags less than 0 and %d between 0 and 2' % (timev
```

```
Negative lags exceeding 2 minutes happened 0 times

Excluding instant booked:
ts_reply_at_first had 112 lags less than 0 and 254 between 0 and 2
ts_accepted_at_first had 67 lags less than 0 and 97 between 0 and 2
ts_booking_at had 45 lags less than 0 and 48 between 0 and 2
```

My guess is that there is some kind of bug in the determination of first interaction time, but it seems to be only fudging the numbers by a minute or two. Since it looks like there are a lot of very quick response times (maybe some sort of auto reply by the host), I'm going with that the negative lags really represent small positive lags which have a small error on them. Thus, I'm leaving them in the data set.

Make sure the treatment group really did write messages longer than 140 characters

In [22]:
```
# encode missing lengths as 0
data.m_first_message_length.loc[pd.isnull(data.m_first_message_length)

less_than_req = np.logical_and(data.ab=='treatment',data.m_first_messa
print "there were %d in the treatment group who didn't write 140 charc
```

```
there were 730 in the treatment group who didn't write 140 charchter
s
```

Well, we can't really have that. I'm going to exclude those who got the treatment but didn't write 140 charachters.

In [23]:
```
data = data[np.logical_not(less_than_req)]
```

Create some additional variables

In [24]:
```
# Did the host ever reply?
data['replied'] = pd.notnull(data['ts_reply_at_first'])
# Did the host accept?
data['accepted'] = pd.notnull(data['ts_accepted_at_first'])
# Did the guest book?
data['booked'] = pd.notnull(data['ts_booking_at'])
# What hour of the day did the guest initiate contact?
data['interaction_hour'] = data.ts_interaction_first.dt.hour
# Was contact on a weekend?
data['weekend_interaction'] = data.ts_interaction_first.dt.dayofweek<5
# What month of 2013 did the contact occur in?
data['month_interaction'] = data.ts_interaction_first.dt.month.astype(
# Was the message longer than 140 charchters?
data['long_message'] = data.m_first_message_length>=140
```

Subset the data to exclude instant booked

instant_booked books without the host seeing the message, so there is no point in looking into them for this experiment

In [25]:
```
full_data, data = data.copy(), data.loc[not_instant].copy() # this is
n = data.shape[0]
print 'We are left with %d observations' % n
```

