ECON108 Final Exam Q1

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Saturday, June 4, 2022 5:16 PM

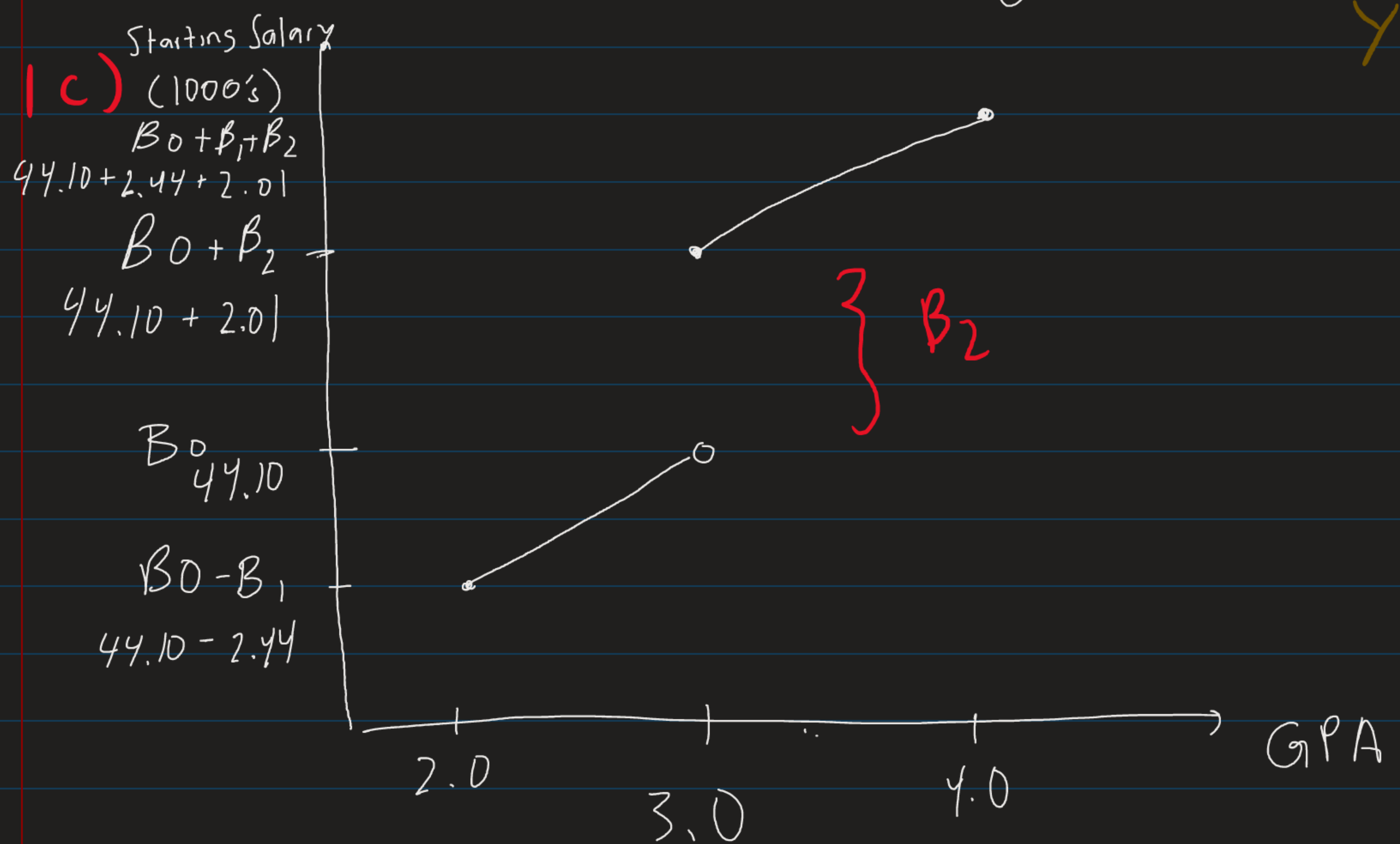
1a) The constant β_0 represents that on average, the starting salary of a U.C.R alumni when their GPA is at a 3.0 in the five core bussiness courses in the 1000's, is 42.25 (42,250). The coefficient on β_1 represents that on average, a student who has a one-unit increase in G.P.A relative to 3.0, (i.e. 4.0) recieves a higher starting salary by 4.87 (1000's or 4,870). No, the coefficient on GPA is not unbiased, considering UCR students cannot major in Business if their GPA is under 3.00, there are omitted variable biases that don't cont for this cut-off, as it contains in the error term whether student's could have even majored in Business.

