

ARE 213 PS 1b

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Contents

Packages	1
Data cleaning from PS 1a	2
Problem 1	2
Part (a)	2
Part (b)	3
Part (c)	24
Problem 2	31
Part (a)	31
Part (b)	31
Part (c)	31
Part (d)	32
Part (e)	32
Part (f)	32
Part (g)	32
Problem 3	33
Problem 4	33
Problem 5	33
Part (a)	33
Part (b)	33
Part (c)	33
Part (d)	34
Part (e)	34
Part (f)	34
Problem 6	34

Packages

```
# install.packages("pacman")
# install.packages("tidyverse")
# install.packages("plm")
# install.packages('foreign')
# install.packages('stargazer')
# install.packages("finalfit")
```

```

# install.packages("glmnet")
# install.packages("jtools")
# install.packages("Hmisc")
library(tidyverse)
library(foreign)
# library(xtable)
library(stargazer)
library(finalfit)
library(glmnet)
library(jtools) # summ() for regression summaries

```

Data cleaning from PS 1a

```

data = read.dta('ps1.dta')
missing_codes = read.csv('missing_codes.csv')
mvars = as.character(missing_codes$varname)
missing_codes$num_missing = as.integer(0)
for (row in 1:nrow(missing_codes)) {
  var = as.character(missing_codes[row, "varname"])
  code = as.numeric(missing_codes[row, "missing_code"])
  nmissing = as.integer(sum(data[, var] == code))
  missing_codes$num_missing[missing_codes$varname==var] = nmissing
  data[, var] = na_if(data[, var], code)
}
# Convert all variables with <7 unique values to factor (and 3 additional variables)
factor_vars = c("isllb10", "birmon", "weekday")
for (var in colnames(data)) {
  if (length(unique(data[!is.na(data[, var]), var])) < 7 || var %in% factor_vars) {
    data[, var] = factor(data[, var])
  }
}
# label data
variable_labels_df = read.csv('variable_labels.csv')
variable_labels <- setNames(as.character(variable_labels_df$label), variable_labels_df$varname)
data <- Hmisc::upData(data, labels = variable_labels)

## Input object size: 30868856 bytes; 48 variables 120461 observations
## New object size: 30886992 bytes; 48 variables 120461 observations

# Dataframe with missing dropped
df = data[complete.cases(data), ]

```

Problem 1

In Problem Set 1a, you used linear regression to relate infant health outcomes and maternal smoking during pregnancy.

Part (a)

Under the assumption of random assignment conditional on the observables, what are the sources of misspecification bias in the estimates generated by the linear model estimated in Problem Set 1a?

- functional form: what if the CEF isn't linear in parameters. Even if we have a linear CEF, what if we didn't include important interaction terms?

Part (b)

Now, consider a series estimator. Estimate the smoking effects using a flexible functional form for the control variables (e.g., higher order terms and interactions). What are the benefits and drawbacks to this approach?

```
df1b = df %>% select(dbrwt, tobacco, csex, mrace3, preterm,
                    dmage, dfage, dmeduc, dfeduc, ormoth, orfath,
                    disllb, dtotord, dmar, adequacy, nprevist)

# indicator vars (no higher order terms)
vars1 = names(Filter(is.factor, select(df1b, -dbrwt)))
# quantitative vars (need to create higher order terms)
vars2 = names(Filter(is.integer, select(df1b, -dbrwt)))

birthweight = df1b$dbrwt
x = df1b %>% select(-dbrwt)
# Create dummies from factor variables, all interactions, and squared continuous vars
formula1 = as.formula(paste("~ .^2 +", paste0("I(", vars2, "^2)", collapse=" + ") ))
xx <- model.matrix(formula1, x)[, -1]

# Series Regression
reg_1b = lm(birthweight ~ xx)
# rename the coefficients
names(reg_1b$coefficients) <- gsub("xx", "", names(reg_1b$coefficients))
coefficients(reg_1b)
```

```
##      (Intercept)      tobacco2      csex2      mrace32
##      9.888205e+02      2.144189e+02      -2.460893e+01      -2.149490e+02
##      mrace33      preterm2      dmage      dfage
##      -1.219773e+02      8.118905e+02      4.227047e+01      -5.473113e+00
##      dmeduc      dfeduc      ormoth1      ormoth2
##      1.791153e+01      -1.928443e+01      3.887857e+02      6.658417e+01
##      ormoth3      ormoth4      ormoth5      orfath1
##      -9.894276e+02      3.895786e+02      -1.888306e+02      -6.865286e+02
##      orfath2      orfath3      orfath4      orfath5
##      -1.378863e+02      3.982333e+02      1.606181e+02      4.247760e+02
##      disllb      dtotord      dmar2      adequacy2
##      -7.281393e-02      -4.211551e+01      -2.200343e+02      5.923781e+02
##      adequacy3      nprevist      I(dmage^2)      I(dfage^2)
##      1.047928e+03      1.661254e+02      -9.170697e-01      -1.479438e-02
##      I(dmeduc^2)      I(dfeduc^2)      I(disllb^2)      I(dtotord^2)
##      -3.130084e-02      4.486755e-01      -9.403191e-04      -1.545961e+00
##      I(nprevist^2)      tobacco2:csex2      tobacco2:mrace32      tobacco2:mrace33
##      -3.866891e+00      1.851477e+00      -4.178789e+01      -6.325021e+01
##      tobacco2:preterm2      tobacco2:dmage      tobacco2:dfage      tobacco2:dmeduc
##      -1.402385e+00      4.805547e+00      1.393528e+00      -1.100485e+01
##      tobacco2:dfeduc      tobacco2:ormoth1      tobacco2:ormoth2      tobacco2:ormoth3
##      -2.502236e+00      -6.168336e+01      2.487877e+00      -3.678457e+02
##      tobacco2:ormoth4      tobacco2:ormoth5      tobacco2:orfath1      tobacco2:orfath2
##      -1.700206e+02      -4.560742e+01      2.174027e+02      -8.900712e+01
##      tobacco2:orfath3      tobacco2:orfath4      tobacco2:orfath5      tobacco2:disllb
```

