Econometric Problem Set 2

Question 1

Show in detail the expected value μ_Y is obtained as $\mu_Y = argmin_c E[(Y-c)^2]$.

We take the first derivative and set to zero, then solve for $E(Y)$:

$$\begin{aligned} 0 =& \frac{\partial}{\partial c} E[(Y-c)^2] \\ 0 =& 2E[(Y-c)] \\ 0 =& E(Y) - E(c) = E(Y) - c \\ \textit{Solve to get}& \\ E(Y) =& c \end{aligned}$$

Since we know $E(Y) = \mu_Y$, then $c = \mu_Y$.

Question 2: Working with barro dataset and quantreg package in R

I will load the dataset *barro* from packages *quantreg* and *texreg*. To build my table of the QR and OLS coefficients with s.e. in brackets:

1. Run the OLS linear model of the 13 covariates on annual change per capita GDP ($y.net$). Save the coefficients in $coef_ols22$. I run a QR in a similar fashion and save coefficients in $coef_qr22$. I then bind column-wise coefficients from both regressions in $qr23$.

```
qs <- 1:9/10 # my sequence of quantiles from 0.1 to 0.9

ols22 <- lm(y.net ~ mse2 + lexp2 + gcony2 + fse2 + lintr2 +
              lblakp2 + fhe2 + gedy2 + pol2 + mhe2 + Iy2 + ttrad2 +
              lgdp2, data = barro)
coef_ols22 <- coef(ols22)

qr22 <- rq(y.net ~ mse2 + lexp2 + gcony2 + fse2 + lintr2 +
             lblakp2 + fhe2 + gedy2 + pol2 + mhe2 + Iy2 + ttrad2 +
             lgdp2, tau=qs, data = barro)
coef_qr22 <- coef(qr22)

qr23 <- cbind(coef_qr22, coef_ols22)
```

2. We can add the se's by extracting coefficients from QR for each quantile $0.1 \to 0.9$, and add in parentheses under coefficient estimate. I do this by creating a for loop that populates a matrix (se) with the se's for each τ from $0.1 \to 0.9$. I do the same for the se of OLS LM, and bind columnwise to the se of QR.

3. Using a Texreg object, for every column in my qr23, the se is populated under the coefficient. I print the table by LaTex output.

```
i = 1 # counter
se <- matrix( , nrow=14, ncol=9)
# create matrix to hold se's
```

```r
#find se of QR
for(i in 1:9) {
  QR_serrors <- c(coef(summary.rq(qr22, se="boot"))[1:14,2])
  #bootstrap to find se coefficients to save
  se[,i] <-  QR_serrors
  # fill columns of y with quantile[i] se's
  i = i+1
}

#set coef names
colnames(qr23) <- c("q=0.1", "q=0.2", "q=0.3",
                    "q=0.4", "q=0.5", "q=0.6",
                    "q=0.7", "q=0.8", "q=0.9", "OLS")
rownames(se) <- rownames(qr23)

# add in OLS se too
ols22_sum <- summary(ols22)
ols_errors <- c(coef(ols22_sum)[1:14,2])
se <- cbind(se, ols_errors)
colnames(se) <- colnames(qr23)

# create a texreg object:
tr <- list()
for (j in 1:ncol(qr23)) {
  tr[[j]] <- createTexreg(
      coef.names = rownames(qr23),
      coef = (qr23[, j]),
      se = se[, j]
  )
}
```

Q2.2

To display the other 13 covariates (as in Figure 3), I use the plot() function, and the table below includes coefficients for both QR and OLS estimates.

```r
to_plot <- c("mse2", "lexp2", "gcony2", "fse2",
             "lintr2", "lblakp2", "fhe2", "gedy2",
             "pol2", "mhe2", "Iy2", "ttrad2")
names <- c("Male Secondary Education", "Life Expectancy",
           "Public Consumption/GDP", "Female Secondary Education",
           "Human Capital", "Black Market Premium",
           "Female Higher Education", "Education/GDP",
           "Political Instability", "Male Higher Education",
           "Investment/GDP", "Growth Rate Terms Trade")
```