$Y_i = \beta_0 + \beta_1 \cdot X_i + U_i$

1b) The coefficient β_2 represents a discontinuity from GPA's below 3.0 & GPA's at a 3.0 or higher, in this case it shows, on average, a student at or above this cutoff have a higher starting salary by 2.01 (1000s, or 2,010). This coefficient still contains biases, as there are omitted variation in the error term; controlling differences in relation to the distance of a student's GPA from 3.0 will have varying effects when passed the cutoff (increasing GPA from 1.0 → 2.0 vs 3.0 → 4.0 will have varying effects as one can declare Business as a major), thus the coefficient is still biased.

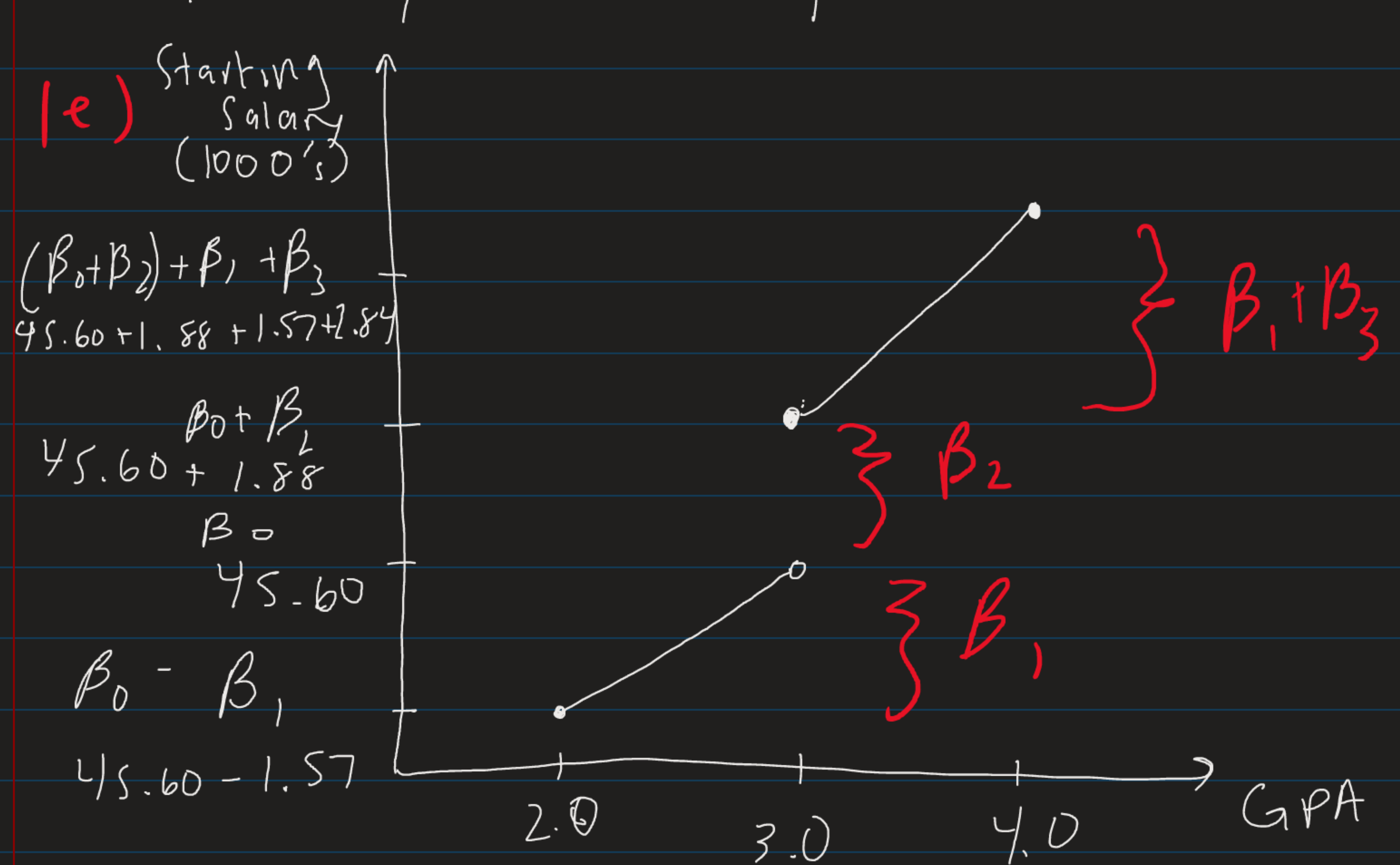
$Y_i = \beta_0 + \beta_1 X_i + \beta_2 T_i + U_i$

1c)



1d) β_3 represents the interaction term between GPA relative to 3.0 & the cutoff, and represents a variating slope before & after the cutoff, in this case the effect of a single unit increase in GPA past the cutoff yields a 2.84 (in 1000's or 2,840) increase in starting salary, in addition to β_1 (1.57 in 1000's or 1,570), on average. This means that increases in GPA increase starting salary more past the cutoff than before the cutoff, on average. Despite including this interaction term, there are still possibilities of omitted variable biases that could make the coefficient biased; this can include whether they had prior work experience or other factors.

