

# final\_project

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## 1 *Econ 143 - Advanced Econometrics Final Project*

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### Introduction and Initial Survey Data

My final project is a fun, Berkeley-related showcase of contingent valuation of students' willingness-to-pay for a campus-wide ski lift. I remember back to three years ago, when reading about Berkeley upon my acceptance, I came across some students' proposal for something called BearLift. Here is the link to the comment under Carol Christ's Reddit Ask-Me-Anything from three years ago: [https://www.reddit.com/r/berkeley/comments/9mhs3p/i\\_am\\_carol\\_christ\\_chancellor\\_of\\_uc\\_berkeley\\_ask/e7](https://www.reddit.com/r/berkeley/comments/9mhs3p/i_am_carol_christ_chancellor_of_uc_berkeley_ask/e7)

When we began covering nonparametric analysis in class, I knew that I can put two and two together and apply this nonparametric technique to a very playful topic. So, I first developed a survey through Google Forms and collected 57 responses from fellow Berkeley students (<https://forms.gle/jSU8tq5m7x37S58X6>). The form has far greater detail about the pros and cons of a potential ski lift. I randomly assigned students to different initial prices (\$100, \$200, \$300, \$400, \$500), then would direct them to the respective following price points (half or double) depending on their answer.

```
[ ]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

```
[ ]: survey = pd.read_csv("Econ143_Ski_Slope_CV_Responses_Form_Responses.csv")
survey.tail()
```

```
[ ]:
      Email Address      Timestamp \
53      rdison@berkeley.edu  5/12/2022 9:53
54      jholobetz@berkeley.edu  5/12/2022 10:18
55      gabrielcharoes@berkeley.edu  5/12/2022 11:16
56      michele.strazza.2000@gmail.com  5/12/2022 12:11
57      1022charlotte@gmail.com  5/12/2022 13:17
```

Per the nature of this experiment, these 5 symbols have been sorted into a random order. Please pick just the top answer. \

```
53      $
54      !
55      %
```

56 \$  
57 \$

Are you willing to pay \$100 in annual student fees for BearLift? \  
53 NaN  
54 No  
55 NaN  
56 NaN  
57 NaN

You said no to \$100 in annual student fees for Bear Lift. Are you willing to  
pay \$50 in annual student fees for BearLift? \  
53 NaN  
54 No  
55 NaN  
56 NaN  
57 NaN

You said yes to \$100 in annual student fees for Bear Lift. Are you willing to  
pay \$200 in annual student fees for BearLift? \  
53 NaN  
54 NaN  
55 NaN  
56 NaN  
57 NaN

Are you willing to pay \$200 in annual student fees for BearLift? \  
53 NaN  
54 NaN  
55 NaN  
56 NaN  
57 NaN

You said no to \$200 in annual student fees for Bear Lift. Are you willing to  
pay \$100 in annual student fees for BearLift? \  
53 NaN  
54 NaN  
55 NaN  
56 NaN  
57 NaN

You said yes to \$200 in annual student fees for Bear Lift. Are you willing to  
pay \$400 in annual student fees for BearLift? \  
53 NaN  
54 NaN  
55 NaN  
56 NaN

57 NaN

Are you willing to pay \$300 in annual student fees for BearLift? \  
53 NaN  
54 NaN  
55 NaN  
56 NaN  
57 NaN

You said no to \$300 in annual student fees for Bear Lift. Are you willing to  
pay \$150 in annual student fees for BearLift? \  
53 NaN  
54 NaN  
55 NaN  
56 NaN  
57 NaN

You said yes to \$300 in annual student fees for Bear Lift. Are you willing to  
pay \$600 in annual student fees for BearLift? \  
53 NaN  
54 NaN  
55 NaN  
56 NaN  
57 NaN

Are you willing to pay \$400 in annual student fees for BearLift? \  
53 No  
54 NaN  
55 NaN  
56 Yes  
57 Yes

You said no to \$400 in annual student fees for Bear Lift. Are you willing to  
pay \$200 in annual student fees for BearLift? \  
53 Yes  
54 NaN  
55 NaN  
56 NaN  
57 NaN

You said yes to \$400 in annual student fees for Bear Lift. Are you willing to  
pay \$800 in annual student fees for BearLift? \  
53 NaN  
54 NaN  
55 NaN  
56 No  
57 Yes