	q=0.1	q=0.2	q=0.3	q=0.4	q=0.5	q=0.6	q=0.7	q=0.8	q=0.9	OLS
(Intercept)	0.01	−0.01	0.00	−0.06	−0.04	−0.04	−0.01	−0.08	−0.04	−0.04
	(0.08)	(0.09)	(0.09)	(0.08)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.05)
mse2	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
lexp2	0.06	0.06	0.05	0.07	0.07	0.07	0.06	0.08	0.08	0.07
	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)
gcony2	−0.20	−0.18	−0.14	−0.13	−0.09	−0.11	−0.10	−0.09	−0.10	−0.10
	(0.07)	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)	(0.07)	(0.06)	(0.06)	(0.03)
fse2	0.00	0.01	0.00	−0.00	−0.00	−0.00	−0.00	−0.01	−0.01	−0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
lintr2	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
lblakp2	−0.03	−0.02	−0.03	−0.03	−0.03	−0.03	−0.03	−0.03	−0.03	−0.03
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
fhe2	−0.03	−0.03	0.01	−0.00	0.01	0.01	−0.02	−0.02	−0.01	−0.02
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.03)
gedy2	−0.47	−0.30	−0.10	−0.07	−0.05	−0.14	−0.07	0.19	−0.07	−0.10
	(0.21)	(0.22)	(0.22)	(0.20)	(0.22)	(0.19)	(0.20)	(0.20)	(0.23)	(0.12)
pol2	−0.03	−0.03	−0.03	−0.03	−0.03	−0.02	−0.02	−0.01	0.00	−0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
mhe2	0.01	0.01	0.00	0.01	0.01	0.01	0.03	0.01	0.01	0.02
	(0.04)	(0.05)	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.05)	(0.04)	(0.02)
Iy2	0.07	0.08	0.09	0.08	0.07	0.07	0.07	0.06	0.06	0.06
	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.02)
ttrad2	0.11	0.12	0.10	0.12	0.16	0.18	0.22	0.21	0.23	0.18
	(0.05)	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)	(0.06)	(0.06)	(0.06)	(0.04)
lgdp2	−0.03	−0.03	−0.03	−0.03	−0.03	−0.03	−0.03	−0.03	−0.03	−0.03
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)

Table 1: QR and OLS coefficients

Q2.2, Figure 2

```r
plot(summary(qr22), parm = "lgdp2",
     main = "Initial Per-Capita GDP on GDP Growth", lcol = 4, lty = 1:2)
```