```
We are left with 9233 observations
```

Look at some univariate statistics

First, compare the treatment to control groups. Did the randominization seem to work correctly?

In [26]:
```
pd.crosstab(data['ab'],data['dim_contact_channel']).apply(lambda r: r/
```

Out[26]:

dim_contact_channel	book_it	contact_me
ab		
control	0.182785	0.817215
treatment	0.174394	0.825606

In [27]:
```
pd.crosstab(data['ab'],data['interaction_hour']).apply(lambda r: r/r.s
```

Out[27]:

interaction_hour	0	1	2	3	4	5	6
ab							
control	0.048154	0.049157	0.043539	0.042737	0.043740	0.042937	0.0335
treatment	0.045893	0.043069	0.047070	0.044481	0.041657	0.039068	0.0322

2 rows × 24 columns

In [28]:
```
osstab(data['ab'],data['weekend_interaction']).apply(lambda r: r/r.sum
```

Out[28]:

weekend_interaction	False	True
ab		
control	0.238965	0.761035
treatment	0.239821	0.760179

In [29]:
```
pd.crosstab(data['ab'],data['month_interaction']).apply(lambda r: r/r.
```

Out[29]:

month_interaction	1	2	3	4	5	6	7
ab							
control	0.062400	0.062801	0.084872	0.105738	0.107143	0.097311	0.108
treatment	0.058602	0.068487	0.094610	0.100024	0.114380	0.093434	0.104

These all pass the sniff test; both groups seemed to be contacting hosts at similar times. If there are meaningful differences in the group up to the point they send the request, it has to be burried in the joint distribution.

See initial differences in booking and respnse time between the groups

In [30]:
```
pd.crosstab(data['ab'],data['replied']).apply(lambda r: r/r.sum(), axi
```

Out[30]:

replied	False	True
ab		
control	0.147071	0.852929
treatment	0.138856	0.861144

In [31]:
```
pd.crosstab(data['ab'],data['booked']).apply(lambda r: r/r.sum(), axis
```

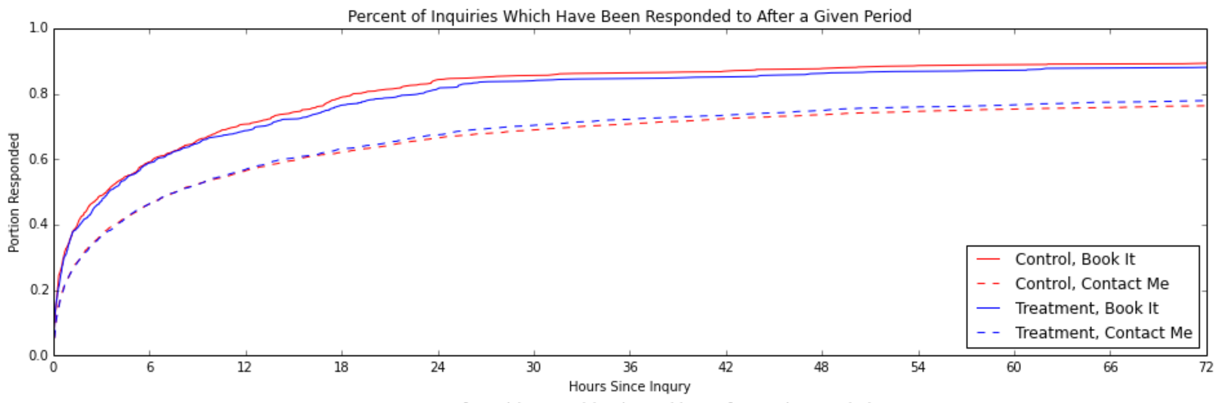
Out[31]:

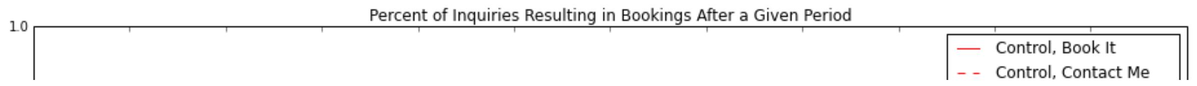
booked	False	True
ab		
control	0.787721	0.212279
treatment	0.789833	0.210167

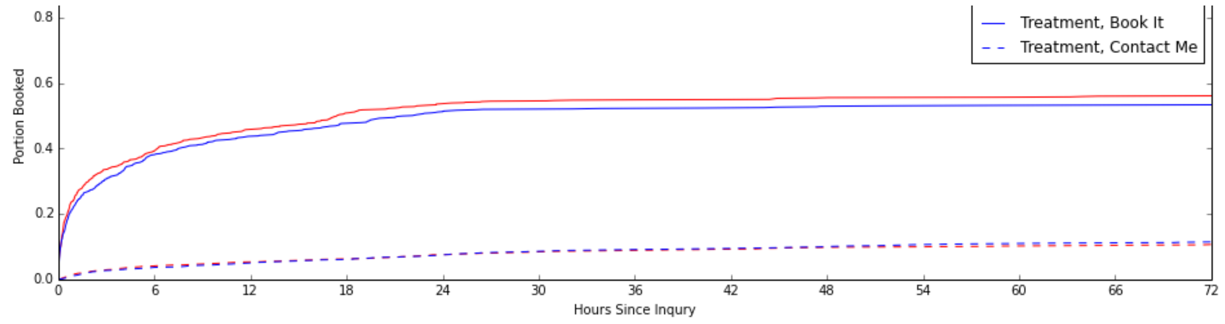
The control group got responses a little more often, but this just looks like noise to me. Maybe the response or acceptances were quicker though. Let's take a look at the cumulative response and acceptance rate over time.

In [32]:

```
# Initalize the plots
f,subplts = plt.subplots(2,1)
f.set_size_inches(16,10)
hours = 72