1e)



$Y_i = \beta_0 + \beta_1 X_i + \beta_2 T_i + \beta_3 \cdot X_i + U_i$

$Y_i = \beta_0 + \beta_1 X_i$ CG $(T_i = 0)$

$Y_i = (\beta_0 + \beta_2) + (\beta_1 + \beta_3)$ TG $(T_i = 1)$

ECON108 Final Exam Q2 EUGENE BALDONADO SID:862070316

Sunday, June 5, 2022 11:04 PM

2a) There are issues with concluding that a higher GPA will more likely lead to higher job satisfaction, this is due to omitted variable biases as the error term could be accounting for variables related to job satisfaction. Another concern is seen with the assumption that $\hat{Y} \in (0,1)$. When $Y=0$ (unsatisfied with job) is $< \hat{Y}$, and when $Y=1$ (satisfied) it is $> \hat{Y}$, this means at 0, error < 0 & at 1 error > 0. This is concerning as $E(U \mid GPA\ (low))$ & $E(U \mid GPA\ (high))$ is NOT $= 0$.

2b) The coefficient of the first regression (B_1) interprets as for each per unit increase of Undergraduate GPA, the probability of the UCR Economics Alumni being satisfied with their job increases by 0.15, on average (15% in its Linear Progression Model).
For the third regression B_1 represents the Z^2 score increasing by 0.45 for a one-unit increase of undergraduate GPA, on average. They differ as in the Probit model, the % change may vary depending on what GPA increase there is (differ from 1.0 → 2.0 & 2.0 → 3.0) vs. all changes being the same in per-unit changes in the L.P.M.

2c) LPM $\hat{Y}_i = B_0(0.25) + B_1(0.15) \times GPA(3.00)$

$\hat{Y}_i = 0.70$

The individual in the 1st regression (LPM) would have a 70% probability of being satisfied w/ their job given they have a 3.0 GPA on average.

Probit $\hat{Y}_i = B_0(-0.60) + B_1(0.45) \times GPA(3.00)$

$\hat{Y}_i = 0.75$ $\quad \Phi(0.75) = 0.7734$

(Z-score calculator)

According to the probit model, the individual would yield a Z-score of 0.75, calculating for the probability on a normal distribution, yields a 0.7734 (77.34%) probability they are satisfied with their job, on average.
The probit model keeps the percentages in between 0 & 1, while "theoretically" a high or low enough GPA can raise $\hat{Y}$ over 100% (1) or less than 0% (0); this cannot happen in the probit model as it takes the percentage related to the Z-score.

2D) LPM: $Y_i = 0.10(B_0) + B_1(0.05) \times GPA(4.0) + \cancel{B_2}_{(Tenure)} + B_3(0.20) \times \overset{000's}{Wage}(3) + \cancel{B_4}_{(club)}$

$0.9 = 0.10 + 0.20 + 0.6$

LPM, on average individual has a .90 (90% probability) of being satisfied w/ their job, but this particular individual isn't.

Probit: $Y_i = \underset{(B_0)}{-1.10} + B_1(0.25) \times GPA(4.0) + \cancel{B_2} + B_3(0.50) \times Wage(3) + \cancel{B_4}$

$Y_i = -1.10 + 1 + 1.50 = z = 1.50 \quad \Phi(1.50) = .9332$

Probit, on average individual has a .9332 (93.32% probability) of being satisfied w/ their job, on average, although this one isn't.

LPM $Y_i = 0.10 + \underset{B_1\ GPA}{(0.05)(3.5)} + \underset{(Tenure)}{\cancel{B_2}} + \underset{B_3\ Wage}{(0.20) \times (2.5)} + \underset{Club}{(0.07) \times (1)}$

$Y_i = 0.10 + 0.175 + 0.5 + 0.07 = .845$

Probit $Y_i = -1.10 + (0.25) \times (3.5) + \cancel{B_2} + (0.50) \times (2.5) + (0.1) \times (1)$

$Y_i = -1.10 + .875 + 1.25 + .1 \quad \Phi(1.125) = .8697$

From this analysis, it cannot really be concluded that "in the real world grades don't matter". Not only are the two scenarios not necessarily controlling for GPA (all other variables / some are changing), but there are interactions w/ variables in the regression equation that do affect the probability of job satisfaction. A higher GPA can net a higher wage, which can lead to higher job satisfaction. The variability of these factors, and possible omitted variable bias can make this hard to conclude how "beneficial" GPA is, or how "unbeneficial" it is. Note: It can be noticed that GPA is statistically significant in affecting probability of Job satisfaction, but in this analysis, it disproves GPA being a sole factor of Job satisfaction.