```

Are you willing to pay $500 in annual student fees for BearLift? \
53                                     NaN
54                                     NaN
55                                     No
56                                     NaN
57                                     NaN

```

```

You said no to $500 in annual student fees for Bear Lift. Are you willing to
pay $250 in annual student fees for BearLift? \
53                                     NaN
54                                     NaN
55                                     No
56                                     NaN
57                                     NaN

```

```

You said yes to $500 in annual student fees for Bear Lift. Are you willing to
pay $1000 in annual student fees for BearLift?
53                                     NaN
54                                     NaN
55                                     NaN
56                                     NaN
57                                     NaN

```

## Survey DataFrame Cleaning

Although we have collected our survey data with Google Forms, we still have a ways to go before we can derive students' willingness-to-pay for this ski slope. We still have to reformat this data in such a way that we can continue with our contingent valuation.

```

[ ]: survey_drop_unnecessary_cols = survey.drop(survey.columns[:3], axis=1) # Drop
    ↪ emails, time-stamps, and randomizer
survey_fill_nan_and_replace_yes_no = survey_drop_unnecessary_cols.
    ↪ replace("Yes", 1).replace("No", 2).fillna(0) # Replace Yes with 1 and No
    ↪ with 2, fill na w/ 0
survey_cleaned = survey_fill_nan_and_replace_yes_no.iloc[1:].astype(int) #
    ↪ remove the 1st row (it errors) and set everything from float to int
survey_cleaned.head()

```

```

[ ]: Are you willing to pay $100 in annual student fees for BearLift? \
1                                     0
2                                     0
3                                     0
4                                     1
5                                     0

```

```

You said no to $100 in annual student fees for Bear Lift. Are you willing to
pay $50 in annual student fees for BearLift? \

```

1	0
2	0
3	0
4	0
5	0

You said yes to \$100 in annual student fees for Bear Lift. Are you willing to pay \$200 in annual student fees for BearLift? \

1	0
2	0
3	0
4	1
5	0

Are you willing to pay \$200 in annual student fees for BearLift? \

1	0
2	0
3	1
4	0
5	0

You said no to \$200 in annual student fees for Bear Lift. Are you willing to pay \$100 in annual student fees for BearLift? \

1	0
2	0
3	0
4	0
5	0

You said yes to \$200 in annual student fees for Bear Lift. Are you willing to pay \$400 in annual student fees for BearLift? \

1	0
2	0
3	2
4	0
5	0

Are you willing to pay \$300 in annual student fees for BearLift? \

1	1
2	0
3	0
4	0
5	0

You said no to \$300 in annual student fees for Bear Lift. Are you willing to pay \$150 in annual student fees for BearLift? \

1	0
---	---

2	0
3	0
4	0
5	0

You said yes to \$300 in annual student fees for Bear Lift. Are you willing to pay \$600 in annual student fees for BearLift? \

1	2
2	0
3	0
4	0
5	0

Are you willing to pay \$400 in annual student fees for BearLift? \

1	0
2	0
3	0
4	0
5	0

You said no to \$400 in annual student fees for Bear Lift. Are you willing to pay \$200 in annual student fees for BearLift? \

1	0
2	0
3	0
4	0
5	0

You said yes to \$400 in annual student fees for Bear Lift. Are you willing to pay \$800 in annual student fees for BearLift? \

1	0
2	0
3	0
4	0
5	0

Are you willing to pay \$500 in annual student fees for BearLift? \

1	0
2	1
3	0
4	0
5	2

You said no to \$500 in annual student fees for Bear Lift. Are you willing to pay \$250 in annual student fees for BearLift? \

1	0
2	0

3	0
4	0
5	2

You said yes to \$500 in annual student fees for Bear Lift. Are you willing to pay \$1000 in annual student fees for BearLift?

1	0
2	1
3	0
4	0
5	0