# Initalize some arrays for plot
lincol = ['r','b']  # the line colors I'll use
linsty = ['-','--'] # line styles I'll use
loc    = ['lower right','upper right'] # where to put the legend
labels = np.array([['Control, Book It','Control, Contact Me'],['Treatm

# Loop to add plots
for i in [0,1]:
    if i==0:
        subplts[0].set_title('Percent of Inquiries Which Have Been Res
        subplts[0].set_ylabel('Portion Responded')
        var = data.ts_reply_at_first_lag
    else:
        subplts[1].set_title('Percent of Inquiries Resulting in Bookin
        subplts[1].set_ylabel('Portion Booked')
        var = data.ts_booking_at_lag
    subplts[i].set_xlabel('Hours Since Inqury')
    subplts[i].set_ylim(0,1)
    subplts[i].set_xlim(0,60*60*hours)
    subplts[i].set_xticks(np.arange(0,hours+1,6)*60*60)
    subplts[i].set_xticklabels(np.arange(0,hours+1,6))
    # Loop over treatments
    for t in [0,1]:
        trt = ['control','treatment'][t]
        # Loop over booking criteria
        for b in [0,1]:
            book = ['book_it','contact_me'][b]
            subset = np.logical_and(data.ab==trt,data.dim_contact_chan
            cond   = np.logical_and(pd.notnull(var),subset)
            count  = sum(cond)
            y      = np.linspace(0,count/sum(subset),count)
            subplts[i].plot(var.loc[cond].sort(inplace=False).astype('
    subplts[i].legend(loc=loc[i])

plt.show()
```







If there is any meaningful effect, it looks like "book it" requests are more successful in the control group. At first glance though, the difference between treatment and control is small at best.

Fit a few regressions

There are a bunch of sexier models one might fit here, but this looks like a pretty cut and dry case, so I'm just going to fit a few old fashioned GLMs. This already is kind of overkill with this dataset.

Logits predicting reply or booking

I throw a bunch of polynomial terms to deal with the time of day the request was made and time of the year the request was made. For both of these, going to five degrees is likely gratuitous, but I'm not that interested in those effect and have plenty of data to spare a few degrees of freedom on.

In [33]:
```
# Orthogoanl Polynomial for the minute of day.
timeofday_poly, hour_norm, hour_alpha = \
    ortho_poly_fit(data.ts_interaction_first.dt.hour*60 + data.ts_inte

# Polynomial for day of year contact was made
dayofyear_poly, day_norm, day_alpha = ortho_poly_fit(data.ts_interacti
```

In [34]:
```
fit a logit on a response
sponse_logit = smf.glm(formula="replied ~ ab*dim_contact_channel + time
sponse_logit.summary()
```

Out[34]:

Generalized Linear Model Regression Results

Dep. Variable:	['replied[False]', 'replied[True]']	**No. Observations:**	9233
Model:	GLM	**Df Residuals:**	9218
Model Family:	Binomial	**Df Model:**	14
Link Function:	logit	**Scale:**	1.0

Method:	IRLS	**Log-Likelihood:**	-3730.2
Date:	Wed, 01 Jul 2015	**Deviance:**	7460.4
Time:	09:07:30	**Pearson chi2:**	9.21e+03
No. Iterations:	7		

	coef	**std err**	**z**	**P>|z|**
Intercept	-2.2673	0.129	-17.550	0.000
ab[T.treatment]	0.0931	0.175	0.531	0.596
dim_contact_channel[T.contact_me]	0.7160	0.127	5.622	0.000
weekend_interaction[T.True]	-0.1634	0.068	-2.389	0.017
ab[T.treatment]:dim_contact_channel[T.contact_me]	-0.1867	0.187	-1.000	0.317
timeofday_poly[0]	-0.0236	0.001	-17.550	0.000
timeofday_poly[1]	-5.5307	2.838	-1.949	0.051
timeofday_poly[2]	4.9215	2.898	1.699	0.089
timeofday_poly[3]	1.1730	2.876	0.408	0.683
timeofday_poly[4]	-4.8016	2.884	-1.665	0.096
timeofday_poly[5]	0.9561	2.868	0.333	0.739
dayofyear_poly[0]	-0.0236	0.001	-17.550	0.000
dayofyear_poly[1]	-6.2970	3.140	-2.006	0.045
dayofyear_poly[2]	-18.1659	3.043	-5.969	0.000

dayofyear_poly[3]	7.0050	3.022	2.318	0.020
dayofyear_poly[4]	7.5630	3.014	2.509	0.012
dayofyear_poly[5]	1.3697	3.024	0.453	0.651