ECON108 Final Exam Q3 EUGENE BALDONADO SID: 862070316

Monday, June 6, 2022 1:12 AM

3a) β_0 represents the arrest rate for Meth use (per 100,000) for a country when that country allows alcohol to be sold, on average.

β_1 represents a difference between a county, when that country is "dry_i", in terms of meth arrest (in comparison to non-dry countries), on average. β_1 is likely biased, as β_1 is the average slope of the differences when a country is dry_i and assumes all countries are similar in meth arrests. This provides omitted variable biases since we donot control for individual county differences (regularily higher/lower) in meth arrests. This bias is likely towards zero, as countries with higher meth arrests are grouped w/ counties with lower meth arrests on average to produce an average β_1 across all countries.

3b) Exogenous parts of Dry_i: primary religions of individuals preventing dinking of alcohol; availability of alcohol, in counties

Endogenous parts of Dry_i: County wanting less problems w/ addiction to alcohol, so ban selling

The exogenous parts of Dry_i are external factors affecting Dry_i, while endogenous parts are internal factors that relate to Dry_i.

3c) Proposed Z_i: Binary variable for Baptists (Fraction of baptists in country > 0.5)

I) Related to Dry_i, relevant as county would be more willing to accept prohibition of alc if baptist $[\text{Corr}(Dry_i, \text{Baptist}) \neq 0]$

II) Unrelated to # of meth arrests in county; $\Rightarrow$ this is exogenous to the amount of meth $[\text{Corr}(\text{Baptist}, U_i[\text{Meth Arrests}]) = 0]$

Baptist fulfills conditions to be a valid instrument.

3d) 1st stage: Regress Meth Arrests on Z_i (Baptist) $Y_i = \gamma_0 + \gamma_1 Z_i$

Dry_i (X_i) on Baptist (Z_i)

$$\hat{X}_i = \hat{\pi}_0 + \hat{\pi}_1 Z_i$$

If a county has more than a 0.5 ratio of baptists, then possibility of Dry_i changes by $\hat{\pi}_1$, on average. (Compared to counties that have less than a 0.5 ratio of baptists)

2nd stage: $X_i = Dry_i$

$$MethArrests_i = \beta_0 + \beta_1 \hat{X}_i + U_i$$

Normalize the effect of Dry_i on a random county

$$\hat{\beta}_1^{TSLS} = \frac{\gamma_1}{\pi_1}$$

γ_1 (Coefficient of Baptist on Meth arrest)

π_1 (Coefficient of Baptist on Dry_i) (not selling alcohol)

β_1 reveals effect of Dry_i on random county on Meth Arrests, on average.

3e) β_1 (Equation 1) $= 3.30$

$$\beta_1 TSLS (\text{Equation } 7\text{?}3) = \frac{\gamma_1}{\pi_1}$$

$\gamma_1 \leftarrow \beta_1$ (Baptist on Meth Arrests)

$\pi_1 \leftarrow \beta_1$ (Baptist on Dry_i)

$$\beta_1^{TSLS} = \frac{2.10}{0.5} = 4.2$$

β_1^{TSLS} represents the effects of a random county meth arrests rate increasing by 4.2 (per 100,000), when alcohol is more restricted, on average. This differs from the first β_1 (3.30) and has a stronger effect, when the equation seperates out the exogenous part of Dry_i in Baptist. (When county is more than half Baptist)

ECON108 Final Exam Q4

EUGENE BALDONADO SID: 862070316

Monday, June 6, 2022 1:45 PM

4a) $MethArrests_{it} = B_0 + B_1 Dry_{it} + B_2 Z_i + B_3 S_t + U_{it}$

The benefits of using panel data for this question is the ability to control for specific county differences, as well as time differences regarding Meth Arrests rate. For example, a county may have naturally higher Meth Arrests rates (per 100,000) than other counties (or lower) and controlling for this allows a B_1 for all counties, but each county having a different intercept, controlling for the difference. Similarly, certain time periods may have higher Meth Arrest rates across all counties, and including them in the regression controls for those time-based fixed effects. (Controlling for these fixed effects can result in a stronger B_1 correlation (Dry_{it}) w/ Meth arrests).