##	-2.287477e+02	-2.542848e+02	-6.681166e+01	-1.951305e-02
##	tobacco2:dtotord	tobacco2:dmr2	tobacco2:adequacy2	tobacco2:adequacy3
##	8.154257e+00	-3.697862e+01	3.134864e+01	2.348893e+01
##	tobacco2:nprevist	csex2:mrace32	csex2:mrace33	csex2:preterm2
##	4.642094e-02	2.656400e+01	1.084581e+01	-1.366212e+01
##	csex2:dmage	csex2:dfage	csex2:dmeduc	csex2:dfeduc
##	1.317171e-01	-1.104886e+00	2.759663e+00	-3.474496e+00
##	csex2:ormoth1	csex2:ormoth2	csex2:ormoth3	csex2:ormoth4
##	1.181547e+02	1.787680e+01	-2.727092e+01	-3.465208e+00
##	csex2:ormoth5	csex2:orfath1	csex2:orfath2	csex2:orfath3
##	1.112386e+02	-1.454543e+02	-2.383637e+01	-8.227054e+00
##	csex2:orfath4	csex2:orfath5	csex2:disllb	csex2:dtotord
##	7.675028e+01	-3.865138e+01	1.865434e-02	-3.701548e+00
##	csex2:dmr2	csex2:adequacy2	csex2:adequacy3	csex2:nprevist
##	-4.395974e+00	-1.151253e+01	-3.651453e+01	-3.984337e+00
##	mrace32:preterm2	mrace33:preterm2	mrace32:dmage	mrace33:dmage
##	6.161528e+01	2.848803e+01	7.125760e+00	-1.048850e+00
##	mrace32:dfage	mrace33:dfage	mrace32:dmeduc	mrace33:dmeduc
##	-3.940058e+00	-8.698864e-01	-3.095915e+00	-6.617296e-01
##	mrace32:dfeduc	mrace33:dfeduc	mrace32:ormoth1	mrace33:ormoth1
##	1.284459e+00	-8.763940e+00	1.216725e+02	2.744671e+02
##	mrace32:ormoth2	mrace33:ormoth2	mrace32:ormoth3	mrace33:ormoth3
##	1.049448e+02	1.920420e+02	-4.502423e+00	-2.517420e+01
##	mrace32:ormoth4	mrace33:ormoth4	mrace32:ormoth5	mrace33:ormoth5
##	2.748790e+02	2.577802e+01	3.673992e+02	-3.778896e+00
##	mrace32:orfath1	mrace33:orfath1	mrace32:orfath2	mrace33:orfath2
##	-7.637054e+01	-1.939242e+01	1.637044e+02	2.002011e+01
##	mrace32:orfath3	mrace33:orfath3	mrace32:orfath4	mrace33:orfath4
##	NA	5.410640e+02	2.297409e+02	7.550759e+01
##	mrace32:orfath5	mrace33:orfath5	mrace32:disllb	mrace33:disllb
##	-3.312549e+02	1.081440e+02	5.199514e-02	-4.686480e-03
##	mrace32:dtotord	mrace33:dtotord	mrace32:dmr2	mrace33:dmr2
##	2.256630e-02	-8.223725e+00	8.361100e+01	-2.498313e+01
##	mrace32:adequacy2	mrace33:adequacy2	mrace32:adequacy3	mrace33:adequacy3
##	-6.314167e+01	2.847886e+01	-1.900216e+01	1.052331e+02
##	mrace32:nprevist	mrace33:nprevist	preterm2:dmage	preterm2:dfage
##	-8.383459e+00	1.324633e+01	-3.405302e+00	-2.180616e+00
##	preterm2:dmeduc	preterm2:dfeduc	preterm2:ormoth1	preterm2:ormoth2
##	1.467995e+00	6.611429e+00	-3.996192e+02	-1.929205e+02
##	preterm2:ormoth3	preterm2:ormoth4	preterm2:ormoth5	preterm2:orfath1
##	NA	1.051697e+02	1.082922e+02	8.902877e+02
##	preterm2:orfath2	preterm2:orfath3	preterm2:orfath4	preterm2:orfath5
##	2.023559e+02	NA	-3.941754e+02	-6.667618e+01
##	preterm2:disllb	preterm2:dtotord	preterm2:dmr2	preterm2:adequacy2
##	5.292998e-01	-6.075104e+00	-1.006683e+01	-1.141571e+02
##	preterm2:adequacy3	preterm2:nprevist	dmage:dfage	dmage:dmeduc
##	-2.953670e+02	-2.527863e+01	1.313347e-01	3.417724e-01
##	dmage:dfeduc	dmage:ormoth1	dmage:ormoth2	dmage:ormoth3
##	1.902418e-02	5.871341e+00	2.501944e-01	2.285636e+01
##	dmage:ormoth4	dmage:ormoth5	dmage:orfath1	dmage:orfath2
##	-4.765782e+00	1.137417e+00	-8.048578e+00	3.588383e+00
##	dmage:orfath3	dmage:orfath4	dmage:orfath5	dmage:disllb
##	-9.368101e+00	-6.200945e+00	4.517460e+00	-6.642264e-03
##	dmage:dtotord	dmage:dmr2	dmage:adequacy2	dmage:adequacy3

##	1.784992e+00	-5.039936e+00	-1.040993e+00	-3.533706e+00
##	dmage:nprevist	dfage:dmeduc	dfage:dfeduc	dfage:ormoth1
##	-2.812148e-01	-3.166786e-01	-9.461215e-03	-1.943479e-01
##	dfage:ormoth2	dfage:ormoth3	dfage:ormoth4	dfage:ormoth5
##	1.623410e-01	-1.482097e+01	4.803686e+00	-1.390343e+00
##	dfage:orfath1	dfage:orfath2	dfage:orfath3	dfage:orfath4
##	-8.123761e+00	-1.395197e+00	1.949553e+01	1.141395e+01
##	dfage:orfath5	dfage:disllb	dfage:dtotord	dfage:dmар2
##	-8.361689e-01	1.261312e-03	3.723985e-01	7.323969e-01
##	dfage:adequacy2	dfage:adequacy3	dfage:nprevist	dmeduc:dfeduc
##	8.059195e-01	3.166813e+00	5.957992e-01	6.692504e-01
##	dmeduc:ormoth1	dmeduc:ormoth2	dmeduc:ormoth3	dmeduc:ormoth4
##	-1.426528e+01	-2.496920e+01	-4.716511e+01	-1.599738e+01
##	dmeduc:ormoth5	dmeduc:orfath1	dmeduc:orfath2	dmeduc:orfath3
##	2.533409e+01	1.837127e+01	1.645496e+00	-1.517077e+01
##	dmeduc:orfath4	dmeduc:orfath5	dmeduc:disllb	dmeduc:dtotord
##	1.244237e+01	-4.575611e+00	4.616856e-03	-5.572140e-01
##	dmeduc:dmар2	dmeduc:adequacy2	dmeduc:adequacy3	dmeduc:nprevist
##	2.678595e+00	-6.460783e+00	-1.086803e+01	-1.150319e+00
##	dfeduc:ormoth1	dfeduc:ormoth2	dfeduc:ormoth3	dfeduc:ormoth4
##	3.283190e+00	2.397848e+01	5.879949e+01	3.921535e+00
##	dfeduc:ormoth5	dfeduc:orfath1	dfeduc:orfath2	dfeduc:orfath3
##	-5.534116e+00	-2.120640e+01	-8.056381e+00	2.675163e+00
##	dfeduc:orfath4	dfeduc:orfath5	dfeduc:disllb	dfeduc:dtotord
##	-3.093351e-01	-2.033237e+00	-2.503926e-03	-6.272049e-01
##	dfeduc:dmар2	dfeduc:adequacy2	dfeduc:adequacy3	dfeduc:nprevist
##	1.253461e+01	2.335086e+00	7.385599e+00	-1.971177e-01
##	ormoth1:orfath1	ormoth2:orfath1	ormoth3:orfath1	ormoth4:orfath1
##	-1.776174e+02	-3.307756e+01	5.804182e+02	-7.116497e+01
##	ormoth5:orfath1	ormoth1:orfath2	ormoth2:orfath2	ormoth3:orfath2
##	-4.135189e+02	1.687862e+02	-2.319910e+01	4.438676e+02
##	ormoth4:orfath2	ormoth5:orfath2	ormoth1:orfath3	ormoth2:orfath3
##	9.760434e+01	-1.592669e+01	NA	-2.064433e+02
##	ormoth3:orfath3	ormoth4:orfath3	ormoth5:orfath3	ormoth1:orfath4
##	-1.142997e+02	-6.104628e+02	NA	-1.053158e+02
##	ormoth2:orfath4	ormoth3:orfath4	ormoth4:orfath4	ormoth5:orfath4
##	3.191826e+01	2.946576e+02	6.953357e+01	4.612715e+01
##	ormoth1:orfath5	ormoth2:orfath5	ormoth3:orfath5	ormoth4:orfath5
##	-3.547698e+02	-5.914413e+01	-4.682794e+02	-2.481097e+02
##	ormoth5:orfath5	ormoth1:disllb	ormoth2:disllb	ormoth3:disllb
##	-4.735882e+01	-1.286068e-01	2.383762e-02	2.653143e-01
##	ormoth4:disllb	ormoth5:disllb	ormoth1:dtotord	ormoth2:dtotord
##	-7.031207e-02	1.232049e-01	-1.350182e+01	2.198941e+01
##	ormoth3:dtotord	ormoth4:dtotord	ormoth5:dtotord	ormoth1:dmар2
##	1.376697e+02	-4.039166e+01	-8.720333e+00	8.158766e+01
##	ormoth2:dmар2	ormoth3:dmар2	ormoth4:dmар2	ormoth5:dmар2
##	-5.239427e+01	2.071374e+02	1.640844e+01	2.835995e+01
##	ormoth1:adequacy2	ormoth2:adequacy2	ormoth3:adequacy2	ormoth4:adequacy2
##	-8.548134e+01	-2.450428e+01	-7.218578e+01	-9.999306e+01
##	ormoth5:adequacy2	ormoth1:adequacy3	ormoth2:adequacy3	ormoth3:adequacy3
##	-7.364570e+01	1.450182e+02	-4.475147e+01	7.405109e+02
##	ormoth4:adequacy3	ormoth5:adequacy3	ormoth1:nprevist	ormoth2:nprevist
##	5.201581e+01	-2.032143e+02	9.073751e+00	-1.146680e+00
##	ormoth3:nprevist	ormoth4:nprevist	ormoth5:nprevist	orfath1:disllb