```
Neither the treatment nor treatment/contact channel interaction is
signficant.
```

In [36]:
```
# fit a logit on a booking
response_logit = smf.glm(formula="booked ~ ab*dim_contact_channel + ti
response_logit.summary()
```

Out[36]:

Generalized Linear Model Regression Results

Dep. Variable:	['booked[False]', 'booked[True]']	**No. Observations:**	9233
Model:	GLM	**Df Residuals:**	9218
Model Family:	Binomial	**Df Model:**	14
Link Function:	logit	**Scale:**	1.0
Method:	IRLS	**Log-Likelihood:**	-4126.1
Date:	Wed, 01 Jul 2015	**Deviance:**	8252.2
Time:	09:08:38	**Pearson chi2:**	9.25e+03
No. Iterations:	7		

	coef	**std err**	**z**	**P>|z|**	**[9 C In**
Intercept	-0.2762	0.083	-3.330	0.001	-0 -0
ab[T.treatment]	0.1044	0.100	1.045	0.296	-0 0.
dim_contact_channel[T.contact_me]	2.1922	0.082	26.607	0.000	2. 2.
weekend_interaction[T.True]	-0.0323	0.065	-0.494	0.622	-0 0.
ab[T.treatment]:dim_contact_channel[T.contact_me]	-0.1647	0.121	-1.367	0.172	-0 0.
					-0

timeofday_poly[0]	-0.0029	0.001	-3.330	0.001	-0
timeofday_poly[1]	-3.8737	2.700	-1.435	0.151	-9 1.
timeofday_poly[2]	5.0489	2.701	1.869	0.062	-0 10
timeofday_poly[3]	2.0711	2.689	0.770	0.441	-3 7.
timeofday_poly[4]	-0.8987	2.693	-0.334	0.739	-6 4.
timeofday_poly[5]	2.4364	2.699	0.903	0.367	-2 7.
dayofyear_poly[0]	-0.0029	0.001	-3.330	0.001	-0 -0
dayofyear_poly[1]	3.0181	2.661	1.134	0.257	-2 8.
dayofyear_poly[2]	-8.2208	2.652	-3.100	0.002	-1 -3
dayofyear_poly[3]	0.4402	2.652	0.166	0.868	-4 5.
dayofyear_poly[4]	2.9541	2.652	1.114	0.265	-2 8.
dayofyear_poly[5]	0.6068	2.649	0.229	0.819	-4 5.

Both of these models say the same thing; neither for contact_me or book it does requiring a 140 word message result in a meaningful change in response or booking reates. There is plenty of room for improoved model selection, such as by interacting coefficients, but its pretty unlikely that main result will change.

Linear model predicting log time to response or booking

Just to beat on this dead horse a little more, lets see if the guests that get a response or booking do so quicker under the treatment.

In [37]:

```
te the outcome
me time to ensure no missing values after taking the log
 = np.log(data.ts_reply_at_first_lag.astype('timedelta64[s]')+120)