```
[ ]: def build_cv(respondent):
    '''
    Will take a respondent's answer to the survey and reformat their answer,
    by marking the answers and prices they chose for both parts of the survey
    '''
    cv = np.empty(4)
    for price_index_pair in [[100, 0], [200, 3], [300, 6], [400, 9], [500, 12]]: #
        ↳ identifies the 5 prices and their corresponding col index in surveys_cleaned.
        ↳ csv
        price = price_index_pair[0] # initial price
        index = price_index_pair[1] # col index for initial price
        if respondent[index] != 0: # signifies this is the initial price the
            ↳ respondent was given
            cv[0] = respondent[index] # 1st response: 1 (yes) or 2 (no)
            cv[1] = price
            if respondent[index] == 2: # if response is no, go to
                ↳ price-corresponding "no" col
                cv[2] = respondent[index + 1] # 2nd response: 1 (yes) or 2 (no)
                cv[3] = price / 2 # half price
            else:
                cv[2] = respondent[index + 2] # if response is yes, go to
                ↳ price-corresponding "yes" col
                cv[3] = price * 2 # double price
    return cv.astype(int) # set from float to int
```

```
[ ]: cv_data = survey_cleaned.apply(build_cv, axis=1) # apply build_cv to every row/
        ↳ respondent in the survey
cv_data = np.array([np.array(xi) for xi in cv_data]) # reformat cv_data as a np.
        ↳ array
cv = pd.DataFrame(cv_data, columns=['Yes1DK', 'PT1', 'Yes2DK', 'PT2']) # turn into
        ↳ a DF
cv.head()
```

```
[ ]:      Yes1DK  PT1  Yes2DK  PT2
0         1  300         2   600
1         1  500         1  1000
2         1  200         2   400
3         1  100         1   200
4         2  500         2   250
```

```
[ ]: cv["LB"] = -9
      cv["UB"] = -9

      # LOWER BOUND construction
      # yes-yes responders
      cv.loc[(cv["Yes1DK"]==1) & (cv["Yes2DK"]==1), "LB"] = cv["PT2"]

      # yes-no responders
      cv.loc[(cv["Yes1DK"]==1) & (cv["Yes2DK"]==2), "LB"] = cv["PT1"]

      # no-yes responders
      cv.loc[(cv["Yes1DK"]==2) & (cv["Yes2DK"]==1), "LB"] = cv["PT2"]

      # no-no responders
      cv.loc[(cv["Yes1DK"]==2) & (cv["Yes2DK"]==2), "LB"] = 0

      # UPPER BOUND construction
      # yes-yes responders
      cv.loc[(cv["Yes1DK"]==1) & (cv["Yes2DK"]==1), "UB"] = np.inf

      # yes-no responders
      cv.loc[(cv["Yes1DK"]==1) & (cv["Yes2DK"]==2), "UB"] = cv["PT2"]

      # no-yes responders
      cv.loc[(cv["Yes1DK"]==2) & (cv["Yes2DK"]==1), "UB"] = cv["PT1"]

      # no-no responders
      cv.loc[(cv["Yes1DK"]==2) & (cv["Yes2DK"]==2), "UB"] = cv["PT2"]
```

Below are 10 of the lower and upper bounds for students' willingness-to-pay for the ski slope based on our double-bounded dichotomous choice process

```
[ ]: cv[["LB", "UB"]][0:10]
```

```
[ ]:      LB      UB
0     300    600.0
1    1000     inf
2     200    400.0
3     200     inf
4        0    250.0
```



```

5    500  1000.0
6     0    200.0
7    200     inf
8     0    50.0
9     0    150.0

```

Now armed with the pairs of lower and upper bounds, we can build our matrix of dummy variables that indicate what prices respondents are willing to pay.

```

[ ]: cv["D1"] = ((cv["LB"]<=0) & (cv["UB"]>=50) )*1
cv["D2"] = ((cv["LB"]<=50) & (cv["UB"]>=100) )*1
cv["D3"] = ((cv["LB"]<=100) & (cv["UB"]>=150) )*1
cv["D4"] = ((cv["LB"]<=150) & (cv["UB"]>=200) )*1
cv["D5"] = ((cv["LB"]<=200) & (cv["UB"]>=250) )*1
cv["D6"] = ((cv["LB"]<=250) & (cv["UB"]>=300) )*1
cv["D7"] = ((cv["LB"]<=300) & (cv["UB"]>=400) )*1
cv["D8"] = ((cv["LB"]<=400) & (cv["UB"]>=500) )*1
cv["D9"] = ((cv["LB"]<=500) & (cv["UB"]>=600) )*1
cv["D10"] = ((cv["LB"]<=600) & (cv["UB"]>=800) )*1
cv["D11"] = ((cv["LB"]<=800) & (cv["UB"]>=1000) )*1
cv["D12"] = ((cv["LB"]<=1000) & (cv["UB"]>=np.inf) )*1
cv[["D1", "D2", "D3", "D4", "D5", "D6", "D7", "D8", "D9", "D10", "D11", "D12"]][0:10]

```