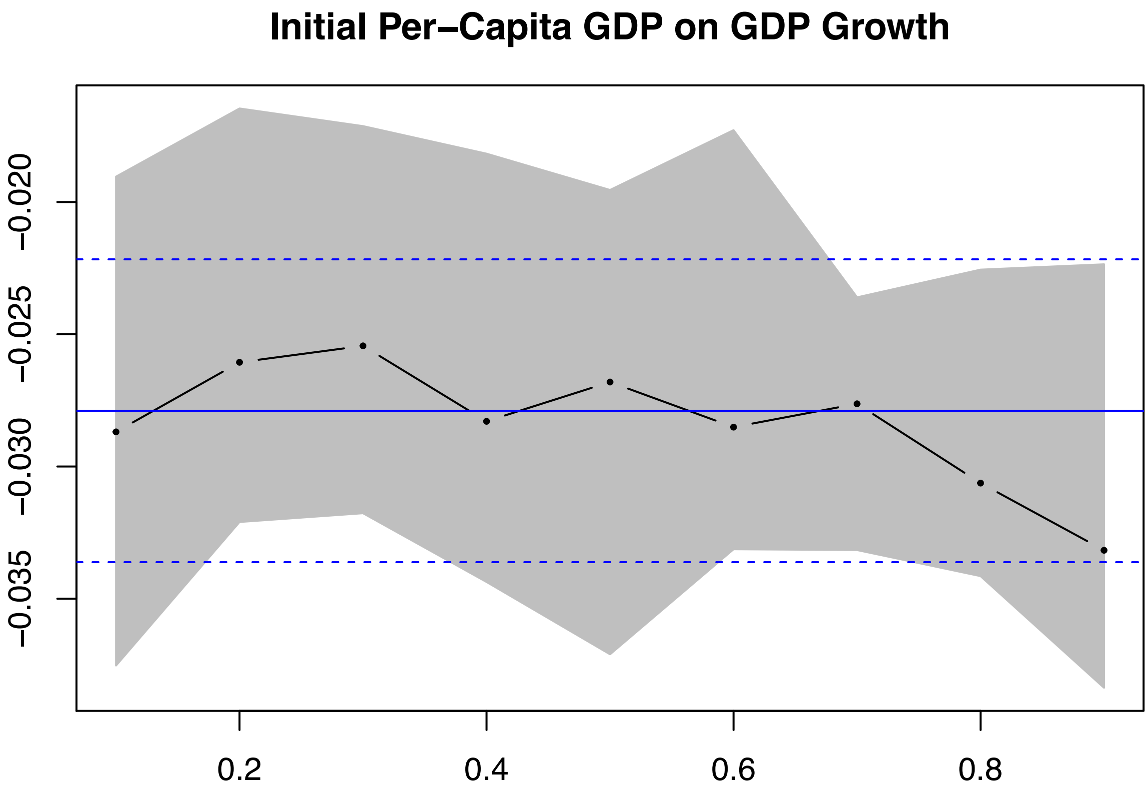
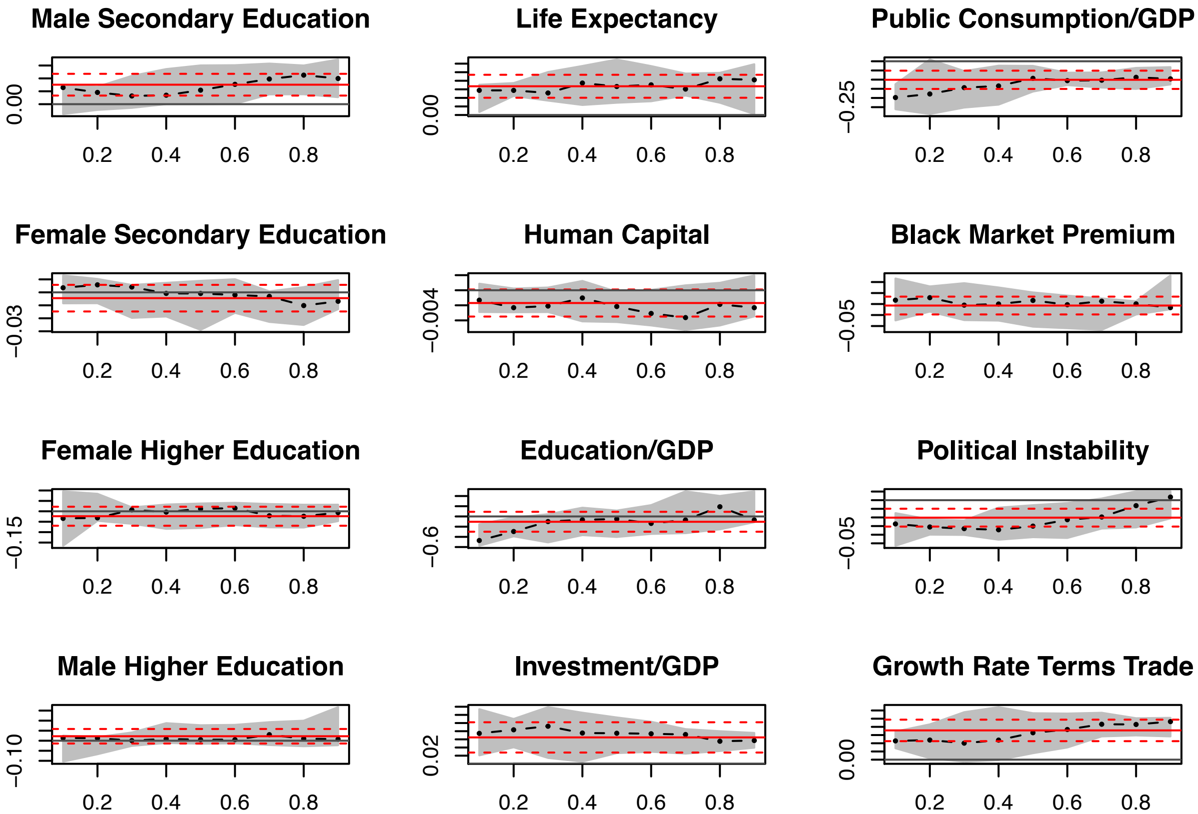


Figure 3

```r
plot(summary(qr22), parm = to_plot, main = names)
```



The confidence bands for each graph is indicated by the jagged blue lines.The solid thick blue line moreso in the middle is the least squares estimate.

Write a paragraph of comments on the results

In Figure 2, we see 'initial per cap gdp (lgdp2)' is relatively constant as the initial level of GDP does not change much. The upper right tail of the distribution exhibits falling gdp levels. However, the authors caution on interpreting the initial GDP effect as a downward sloping effect.

The effects of the remaining variables vary. The terms of trade (ttrad2) variable have a larger impact on faster growing countries (higher tau's) than slower growing countries. For political instability there is an invervse relationship. Countries in the lower quantiles exhibit an inverse relationship in terms of high political instability and its effects on country growth. We see also that the various education variables have a weak effect on growth but inconclusive. The effect of public consumption show that the this effect is relatively constant over the upper half of the distribution, but is larger in the lower tail.