##	3.910174e+01	-1.107515e+01	-2.285245e+01	1.174103e-01
##	orfath2:disllb	orfath3:disllb	orfath4:disllb	orfath5:disllb
##	-8.585136e-02	5.397238e-02	-3.397815e-02	-9.326690e-02
##	orfath1:dtotord	orfath2:dtotord	orfath3:dtotord	orfath4:dtotord
##	4.550441e+01	-3.079793e+01	-2.412029e+01	-1.057973e+01
##	orfath5:dtotord	orfath1:dmар2	orfath2:dmар2	orfath3:dmар2
##	-4.379531e+01	8.841007e+01	2.853187e+01	2.855421e+02
##	orfath4:dmар2	orfath5:dmар2	orfath1:adequacy2	orfath2:adequacy2
##	3.667375e+01	-3.291933e+01	6.500342e+01	6.563400e+01
##	orfath3:adequacy2	orfath4:adequacy2	orfath5:adequacy2	orfath1:adequacy3
##	2.997188e+01	1.756439e+01	-2.688476e+01	-2.040077e+01
##	orfath2:adequacy3	orfath3:adequacy3	orfath4:adequacy3	orfath5:adequacy3
##	1.250236e+02	-1.092874e+03	8.306446e+01	-1.448977e+02
##	orfath1:nprevist	orfath2:nprevist	orfath3:nprevist	orfath4:nprevist
##	-7.475106e+00	8.818509e+00	-1.816355e+01	3.252319e+00
##	orfath5:nprevist	disllb:dtotord	disllb:dmар2	disllb:adequacy2
##	-1.258824e+01	-2.604213e-02	2.020447e-02	7.267905e-02
##	disllb:adequacy3	disllb:nprevist	dtotord:dmар2	dtotord:adequacy2
##	1.986484e-01	2.369469e-02	8.046503e+00	2.098157e+01
##	dtotord:adequacy3	dtotord:nprevist	dmар2:adequacy2	dmар2:adequacy3
##	2.735461e+01	5.057545e-01	-8.390896e+00	3.123210e+01
##	dmар2:nprevist	adequacy2:nprevist	adequacy3:nprevist	
##	1.034898e+01	-3.358381e+01	-6.527302e+01	

Need to change to longtable before final submission

A table enviroment cannot be broken across pages. Delete \begin{table}\centering and \end{table}, repla

```
stargazer(reg_1b, title="Series Regression", header=FALSE, single.row=TRUE,
          se = NULL, notes = 'SEs omitted for brevity', type ="html", report = "vc*") # , align = TRU
```

Series Regression

Dependent variable:

birthweight

tobacco2

214.419***

csex2

-24.609

mrace32

-214.949

mrace33

-121.977

preterm2

811.890***

dmage

42.270***

dfage

-5.473

dmeduc
17.912
dfeduc
-19.284
ormoth1
388.786
ormoth2
66.584
ormoth3
-989.428
ormoth4
389.579
ormoth5
-188.831
orfath1
-686.529
orfath2
-137.886
orfath3
398.233
orfath4
160.618
orfath5
424.776
disllb
-0.073
dtotord
-42.116**
dmar2
-220.034***
adequacy2
592.378***
adequacy3
1,047.928***
nprevist
166.125***

I(dmage2)
 -0.917***
 I(dfage2)
 -0.015
 I(dmeduc2)
 -0.031
 I(dfeduc2)
 0.449
 I(disllb2)
 -0.001***
 I(dtotord2)
 -1.546***
 I(nprevist2)
 -3.867***
 tobacco2:csex2
 1.851
 tobacco2:mrace32
 -41.788
 tobacco2:mrace33
 -63.250***
 tobacco2:preterm2
 -1.402
 tobacco2:dmage
 4.806***
 tobacco2:dfage
 1.394
 tobacco2:dmeduc
 -11.005***
 tobacco2:dfeduc
 -2.502
 tobacco2:ormoth1
 -61.683
 tobacco2:ormoth2
 2.488
 tobacco2:ormoth3
 -367.846

tobacco2:ormoth4
 -170.021
 tobacco2:ormoth5
 -45.607
 tobacco2:orfath1
 217.403**
 tobacco2:orfath2
 -89.007**
 tobacco2:orfath3
 -228.748
 tobacco2:orfath4
 -254.285**
 tobacco2:orfath5
 -66.812
 tobacco2:disllb
 -0.020
 tobacco2:dtotord
 8.154**
 tobacco2:dmr2
 -36.979***
 tobacco2:adequacy2
 31.349**
 tobacco2:adequacy3
 23.489
 tobacco2:nprevist
 0.046
 csex2:mrace32
 26.564
 csex2:mrace33
 10.846
 csex2:preterm2
 -13.662
 csex2:dmage
 0.132
 csex2:dfage
 -1.105

csex2:dmeduc
 2.760
 csex2:dfeduc
 -3.474*
 csex2:ormoth1
 118.155*
 csex2:ormoth2
 17.877
 csex2:ormoth3
 -27.271
 csex2:ormoth4
 -3.465
 csex2:ormoth5
 111.239**
 csex2:orfath1
 -145.454**
 csex2:orfath2
 -23.836
 csex2:orfath3
 -8.227
 csex2:orfath4
 76.750
 csex2:orfath5
 -38.651
 csex2:disllb
 0.019
 csex2:dtotord
 -3.702
 csex2:dmarr2
 -4.396
 csex2:adequacy2
 -11.513
 csex2:adequacy3
 -36.515*
 csex2:nprevist
 -3.984***