```

[ ]:
   D1  D2  D3  D4  D5  D6  D7  D8  D9  D10  D11  D12
0   0   0   0   0   0   0   1   1   1   0   0   0
1   0   0   0   0   0   0   0   0   0   0   0   1
2   0   0   0   0   1   1   1   0   0   0   0   0
3   0   0   0   0   1   1   1   1   1   1   1   1
4   1   1   1   1   1   0   0   0   0   0   0   0
5   0   0   0   0   0   0   0   0   1   1   1   0
6   1   1   1   1   0   0   0   0   0   0   0   0
7   0   0   0   0   1   1   1   1   1   1   1   1
8   1   0   0   0   0   0   0   0   0   0   0   0
9   1   1   1   0   0   0   0   0   0   0   0   0

```

The entire objective of this process is to find some measure of central tendency regarding students' willingness-to-pay for the ski lift. We can achieve this by working our way towards a satisfactory cumulative distribution function and finding the interval at the 50th percentile.

```

[ ]: def E_Step(F, D):

    """
    F : (F(b1),F(b2),...,F(bL)) willingness-to-pay CDF values, numpy (L-1,)
    ↪array
    D : N x L matrix of indicators for WTP
    """

    L = len(F) + 1          # number of disjoint intervals

```

```

F_star = list(F)          # add 0 and 1 to list of CDF values
F_star.insert(0,0)
F_star.append(1)

F_dif = []                # compute probability assigned to each of the l=1,..
↪.,L WTP intervals

                            # given current value of F
for l in range(L):
    F_dif.append(F_star[l+1] - F_star[l])

    delta_0 = D * F_dif    # N x L matrix with numerator values for ↪
↪delta_il, i = 1,...,N, l = 1,...,L
    delta_1 = D @ F_dif    # N - vector with denominator values for ↪
↪delta_il, i = 1,...,N

    delta = delta_0.T / delta_1 # L x N matrix with posterior probability that ↪
↪each of the i = 1,...,N,
                                # units is in the l = 1,...,L bins given the ↪
↪data and current value of F
    return delta.T

```

The next block of code uses Turnbull's method to compute "self-consistent" estimates of  $F = (F(b_1), F(b_2), \dots, F(b_{L-1}))'$ .

```

[ ]: D = cv[["D1", "D2", "D3", "D4", "D5", "D6", "D7", "D8", "D9", "D10", "D11", "D12"]]

# starting values for Turnbull algorithm
F_start = np.array([0.065, 0.19, 0.215, 0.276, 0.34, 0.41, 0.5, 0.59, 0.615, 0.
↪84, 0.97])

finished = False
converged = False
xtol      = 0.0001
maxiter   = 1000

iter = 0 # initialize iteration counter

while not converged:

    # Print optimization output to screen
    if (iter > 0):
        print("Iteration = " + "%.0f" % iter + \
              ", 2-norm of change in F = " + "%.6f" % epsilon)

    # -----#

```

```

# - E-Step: Compute posterior unit-specific WTP bin probabilities -#
# -----#

delta = E_Step(F_start, D)

# -----#
# - M-Step: Update estimates of WTP distribution. -#
# -----#

F_em = np.cumsum(np.mean(delta))[0:-1]

# Assess convergence
epsilon = np.linalg.norm(F_start-F_em)

if (epsilon < xtol) | (iter >= maxiter):
    finished = True
    if (epsilon < xtol):
        converged = True