logit on a response
_logit = smf.ols(formula="logreply ~ ab*dim_contact_channel + timeofday
_logit.summary()
```

Out[37]:

OLS Regression Results

Dep. Variable:	logreply	R-squared:	0.056
Model:	OLS	Adj. R-squared:	0.054
Method:	Least Squares	F-statistic:	33.42
Date:	Wed, 01 Jul 2015	Prob (F-statistic):	3.20e-88
Time:	09:09:12	Log-Likelihood:	-17513.
No. Observations:	7910	AIC:	3.506e+04
Df Residuals:	7895	BIC:	3.516e+04
Df Model:	14		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|
Intercept	9.1091	0.089	102.888	0.000
ab[T.treatment]	0.1112	0.115	0.968	0.333
dim_contact_channel[T.contact_me]	0.5994	0.086	6.956	0.000
weekend_interaction[T.True]	-0.2680	0.059	-4.556	0.000
ab[T.treatment]:dim_contact_channel[T.contact_me]	-0.0855	0.128	-0.670	0.503
timeofday_poly[0]	0.0948	0.001	102.888	0.000
timeofday_poly[1]	-16.0989	2.404	-6.695	0.000
timeofday_poly[2]	-18.5821	2.396	-7.756	0.000

timeofday_poly[3]	18.2011	2.402	7.579	0.000
timeofday_poly[4]	16.1274	2.392	6.741	0.000
timeofday_poly[5]	-13.0939	2.396	-5.465	0.000
dayofyear_poly[0]	0.0948	0.001	102.888	0.000
dayofyear_poly[1]	-18.3957	2.387	-7.706	0.000
dayofyear_poly[2]	-11.1289	2.382	-4.672	0.000
dayofyear_poly[3]	7.7496	2.387	3.246	0.001
dayofyear_poly[4]	-0.5309	2.375	-0.224	0.823
dayofyear_poly[5]	-0.0276	2.375	-0.012	0.991

Omnibus:	9.271	**Durbin-Watson:**	1.980
Prob(Omnibus):	0.010	**Jarque-Bera (JB):**	8.413
Skew:	0.037	**Prob(JB):**	0.0149
Kurtosis:	2.858	**Cond. No.**	2.23e+18

Again, neither the treatment nor treatment/contact channel interaction is signficant.

In [38]:
```
generate the outcome, this time booking lag
greply = np.log(data.ts_booking_at_lag.astype('timedelta64[s]')+120) #

 fit a logit on a response
sponse_logit = smf.ols(formula="logreply ~ ab*dim_contact_channel + ti
sponse_logit.summary()
```

Out[38]:

OLS Regression Results

Dep. Variable:	logreply	**R-squared:**	0.271
Model:	OLS	**Adj. R-squared:**	0.266
Method:	Least Squares	**F-statistic:**	51.40
Date:			

	Wed, 01 Jul 2015	**Prob (F-statistic):**	6.54e-122
Time:	09:09:49	**Log-Likelihood:**	-4118.8
No. Observations:	1951	**AIC:**	8268.
Df Residuals:	1936	**BIC:**	8351.
Df Model:	14		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**
Intercept	8.7405	0.120	72.977	0.000
ab[T.treatment]	0.1085	0.133	0.815	0.415
dim_contact_channel[T.contact_me]	2.2841	0.124	18.355	0.000
weekend_interaction[T.True]	-0.2262	0.107	-2.119	0.034
ab[T.treatment]:dim_contact_channel[T.contact_me]	0.0081	0.183	0.044	0.965
timeofday_poly[0]	0.0910	0.001	72.977	0.000
timeofday_poly[1]	-16.3962	4.422	-3.708	0.000
timeofday_poly[2]	-17.5669	4.444	-3.953	0.000
timeofday_poly[3]	8.8165	4.465	1.975	0.048
timeofday_poly[4]	17.5891	4.419	3.981	0.000
timeofday_poly[5]	-8.8845	4.504	-1.973	0.049
dayofyear_poly[0]	0.0910	0.001	72.977	0.000
dayofyear_poly[1]	-5.3904	4.293	-1.256	0.209

dayofyear_poly[2]	-1.5911	4.320	-0.368	0.713	- 6
dayofyear_poly[3]	6.5022	4.301	1.512	0.131	- 1
dayofyear_poly[4]	-2.5591	4.284	-0.597	0.550	- 5
dayofyear_poly[5]	-0.9927	4.324	-0.230	0.818	- 7

Omnibus:	19.438	**Durbin-Watson:**	2.008
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	19.848
Skew:	-0.247	**Prob(JB):**	4.90e-05
Kurtosis:	3.005	**Cond. No.**	3.69e+18

Again, the treatment doesn't make a statistically signficant difference. Time of day when the request is sent is much more important though, as one might expect.