mrace32:preterm2
 61.615
 mrace33:preterm2
 28.488
 mrace32:dmage
 7.126**
 mrace33:dmage
 -1.049
 mrace32:dfage
 -3.940
 mrace33:dfage
 -0.870
 mrace32:dmeduc
 -3.096
 mrace33:dmeduc
 -0.662
 mrace32:dfeduc
 1.284
 mrace33:dfeduc
 -8.764**
 mrace32:ormoth1
 121.673
 mrace33:ormoth1
 274.467
 mrace32:ormoth2
 104.945
 mrace33:ormoth2
 192.042***
 mrace32:ormoth3
 -4.502
 mrace33:ormoth3
 -25.174
 mrace32:ormoth4
 274.879
 mrace33:ormoth4
 25.778

mrace32:ormoth5
 367.399*
 mrace33:ormoth5
 -3.779
 mrace32:orfath1
 -76.371
 mrace33:orfath1
 -19.392
 mrace32:orfath2
 163.704
 mrace33:orfath2
 20.020
 mrace32:orfath3
 mrace33:orfath3
 541.064*
 mrace32:orfath4
 229.741
 mrace33:orfath4
 75.508
 mrace32:orfath5
 -331.255
 mrace33:orfath5
 108.144
 mrace32:disllb
 0.052
 mrace33:disllb
 -0.005
 mrace32:dtotord
 0.023
 mrace33:dtotord
 -8.224*
 mrace32:dmr2
 83.611*
 mrace33:dmr2
 -24.983*
 mrace32:adequacy2

-63.142*
 mrace33:adequacy2
 28.479*
 mrace32:adequacy3
 -19.002
 mrace33:adequacy3
 105.233***
 mrace32:nprevist
 -8.383*
 mrace33:nprevist
 13.246***
 preterm2:dmage
 -3.405
 preterm2:dfage
 -2.181
 preterm2:dmeduc
 1.468
 preterm2:dfeduc
 6.611
 preterm2:ormoth1
 -399.619
 preterm2:ormoth2
 -192.920**
 preterm2:ormoth3
 preterm2:ormoth4
 105.170
 preterm2:ormoth5
 108.292
 preterm2:orfath1
 890.288***
 preterm2:orfath2
 202.356**
 preterm2:orfath3
 preterm2:orfath4
 -394.175*
 preterm2:orfath5

-66.676
preterm2:disllb
0.529
preterm2:dtotord
-6.075
preterm2:dmarr2
-10.067
preterm2:adequacy2
-114.157***
preterm2:adequacy3
-295.367***
preterm2:nprevist
-25.279***
dmage:dfage
0.131
dmage:dmeduc
0.342
dmage:dfeduc
0.019
dmage:ormoth1
5.871
dmage:ormoth2
0.250
dmage:ormoth3
22.856
dmage:ormoth4
-4.766
dmage:ormoth5
1.137
dmage:orfath1
-8.049
dmage:orfath2
3.588
dmage:orfath3
-9.368
dmage:orfath4

-6.201
dimage:orfath5
4.517
dimage:disllb
-0.007***
dimage:dtotord
1.785***
dimage:dmarr2
-5.040***
dimage:adequacy2
-1.041
dimage:adequacy3
-3.534
dimage:nprevist
-0.281
dfage:dmeduc
-0.317
dfage:dfeduc
-0.009
dfage:ormoth1
-0.194
dfage:ormoth2
0.162
dfage:ormoth3
-14.821
dfage:ormoth4
4.804
dfage:ormoth5
-1.390
dfage:orfath1
-8.124
dfage:orfath2
-1.395
dfage:orfath3
19.496
dfage:orfath4

11.414*
 dfage:orfath5
 -0.836
 dfage:disllb
 0.001
 dfage:dtotord
 0.372
 dfage:dmarr2
 0.732
 dfage:adequacy2
 0.806
 dfage:adequacy3
 3.167
 dfage:nprevist
 0.596***
 dmeduc:dfeduc
 0.669
 dmeduc:ormoth1
 -14.265
 dmeduc:ormoth2
 -24.969***
 dmeduc:ormoth3
 -47.165
 dmeduc:ormoth4
 -15.997
 dmeduc:ormoth5
 25.334
 dmeduc:orfath1
 18.371
 dmeduc:orfath2
 1.645
 dmeduc:orfath3
 -15.171
 dmeduc:orfath4
 12.442
 dmeduc:orfath5

-4.576
dmeduc:disllb
0.005
dmeduc:dtotord
-0.557
dmeduc:dmarr2
2.679
dmeduc:adequacy2
-6.461**
dmeduc:adequacy3
-10.868*
dmeduc:nprevist
-1.150***
dfeduc:ormoth1
3.283
dfeduc:ormoth2
23.978***
dfeduc:ormoth3
58.799
dfeduc:ormoth4
3.922
dfeduc:ormoth5
-5.534
dfeduc:orfath1
-21.206
dfeduc:orfath2
-8.056
dfeduc:orfath3
2.675
dfeduc:orfath4
-0.309
dfeduc:orfath5
-2.033
dfeduc:disllb
-0.003
dfeduc:dtotord

-0.627
dfeduc:dmr2
12.535***
dfeduc:adequacy2
2.335
dfeduc:adequacy3
7.386
dfeduc:nprevist
-0.197
ormoth1:orfath1
-177.617*
ormoth2:orfath1
-33.078
ormoth3:orfath1
580.418
ormoth4:orfath1
-71.165
ormoth5:orfath1
-413.519
ormoth1:orfath2
168.786
ormoth2:orfath2
-23.199
ormoth3:orfath2
443.868
ormoth4:orfath2
97.604
ormoth5:orfath2
-15.927
ormoth1:orfath3
ormoth2:orfath3
-206.443
ormoth3:orfath3
-114.300
ormoth4:orfath3
-610.463*

ormoth5:orfath3
ormoth1:orfath4
-105.316
ormoth2:orfath4
31.918
ormoth3:orfath4
294.658
ormoth4:orfath4
69.534
ormoth5:orfath4
46.127
ormoth1:orfath5
-354.770
ormoth2:orfath5
-59.144
ormoth3:orfath5
-468.279
ormoth4:orfath5
-248.110
ormoth5:orfath5
-47.359
ormoth1:disllb
-0.129
ormoth2:disllb
0.024
ormoth3:disllb
0.265
ormoth4:disllb
-0.070
ormoth5:disllb
0.123
ormoth1:dtotord
-13.502
ormoth2:dtotord
21.989
ormoth3:dtotord

137.670**
ormoth4:dtotord
-40.392
ormoth5:dtotord
-8.720
ormoth1:dmар2
81.588
ormoth2:dmар2
-52.394
ormoth3:dmар2
207.137
ormoth4:dmар2
16.408
ormoth5:dmар2
28.360
ormoth1:adequacy2
-85.481
ormoth2:adequacy2
-24.504
ormoth3:adequacy2
-72.186
ormoth4:adequacy2
-99.993
ormoth5:adequacy2
-73.646
ormoth1:adequacy3
145.018
ormoth2:adequacy3
-44.751
ormoth3:adequacy3
740.511
ormoth4:adequacy3
52.016
ormoth5:adequacy3
-203.214
ormoth1:nprevist