# Update parameters
F_start = F_em
iter += 1

```

```

Iteration = 1, 2-norm of change in F = 0.719990
Iteration = 2, 2-norm of change in F = 0.052285
Iteration = 3, 2-norm of change in F = 0.019912
Iteration = 4, 2-norm of change in F = 0.012506
Iteration = 5, 2-norm of change in F = 0.009025
Iteration = 6, 2-norm of change in F = 0.007418
Iteration = 7, 2-norm of change in F = 0.006689
Iteration = 8, 2-norm of change in F = 0.006321
Iteration = 9, 2-norm of change in F = 0.006074
Iteration = 10, 2-norm of change in F = 0.005855
Iteration = 11, 2-norm of change in F = 0.005635
Iteration = 12, 2-norm of change in F = 0.005406
Iteration = 13, 2-norm of change in F = 0.005172
Iteration = 14, 2-norm of change in F = 0.004936
Iteration = 15, 2-norm of change in F = 0.004702
Iteration = 16, 2-norm of change in F = 0.004472
Iteration = 17, 2-norm of change in F = 0.004249
Iteration = 18, 2-norm of change in F = 0.004035
Iteration = 19, 2-norm of change in F = 0.003829
Iteration = 20, 2-norm of change in F = 0.003633
Iteration = 21, 2-norm of change in F = 0.003447
Iteration = 22, 2-norm of change in F = 0.003270
Iteration = 23, 2-norm of change in F = 0.003103
Iteration = 24, 2-norm of change in F = 0.002946

```

Iteration = 25, 2-norm of change in F = 0.002797  
Iteration = 26, 2-norm of change in F = 0.002657  
Iteration = 27, 2-norm of change in F = 0.002525  
Iteration = 28, 2-norm of change in F = 0.002401  
Iteration = 29, 2-norm of change in F = 0.002285  
Iteration = 30, 2-norm of change in F = 0.002175  
Iteration = 31, 2-norm of change in F = 0.002072  
Iteration = 32, 2-norm of change in F = 0.001975  
Iteration = 33, 2-norm of change in F = 0.001884  
Iteration = 34, 2-norm of change in F = 0.001798  
Iteration = 35, 2-norm of change in F = 0.001717  
Iteration = 36, 2-norm of change in F = 0.001640  
Iteration = 37, 2-norm of change in F = 0.001569  
Iteration = 38, 2-norm of change in F = 0.001501  
Iteration = 39, 2-norm of change in F = 0.001437  
Iteration = 40, 2-norm of change in F = 0.001376  
Iteration = 41, 2-norm of change in F = 0.001319  
Iteration = 42, 2-norm of change in F = 0.001265  
Iteration = 43, 2-norm of change in F = 0.001213  
Iteration = 44, 2-norm of change in F = 0.001165  
Iteration = 45, 2-norm of change in F = 0.001119  
Iteration = 46, 2-norm of change in F = 0.001075  
Iteration = 47, 2-norm of change in F = 0.001034  
Iteration = 48, 2-norm of change in F = 0.000995  
Iteration = 49, 2-norm of change in F = 0.000957  
Iteration = 50, 2-norm of change in F = 0.000922  
Iteration = 51, 2-norm of change in F = 0.000888  
Iteration = 52, 2-norm of change in F = 0.000856  
Iteration = 53, 2-norm of change in F = 0.000825  
Iteration = 54, 2-norm of change in F = 0.000796  
Iteration = 55, 2-norm of change in F = 0.000768  
Iteration = 56, 2-norm of change in F = 0.000741  
Iteration = 57, 2-norm of change in F = 0.000716  
Iteration = 58, 2-norm of change in F = 0.000692  
Iteration = 59, 2-norm of change in F = 0.000669  
Iteration = 60, 2-norm of change in F = 0.000646  
Iteration = 61, 2-norm of change in F = 0.000625  
Iteration = 62, 2-norm of change in F = 0.000605  
Iteration = 63, 2-norm of change in F = 0.000585  
Iteration = 64, 2-norm of change in F = 0.000567  
Iteration = 65, 2-norm of change in F = 0.000549  
Iteration = 66, 2-norm of change in F = 0.000532  
Iteration = 67, 2-norm of change in F = 0.000515  
Iteration = 68, 2-norm of change in F = 0.000500  
Iteration = 69, 2-norm of change in F = 0.000485  
Iteration = 70, 2-norm of change in F = 0.000470  
Iteration = 71, 2-norm of change in F = 0.000456  
Iteration = 72, 2-norm of change in F = 0.000443

Iteration = 73, 2-norm of change in F = 0.000430  
Iteration = 74, 2-norm of change in F = 0.000417  
Iteration = 75, 2-norm of change in F = 0.000405  
Iteration = 76, 2-norm of change in F = 0.000394  
Iteration = 77, 2-norm of change in F = 0.000383  
Iteration = 78, 2-norm of change in F = 0.000372  
Iteration = 79, 2-norm of change in F = 0.000362  
Iteration = 80, 2-norm of change in F = 0.000352  
Iteration = 81, 2-norm of change in F = 0.000343  
Iteration = 82, 2-norm of change in F = 0.000333  
Iteration = 83, 2-norm of change in F = 0.000325  
Iteration = 84, 2-norm of change in F = 0.000316  
Iteration = 85, 2-norm of change in F = 0.000308  
Iteration = 86, 2-norm of change in F = 0.000300  
Iteration = 87, 2-norm of change in F = 0.000292  
Iteration = 88, 2-norm of change in F = 0.000285  
Iteration = 89, 2-norm of change in F = 0.000278  
Iteration = 90, 2-norm of change in F = 0.000271  
Iteration = 91, 2-norm of change in F = 0.000264  
Iteration = 92, 2-norm of change in F = 0.000257  
Iteration = 93, 2-norm of change in F = 0.000251  
Iteration = 94, 2-norm of change in F = 0.000245  
Iteration = 95, 2-norm of change in F = 0.000239  
Iteration = 96, 2-norm of change in F = 0.000234  
Iteration = 97, 2-norm of change in F = 0.000228  
Iteration = 98, 2-norm of change in F = 0.000223  
Iteration = 99, 2-norm of change in F = 0.000218  
Iteration = 100, 2-norm of change in F = 0.000213  
Iteration = 101, 2-norm of change in F = 0.000208  
Iteration = 102, 2-norm of change in F = 0.000203  
Iteration = 103, 2-norm of change in F = 0.000198  
Iteration = 104, 2-norm of change in F = 0.000194  
Iteration = 105, 2-norm of change in F = 0.000190  
Iteration = 106, 2-norm of change in F = 0.000186  
Iteration = 107, 2-norm of change in F = 0.000181  
Iteration = 108, 2-norm of change in F = 0.000178  
Iteration = 109, 2-norm of change in F = 0.000174  
Iteration = 110, 2-norm of change in F = 0.000170  
Iteration = 111, 2-norm of change in F = 0.000166  
Iteration = 112, 2-norm of change in F = 0.000163  
Iteration = 113, 2-norm of change in F = 0.000160  
Iteration = 114, 2-norm of change in F = 0.000156  
Iteration = 115, 2-norm of change in F = 0.000153  
Iteration = 116, 2-norm of change in F = 0.000150  
Iteration = 117, 2-norm of change in F = 0.000147  
Iteration = 118, 2-norm of change in F = 0.000144  
Iteration = 119, 2-norm of change in F = 0.000141  
Iteration = 120, 2-norm of change in F = 0.000138