9.074
ormoth2:nprevist
-1.147
ormoth3:nprevist
39.102
ormoth4:nprevist
-11.075
ormoth5:nprevist
-22.852***
orfath1:disllb
0.117
orfath2:disllb
-0.086
orfath3:disllb
0.054
orfath4:disllb
-0.034
orfath5:disllb
-0.093
orfath1:dtotord
45.504*
orfath2:dtotord
-30.798**
orfath3:dtotord
-24.120
orfath4:dtotord
-10.580
orfath5:dtotord
-43.795
orfath1:dmr2
88.410
orfath2:dmr2
28.532
orfath3:dmr2
285.542
orfath4:dmr2

36.674
 orfath5:dmr2
 -32.919
 orfath1:adequacy2
 65.003
 orfath2:adequacy2
 65.634*
 orfath3:adequacy2
 29.972
 orfath4:adequacy2
 17.564
 orfath5:adequacy2
 -26.885
 orfath1:adequacy3
 -20.401
 orfath2:adequacy3
 125.024*
 orfath3:adequacy3
 -1,092.874***
 orfath4:adequacy3
 83.064
 orfath5:adequacy3
 -144.898
 orfath1:nprevist
 -7.475
 orfath2:nprevist
 8.819*
 orfath3:nprevist
 -18.164
 orfath4:nprevist
 3.252
 orfath5:nprevist
 -12.588
 disllb:dtotord
 -0.026***
 disllb:dmr2

0.020
 disllb:adequacy2
 0.073***
 disllb:adequacy3
 0.199***
 disllb:nprevist
 0.024***
 dtotord:dmар2
 8.047*
 dtotord:adequacy2
 20.982***
 dtotord:adequacy3
 27.355***
 dtotord:nprevist
 0.506
 dmar2:adequacy2
 -8.391
 dmar2:adequacy3
 31.232
 dmar2:nprevist
 10.349***
 adequacy2:nprevist
 -33.584***
 adequacy3:nprevist
 -65.273***
 Constant
 988.820***
 Observations
 114,610
 R2
 0.132
 Adjusted R2
 0.130
 Residual Std. Error
 545.824 (df = 114304)
 F Statistic

57.135*** (df = 305; 114304)

Note:

$p < 0.1$; $p < 0.05$; $p < 0.01$

SEs omitted for brevity

Part (c)

Use the LASSO to determine which covariates (and higher order terms) to include in your regression from part (b). Do you end up dropping some covariates that you had thought might be necessary to include?

```
# use glmnet with alpha=1 for lasso
reg_1c = glmnet(xx, birthweight, family="gaussian", alpha=1)
# print results (Df = # of variables, %Dev = R^2)
print(reg_1c)

##
## Call:  glmnet(x = xx, y = birthweight, family = "gaussian", alpha = 1)
##
##           Df  %Dev  Lambda
##  1         0  0.00 113.900
##  2         1  0.64 103.800
##  3         1  1.18  94.590
##  4         1  1.62  86.180
##  5         3  2.11  78.530
##  6         4  2.78  71.550
##  7         6  3.37  65.200
##  8         6  4.12  59.400
##  9         7  4.77  54.130
## 10        10  5.38  49.320
## 11        10  6.01  44.940
## 12        10  6.53  40.940
## 13        10  6.96  37.310
## 14        11  7.33  33.990
## 15        12  7.63  30.970
## 16        12  7.90  28.220
## 17        13  8.13  25.710
## 18        14  8.32  23.430
## 19        14  8.51  21.350
## 20        15  8.68  19.450
## 21        16  8.84  17.720
## 22        15  9.00  16.150
## 23        16  9.13  14.710
## 24        17  9.27  13.410
## 25        20  9.38  12.220
## 26        23  9.48  11.130
## 27        29  9.57  10.140
## 28        37  9.77   9.241
## 29        46 10.00   8.420
## 30        47 10.34   7.672
## 31        51 10.64   6.991
## 32        53 10.90   6.370
## 33        50 11.09   5.804
```


## 34	53	11.25	5.288
## 35	56	11.38	4.818
## 36	57	11.50	4.390
## 37	60	11.59	4.000
## 38	65	11.68	3.645
## 39	68	11.77	3.321
## 40	70	11.86	3.026
## 41	72	11.93	2.757
## 42	74	12.01	2.512
## 43	77	12.08	2.289
## 44	82	12.14	2.086
## 45	85	12.22	1.900
## 46	92	12.31	1.732
## 47	96	12.39	1.578
## 48	101	12.47	1.438
## 49	105	12.51	1.310
## 50	115	12.56	1.194
## 51	119	12.61	1.088
## 52	122	12.65	0.991
## 53	126	12.70	0.903
## 54	132	12.72	0.823
## 55	140	12.75	0.750
## 56	149	12.79	0.683
## 57	155	12.83	0.622
## 58	159	12.85	0.567
## 59	165	12.88	0.517
## 60	170	12.91	0.471
## 61	183	12.93	0.429
## 62	190	12.96	0.391
## 63	197	12.98	0.356
## 64	200	13.00	0.324
## 65	203	13.02	0.296
## 66	204	13.03	0.269
## 67	211	13.05	0.246
## 68	214	13.06	0.224
## 69	222	13.07	0.204
## 70	222	13.08	0.186
## 71	230	13.09	0.169
## 72	234	13.10	0.154
## 73	240	13.11	0.140
## 74	244	13.12	0.128
## 75	246	13.13	0.117
## 76	251	13.14	0.106
## 77	255	13.15	0.097
## 78	258	13.15	0.088
## 79	261	13.16	0.080
## 80	266	13.16	0.073
## 81	272	13.17	0.067
## 82	272	13.17	0.061
## 83	277	13.18	0.055
## 84	277	13.18	0.050
## 85	277	13.18	0.046
## 86	280	13.19	0.042
## 87	280	13.19	0.038

```
## 88 281 13.19 0.035
## 89 282 13.19 0.032
## 90 284 13.19 0.029
## 91 286 13.20 0.026
## 92 290 13.20 0.024
## 93 291 13.20 0.022
## 94 295 13.20 0.020
## 95 297 13.20 0.018
## 96 299 13.20 0.017
## 97 299 13.20 0.015
## 98 300 13.20 0.014
## 99 301 13.20 0.012
## 100 301 13.20 0.011
```

```
# if we wanted to limit the model to 20 variables, the 25th iteration
# where lambda = 12.220 gives 20 variables (and decreases in )
choice = 25
lambda = reg_1c$lambda[[choice]]
print(paste('# of variables in 25th iteration:', sum(reg_1c$beta[, choice] != 0)))
```

```
## [1] "# of variables in 25th iteration: 20"
```

```
# print the 25th lasso regression coefficients
print(reg_1c$beta[, choice])
```

```
##          tobacco2          csex2          mrace32          mrace33
## 0.000000e+00 -1.004847e+02 -6.707636e+01 -1.645689e+02
##      preterm2          dimage          dfage          dmeduc
## 0.000000e+00 0.000000e+00 0.000000e+00 0.000000e+00
##      dfeduc          ormoth1          ormoth2          ormoth3
## 0.000000e+00 0.000000e+00 -6.372021e+01 0.000000e+00
##      ormoth4          ormoth5          orfath1          orfath2
## 0.000000e+00 0.000000e+00 0.000000e+00 0.000000e+00
##      orfath3          orfath4          orfath5          disllb
## 0.000000e+00 0.000000e+00 0.000000e+00 0.000000e+00
##      dtotord          dmar2          adequacy2          adequacy3
## 0.000000e+00 -4.846922e+01 0.000000e+00 0.000000e+00
##      nprevist          I(dimage^2)          I(dfage^2)          I(dmeduc^2)
## 0.000000e+00 0.000000e+00 0.000000e+00 0.000000e+00
##      I(dfeduc^2)          I(disllb^2)          I(dtotord^2)          I(nprevist^2)
## 0.000000e+00 0.000000e+00 0.000000e+00 0.000000e+00
## tobacco2:csex2 tobacco2:mrace32 tobacco2:mrace33 tobacco2:preterm2
## 0.000000e+00 0.000000e+00 0.000000e+00 1.212800e+02
## tobacco2:dimage tobacco2:dfage tobacco2:dmeduc tobacco2:dfeduc
## 1.139206e+00 0.000000e+00 0.000000e+00 0.000000e+00
## tobacco2:ormoth1 tobacco2:ormoth2 tobacco2:ormoth3 tobacco2:ormoth4
## 0.000000e+00 0.000000e+00 0.000000e+00 0.000000e+00
## tobacco2:ormoth5 tobacco2:orfath1 tobacco2:orfath2 tobacco2:orfath3
## 0.000000e+00 0.000000e+00 -2.533540e+00 0.000000e+00
## tobacco2:orfath4 tobacco2:orfath5 tobacco2:disllb tobacco2:dtotord
## 0.000000e+00 0.000000e+00 0.000000e+00 9.383169e+00
## tobacco2:dmar2 tobacco2:adequacy2 tobacco2:adequacy3 tobacco2:nprevist
## 0.000000e+00 1.233125e-01 0.000000e+00 1.262811e+00
## csex2:mrace32 csex2:mrace33 csex2:preterm2 csex2:dimage
## 0.000000e+00 0.000000e+00 0.000000e+00 0.000000e+00
## csex2:dfage csex2:dmeduc csex2:dfeduc csex2:ormoth1
```

##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	csex2:ormoth2	csex2:ormoth3	csex2:ormoth4	csex2:ormoth5
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	csex2:orfath1	csex2:orfath2	csex2:orfath3	csex2:orfath4
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	csex2:orfath5	csex2:dis1lb	csex2:dtotord	csex2:dmarr2
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	csex2:adequacy2	csex2:adequacy3	csex2:nprevist	mrace32:preterm2
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	mrace33:preterm2	mrace32:dmage	mrace33:dmage	mrace32:dfage
##	0.000000e+00	0.000000e+00	0.000000e+00	-7.236427e-01
##	mrace33:dfage	mrace32:dmeduc	mrace33:dmeduc	mrace32:dfeduc
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	mrace33:dfeduc	mrace32:ormoth1	mrace33:ormoth1	mrace32:ormoth2
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	mrace33:ormoth2	mrace32:ormoth3	mrace33:ormoth3	mrace32:ormoth4
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	mrace33:ormoth4	mrace32:ormoth5	mrace33:ormoth5	mrace32:orfath1
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	mrace33:orfath1	mrace32:orfath2	mrace33:orfath2	mrace32:orfath3
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	mrace33:orfath3	mrace32:orfath4	mrace33:orfath4	mrace32:orfath5
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	mrace33:orfath5	mrace32:dis1lb	mrace33:dis1lb	mrace32:dtotord
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	mrace33:dtotord	mrace32:dmarr2	mrace33:dmarr2	mrace32:adequacy2
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	mrace33:adequacy2	mrace32:adequacy3	mrace33:adequacy3	mrace32:nprevist
##	0.000000e+00	0.000000e+00	0.000000e+00	-8.111708e-02
##	mrace33:nprevist	preterm2:dmage	preterm2:dfage	preterm2:dmeduc
##	0.000000e+00	0.000000e+00	0.000000e+00	3.002415e+00
##	preterm2:dfeduc	preterm2:ormoth1	preterm2:ormoth2	preterm2:ormoth3
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	preterm2:ormoth4	preterm2:ormoth5	preterm2:orfath1	preterm2:orfath2
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	preterm2:orfath3	preterm2:orfath4	preterm2:orfath5	preterm2:dis1lb
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	preterm2:dtotord	preterm2:dmarr2	preterm2:adequacy2	preterm2:adequacy3
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	preterm2:nprevist	dmage:dfage	dmage:dmeduc	dmage:dfeduc
##	1.984857e+01	0.000000e+00	0.000000e+00	0.000000e+00
##	dmage:ormoth1	dmage:ormoth2	dmage:ormoth3	dmage:ormoth4
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	dmage:ormoth5	dmage:orfath1	dmage:orfath2	dmage:orfath3
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	dmage:orfath4	dmage:orfath5	dmage:dis1lb	dmage:dtotord
##	0.000000e+00	0.000000e+00	-3.837685e-03	0.000000e+00
##	dmage:dmarr2	dmage:adequacy2	dmage:adequacy3	dmage:nprevist
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	dfage:dmeduc	dfage:dfeduc	dfage:ormoth1	dfage:ormoth2
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	dfage:ormoth3	dfage:ormoth4	dfage:ormoth5	dfage:orfath1
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	dfage:orfath2	dfage:orfath3	dfage:orfath4	dfage:orfath5