```

Iteration = 121, 2-norm of change in F = 0.000136
Iteration = 122, 2-norm of change in F = 0.000133
Iteration = 123, 2-norm of change in F = 0.000130
Iteration = 124, 2-norm of change in F = 0.000128
Iteration = 125, 2-norm of change in F = 0.000125
Iteration = 126, 2-norm of change in F = 0.000123
Iteration = 127, 2-norm of change in F = 0.000121
Iteration = 128, 2-norm of change in F = 0.000119
Iteration = 129, 2-norm of change in F = 0.000116
Iteration = 130, 2-norm of change in F = 0.000114
Iteration = 131, 2-norm of change in F = 0.000112
Iteration = 132, 2-norm of change in F = 0.000110
Iteration = 133, 2-norm of change in F = 0.000108
Iteration = 134, 2-norm of change in F = 0.000106
Iteration = 135, 2-norm of change in F = 0.000104
Iteration = 136, 2-norm of change in F = 0.000102
Iteration = 137, 2-norm of change in F = 0.000101

```

The code below outputs the CDF we are after: the 50th percentile for willingness-to-pay is somewhere between \$100 and \$150.

```

[ ]: foo = list(F_em)
foo.insert(0,0)
data_em = {"Willingness-To-Pay" : [0, 50, 100, 150, 200, 250, 300, 400, 500, 600, 800, 1000], "F(y), CDF" : foo}
data_em
WTP_em = pd.DataFrame.from_dict(data_em)
WTP_em['Survivorship of WTP'] = 1 - WTP_em['F(y), CDF']

WTP_em

```

```

[ ]:
    Willingness-To-Pay  F(y), CDF  Survivorship of WTP
0                    0    0.000000          1.000000
1                   50    0.196802          0.803198
2                  100    0.275522          0.724478
3                  150    0.535366          0.464634
4                  200    0.550813          0.449187
5                  250    0.759008          0.240992
6                  300    0.759649          0.240351
7                  400    0.760972          0.239028
8                  500    0.839917          0.160083
9                  600    0.879562          0.120438
10                 800    0.919781          0.080219
11                1000    0.920871          0.079129

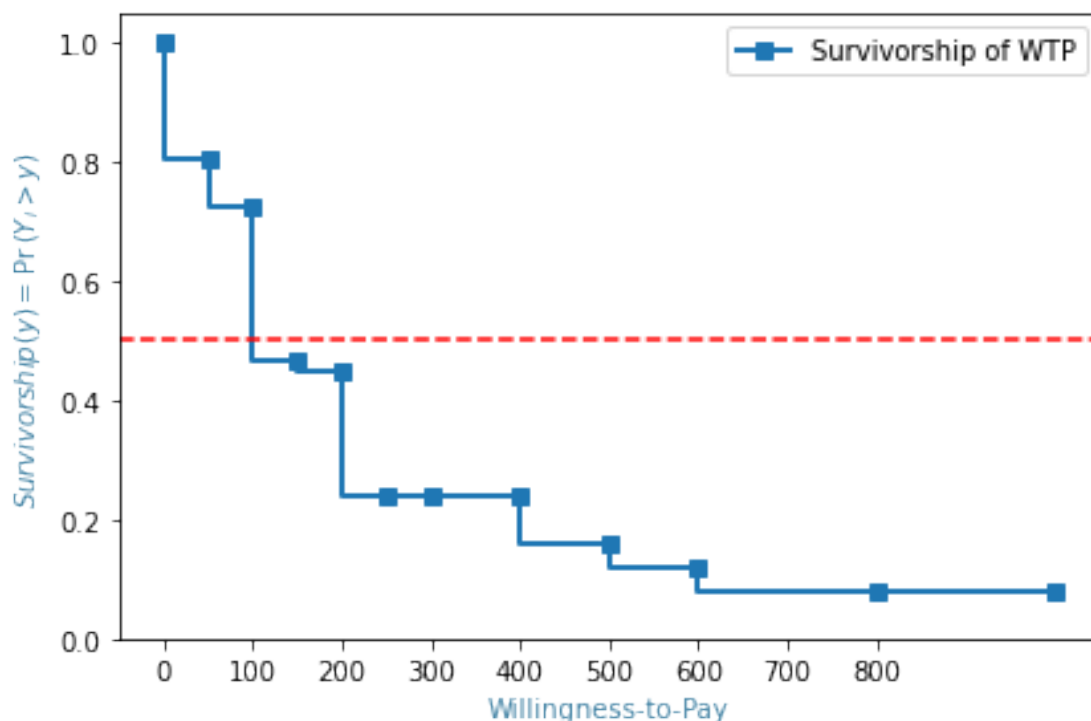
```

Below we plot the willingness-to-pay survivor function for the BearLift proposal.

```
[ ]: # Plot estimate WTP survivor function
fig_wtp_cdf, ax = plt.subplots()

WTP_em.plot(x="Willingness-To-Pay", y="Survivorship of WTP", drawstyle="steps",
            style='s-', linewidth=2, ax=ax)
color = '#3B7EA1' # Founder's Rock
ax.set_xlabel('Willingness-to-Pay', color=color)
ax.set_ylabel(r'$Survivorship(y)=\Pr\left(Y_{\{i\}}>y\right)$', color=color)
plt.axhline(y = 0.5, color = 'r', linestyle = '--')
ax.set_xticks([0,100,200,300,400,500,600,700,800])
ax.set_yticks([0,0.2,0.4,0.6,0.8,1.0])

fig_wtp_cdf.tight_layout() # otherwise the right y-label is slightly clipped
plt.savefig('fig_wtp_cdf', bbox_inches='tight', dpi=500)
```



## 2 Conclusion

We went out and gathered real data about an interesting topic that could have a real impact on the everyday lives of Berkeley students. We then conducted a nonparametric analysis of the data and found some measure of centeredness, by optimizing the posterior probabilities and cumulative distribution. We found that the 50th percentile of willingness-to-pay for BearLift lies in the (\$100, \$150) interval, and we can chart the survivorship function of the willingness-to-pay as we change the

proposed price of the annual fee.