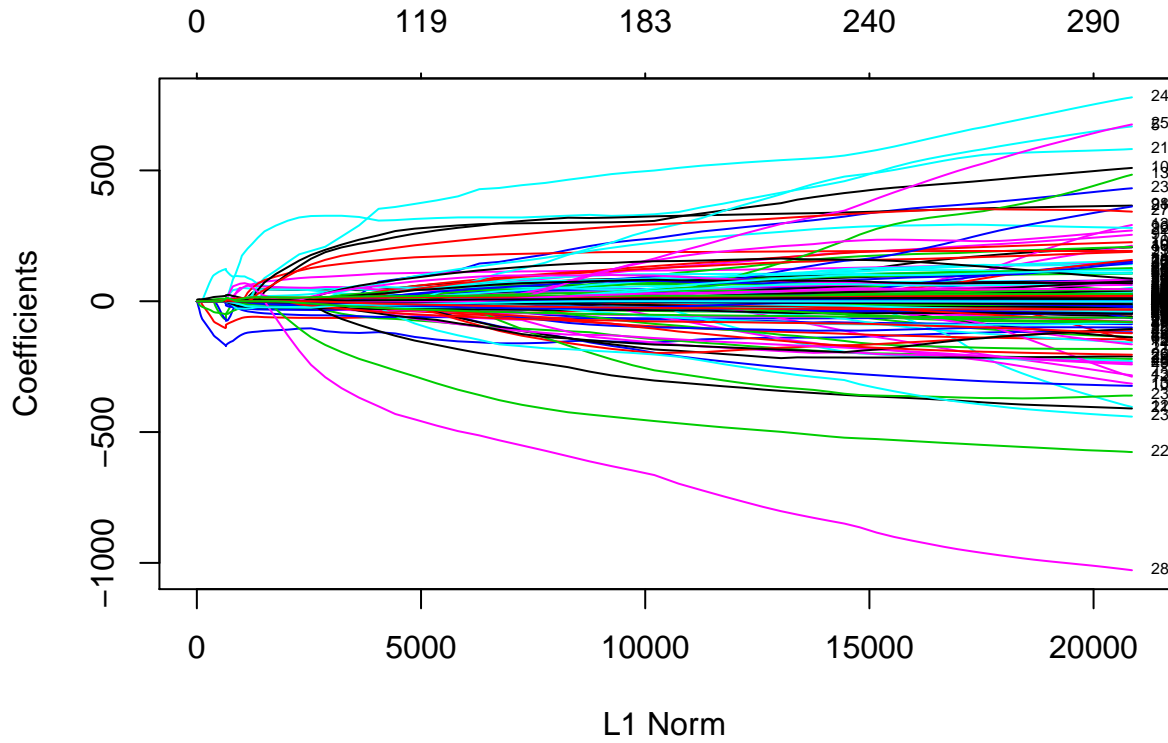
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	dfage:disllb	dfage:dtotord	dfage:dmар2	dfage:adequacy2
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	dfage:adequacy3	dfage:nprevist	dmeduc:dfeduc	dmeduc:ormoth1
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	dmeduc:ormoth2	dmeduc:ormoth3	dmeduc:ormoth4	dmeduc:ormoth5
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	dmeduc:orfath1	dmeduc:orfath2	dmeduc:orfath3	dmeduc:orfath4
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	dmeduc:orfath5	dmeduc:disllb	dmeduc:dtotord	dmeduc:dmар2
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	dmeduc:adequacy2	dmeduc:adequacy3	dmeduc:nprevist	dfeduc:ormoth1
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	dfeduc:ormoth2	dfeduc:ormoth3	dfeduc:ormoth4	dfeduc:ormoth5
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	dfeduc:orfath1	dfeduc:orfath2	dfeduc:orfath3	dfeduc:orfath4
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	dfeduc:orfath5	dfeduc:disllb	dfeduc:dtotord	dfeduc:dmар2
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	dfeduc:adequacy2	dfeduc:adequacy3	dfeduc:nprevist	ormoth1:orfath1
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	ormoth2:orfath1	ormoth3:orfath1	ormoth4:orfath1	ormoth5:orfath1
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	ormoth1:orfath2	ormoth2:orfath2	ormoth3:orfath2	ormoth4:orfath2
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	ormoth5:orfath2	ormoth1:orfath3	ormoth2:orfath3	ormoth3:orfath3
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	ormoth4:orfath3	ormoth5:orfath3	ormoth1:orfath4	ormoth2:orfath4
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	ormoth3:orfath4	ormoth4:orfath4	ormoth5:orfath4	ormoth1:orfath5
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	ormoth2:orfath5	ormoth3:orfath5	ormoth4:orfath5	ormoth5:orfath5
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	ormoth1:disllb	ormoth2:disllb	ormoth3:disllb	ormoth4:disllb
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	ormoth5:disllb	ormoth1:dtotord	ormoth2:dtotord	ormoth3:dtotord
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	ormoth4:dtotord	ormoth5:dtotord	ormoth1:dmар2	ormoth2:dmар2
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	ormoth3:dmар2	ormoth4:dmар2	ormoth5:dmар2	ormoth1:adequacy2
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	ormoth2:adequacy2	ormoth3:adequacy2	ormoth4:adequacy2	ormoth5:adequacy2
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	ormoth1:adequacy3	ormoth2:adequacy3	ormoth3:adequacy3	ormoth4:adequacy3
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	ormoth5:adequacy3	ormoth1:nprevist	ormoth2:nprevist	ormoth3:nprevist
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	ormoth4:nprevist	ormoth5:nprevist	orfath1:disllb	orfath2:disllb
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	orfath3:disllb	orfath4:disllb	orfath5:disllb	orfath1:dtotord
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	orfath2:dtotord	orfath3:dtotord	orfath4:dtotord	orfath5:dtotord
##	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
##	orfath1:dmар2	orfath2:dmар2	orfath3:dmар2	orfath4:dmар2

```
##      0.000000e+00      0.000000e+00      0.000000e+00      0.000000e+00
##      orfath5:dmr2 orfath1:adequacy2 orfath2:adequacy2 orfath3:adequacy2
##      0.000000e+00      0.000000e+00      0.000000e+00      0.000000e+00
##      orfath4:adequacy2 orfath5:adequacy2 orfath1:adequacy3 orfath2:adequacy3
##      0.000000e+00      0.000000e+00      0.000000e+00      0.000000e+00
##      orfath3:adequacy3 orfath4:adequacy3 orfath5:adequacy3 orfath1:nprevist
##      0.000000e+00      0.000000e+00      0.000000e+00      0.000000e+00
##      orfath2:nprevist orfath3:nprevist orfath4:nprevist orfath5:nprevist
##      0.000000e+00      0.000000e+00      0.000000e+00      0.000000e+00
##      disllb:dtotord disllb:dmr2 disllb:adequacy2 disllb:adequacy3
##      -2.014876e-02      0.000000e+00      0.000000e+00      0.000000e+00
##      disllb:nprevist dtotord:dmr2 dtotord:adequacy2 dtotord:adequacy3
##      0.000000e+00      0.000000e+00      1.430495e+00      0.000000e+00
##      dtotord:nprevist dmr2:adequacy2 dmr2:adequacy3 dmr2:nprevist
##      0.000000e+00      0.000000e+00      0.000000e+00      0.000000e+00
##      adequacy2:nprevist adequacy3:nprevist
##      2.450708e+00      5.320214e+00
```

```
# print only non-zero lasso coefficients
print(reg_1c$beta[,25][reg_1c$beta[,25] != 0])
```

```
##      csex2      mrace32      mrace33      ormoth2
##      -1.004847e+02      -6.707636e+01      -1.645689e+02      -6.372021e+01
##      dmr2 tobacco2:preterm2 tobacco2:dmage tobacco2:orfath2
##      -4.846922e+01      1.212800e+02      1.139206e+00      -2.533540e+00
##      tobacco2:dtotord tobacco2:adequacy2 tobacco2:nprevist mrace32:dfage
##      9.383169e+00      1.233125e-01      1.262811e+00      -7.236427e-01
##      mrace32:nprevist preterm2:dmeduc preterm2:nprevist dmage:disllb
##      -8.111708e-02      3.002415e+00      1.984857e+01      -3.837685e-03
##      disllb:dtotord dtotord:adequacy2 adequacy2:nprevist adequacy3:nprevist
##      -2.014876e-02      1.430495e+00      2.450708e+00      5.320214e+00
```

```
# Plot what the coefficients are doing as we increase lambda
plot(reg_1c, label=TRUE)
```



*# Each curve corresponds to a variable. It shows the path of its coefficient
against the L1-norm of the whole coefficient vector as lambda varies. The top axis
indicates the number of nonzero coefficients at the current lambda, which is the
effective degrees of freedom (df) for the lasso.*

```
knitr::kable(reg_1c$beta[,25][reg_1c$beta[,25] != 0], caption=paste0("Lasso Regression for top (lambda = 12.2164603064059)",
  col.names = 'Non-zero Coefficients', align = "l", digits = 3)
```

Table 1: Lasso Regression for top (lambda = 12.2164603064059)

	Non-zero Coefficients
csex2	-100.485
mrace32	-67.076
mrace33	-164.569
ormoth2	-63.720
dmar2	-48.469
tobacco2:preterm2	121.280
tobacco2:dmage	1.139
tobacco2:orfath2	-2.534
tobacco2:dtotord	9.383
tobacco2:adequacy2	0.123
tobacco2:nprevist	1.263
mrace32:dfage	-0.724
mrace32:nprevist	-0.081
preterm2:dmeduc	3.002
preterm2:nprevist	19.849

	Non-zero Coefficients
dmage:disllb	-0.004
disllb:dtotord	-0.020
dtotord:adequacy2	1.430
adequacy2:nprevist	2.451
adequacy3:nprevist	5.320

Problem 2

Describe the propensity score approach to the problem of estimating the average causal effect of smoking when the treatment is randomly assigned conditional on the observables. How does it reduce the dimensionality problem of multivariate matching? Try a few ways to estimate the effects of maternal smoking on birthweight:

Part (a)

First create the propensity score. For our purposes let's use a logit specification. First specify the logit using all of the "predetermined" covariates (don't include interactions). Next, include only those "predetermined" covariates that enter significantly in the first logit specification. How comparable are the propensity scores? If they are similar does this imply that we have the "correct" set of covariates in the logit specification used for our propensity score?

```
# create the propensity score using logit
# using all of the "predetermined" covariates

# then try logit with only the significant covariates

# Compare histograms of p-scores
```

Part (b)

Control directly for the estimated propensity scores using a regression analysis, and estimate an average treatment effect. State clearly the assumptions under which your estimate is correct.

```
# Control for p-score in regression analysis

# Estimate ATE
```

Part (c)

As discussed in class, one can use the estimated propensity scores to reweight the outcomes of non- smokers and estimate the average treatment effect. Compute an estimate of the average treatment effect and the "effect of the treatment on the treated" by appropriate reweighting of the data.

```
# Reweight data using p-score to weight

# Estimate ATE
```

```
# Estimate TOT with reweighted data
```

Part (d)

Estimate the counterfactual densities relevant for the above part with a kernel density estimator. That is, estimate the density of birthweight (or log birthweight) if everyone smoked and again if no one smoked. Hint: Consider directly applying the Hirano, Imbens, and Ridder propensity score reweighting scheme in the context of estimating the densities of the treated and control groups (rather than the means of the treated and control groups). Stata has very useful preprogrammed commands. In addition to using the preprogrammed Stata command to compute/graph the kernel density over the entire range of birthweight, please also calculate by hand the kernel estimator at birthweight equals 3,000 grams (and provide the code you wrote that shows the calculation of the kernel estimator at this single point). Play around with a bandwidth starting with half the default Stata bandwidth. Choose the same bandwidth for all the pictures, and produce a (beautiful, production quality) figure depicting both densities.

```
# Estimate the counterfactual birthweight densities with a kernel density estimator
# See Joel's notes for kernel density estimator
# Play around with a bandwidth starting with half the default Stata bandwidth
# For stata bandwidth, see rkdensity.pdf page 9 in this ps1b github folder.
# You can also run on stata with no bandwidth specified, then print the
# default bandwidth used using `display r(bwidth)`
# Choose the same bandwidth for all the pictures

# Graph both kernel densities over range of birthweight in the same plot

# calculate the kernel estimator at birthweight equals 3,000 grams
```

Part (e)

Take one of your densities and display an estimate of the density using different bandwidths as well as the one you settled on. What happens with bigger (smaller) bandwidths?

Part (f)

What are the benefits of the weighting approach (from part c)? What are the potential drawbacks? Pay particular attention to the issue of people with extremely high and extremely low values of the propensity score.

Part (g)

Present your findings and interpret the results on the relationship between birthweight and smoking. For the estimates in parts (b) and (c), consider which of the following conditions must hold in order for that estimate to be valid:

- The treatment effect heterogeneity is linear in the propensity score.
- The treatment effect heterogeneity is not linear in the propensity score.
- The decision to smoke is completely randomly assigned.
- Conditional on the exogenous variables the decision to smoke is randomly assigned.

Problem 3

A potentially more informative way to describe how birth weight affects smoking is to estimate the “non-parametric” conditional mean of birth weight as a function of the estimated probability of smoking, separately for smokers and non-smokers on the same graph. To do so, divide the data from smokers into 100 approximately equally spaced bins based on the estimated propensity score. Do the same for nonsmokers. Use the blocking estimator we discussed in class. Interpret your findings and relate them to the results in (2b).

Problem 4

Low birth weight births (less than 2500 grams) are considered particularly undesirable since they comprise a large share of infant deaths. Redo question 3 using an indicator for low birth weight birth as the outcome of interest. Interpret your findings.

Problem 5

Let’s link matching back to regression. Consider the conditional expectation function $\mathbb{E}[\text{birthweight} \mid X]$, where X contains the following variables: rectype pldel3 cntocpop stresfip dmage mrace3 dmar adequacy csex dplural.

Part (a)

Develop a regression that you are confident estimates $\mathbb{E}[\text{birthweight} \mid X]$ as $N \rightarrow \infty$? Why are you confident that your regression gets the CEF right?

```
# Select variables
df5a = df %>% select(dbrwt, rectype, pldel3, cntocpop, stresfip,
                    dmage, mrace3, dmar, adequacy, csex, dplural)

# Run regression
```

Part (b)

Now run the regression you propose above, but add the treatment (your binary smoking variable) as the righthand side variable of interest. Prove that if the treatment effect of smoking on birthweight is independent of the covariates in X , then exact matching and your regression estimate the same thing. You may assume the conditional independence assumption holds given the variables in X listed above.

```
# Select vars and smoking indicator
df5b = df %>% select(dbrwt, rectype, pldel3, cntocpop, stresfip,
                    dmage, mrace3, dmar, adequacy, csex, dplural)

# Run regression
```

Part (c)

Develop a weighted version of the exact matching estimator that estimates the same thing as the regression above (regardless of whether the treatment effect is independent of covariates).

Part (d)

Estimate the weighted matching estimator you propose. Compare it to the regression estimate from part (b). Are they similar?

Part (e)

Is the sample size of your regression the same as the sample size of your matching estimator, or does the regression have more observations? If the regression has more observations, why don't these extra observations influence the treatment effect estimate?

Part (f)

Compute a standard error for your matching estimator using the formula from Imbens (2015). Specifically, note that your matching estimator should have a form

$$\frac{1}{N_t} \sum_{d_i=1} w_i y_i - \frac{1}{N_c} \sum_{d_i=0} w_i y_i$$

where $\sum_{d_i=1} w_i = N_t$ and $\sum_{d_i=0} w_i = N_c$. Then the conditional variance is approximately

$$\sum_i \left(\frac{d_i}{N_t^2} + \frac{1-d_i}{N_c^2} w_i^2 \hat{\sigma}_{d_i}^2(x_i) \right),$$

where $\hat{\sigma}_{d_i}^2(x_i) = \frac{1}{2}(y_i - y_{nn(i)})$, and $y_{nn(i)}$ is the nearest neighbor to observation i with the *same* treatment status. Figure out the implicit weights w_i in your estimator from part (d), and compute the conditional variance. Is it close to your regression coefficient variance?

Compute a standard error for your matching estimator using the formula from Imbens (2015).

compute the conditional variance of estimator from (d)

Problem 6

Concisely and coherently summarize your overall results, providing some intuition. Write it like you would the conclusion of a paper. In this summary, describe whether you think your best estimate of the effects of smoking is credibly identified. State why or why not.