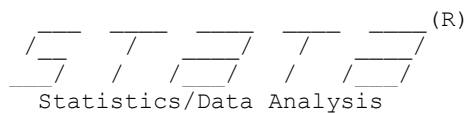
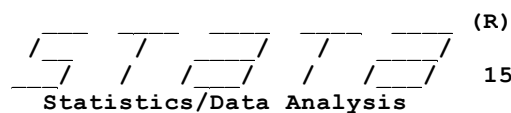


1. Munnell et al. explores the contentious question of whether a borrower's race impacts that borrower's ability to secure a mortgage loan. The broader scope of this question involves examining the effect of race when attempting to access credit of any kind. The narrower scope pursued by Munnell et al. was motivated by the debate surrounding early 90s Home Mortgage Disclosure Act (HMDA) collected data, which, naturally, focused specifically on the home mortgage lending market. Munnell et al. identifies the weaknesses inherent in concluding the existence of race based discrimination in the mortgage lending market solely through either examination of early 90s HMDA data or reviewing earlier attempts to analyze this question, including Black et al. (1978), King (1980), and Shafer et al. (1981). Concerning the HMDA data, the absence of particular information; such as credit history, debt burden, loan-to-value ratio; which Munnell et al. discovered, through interviews with lenders responsible for the outcomes reflected in the HMDA data, also influenced lending decision making, introduces omitted variable bias, which undermines the explanatory power of any estimated coefficient on race derived from such a data set. Concerning the existing literature surrounding this question, omitted variable bias again arises considering the absence of credit and employment histories in the data analyzed in such literature. Furthermore, all of the previously mentioned three works, namely; Black et al. (1978), King (1980), and Shafer et al. (1981); examined only particular types of lending institutions, which complicates efforts to extend some conclusions to the entire mortgage lending market. One study's data was collected using a voluntary survey, which introduces a response bias that is not adequately accounted for within the analysis. Munnell et al. sought to more definitively examine the role of race in mortgage lending by avoiding these concerns, primarily through utilizing the influence and network of the Boston Federal Reserve to collect a comprehensive data set consisting of essentially all information collected on each potential borrower from virtually all lenders in the Boston metropolitan area. Munnell et al. devised four broad categorical considerations taken by lenders under which particular collected information falls: probability of default, costs of default, loan characteristics, and personal characteristics. Munnell et al. makes a robust conclusion that there is a statistically significant difference between the rejection rates for whites and blacks/Hispanics, holding every other collected variable equal. This difference amounts to about a 7% higher rejection rate for black and Hispanic borrowers.
2. The provided commands will result in an appropriate indicator variable to represent a rejected mortgage application because "denied" will equal 1 if the application was rejected and 0 if otherwise. Utilizing the rationale described by Munnell et al., the data set will be restricted to applications that have been denied or accepted, corresponding to s7 values of 3 for denied and 1, 2 and 6 for accepted. Then, a linear probability model will produce estimations for the effect of race on the probability of a mortgage application being denied. This data restriction is helpful as a probability model must have only 2 outcomes, which, in this case, are denied and accepted. Without such a data restriction, the probability model would represent the chance of denial versus not being denied, which can manifest either in an accepted, a withdrawn, or an incomplete application. Considering the presence of conceptually negative outcomes for both the denied and no denied categories, this type of probability model would be less informative than the previously discussed probability model. Munnell et al. argues that withdrawn and incomplete applications, corresponding to s7 values of 4 and 5 respectively, should not be considered akin to rejected applications considering, in almost all circumstances, it is the borrower, without influence from the lender, making the decision to withdraw, with incomplete applications also usually being initiated by

the borrower, albeit earlier in the process when compared to that of the withdrawn category. Therefore, these outcomes do not even truly belong on the side of the dependent variable, which is meant to represent the decision of the lender given information about the borrower and about the requested loan. Munnell et al. also argue that there is no evidence of nor a persuadable argument for correlation between race and an application being either withdrawn or incomplete. Thus, removing such observations will not disproportionately affect any one race's observations.



User: Suraj Anandalwar (sda37)
Project: Empirical Project



MP - Parallel Edition

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Notes:

1. Unicode is supported; see [help unicode advice](#).
2. More than 2 billion observations are allowed; see [help obs advice](#).
3. Maximum number of variables is set to 5000; see [help set maxvar](#).
4. New update available; type - [update all](#) -

```
1 . use "\\rschfs1x\userc1\sda37_ECON3140\Downloads\drive-download-20190425T230810Z-001\hmda_sw.dta"
2 . gen denied = 0
3 . replace denied = 1 if s7==3
   (285 real changes made)
4 . list denied s7 if denied==1
```

	denied	s7
9.	1	3
13.	1	3
21.	1	3
43.	1	3
44.	1	3
47.	1	3
49.	1	3
79.	1	3
83.	1	3
84.	1	3
87.	1	3
91.	1	3
106.	1	3
110.	1	3
114.	1	3
119.	1	3
127.	1	3
129.	1	3
157.	1	3
160.	1	3
177.	1	3
178.	1	3
191.	1	3
192.	1	3
194.	1	3

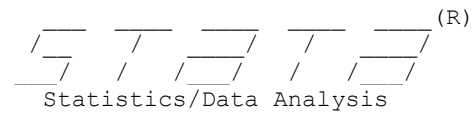
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217.	1	3
238.	1	3
241.	1	3
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320.	1	3
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328.	1	3
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363.	1	3
369.	1	3
370.	1	3
371.	1	3
373.	1	3
376.	1	3
390.	1	3
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418.	1	3
421.	1	3
446.	1	3
447.	1	3
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490.	1	3
500.	1	3
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524.	1	3
527.	1	3
530.	1	3
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555.	1	3
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681.	1	3

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818.	1	3
819.	1	3
820.	1	3
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823.	1	3
824.	1	3
826.	1	3
839.	1	3
844.	1	3
875.	1	3
956.	1	3
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1021.	1	3
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1283.	1	3
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1511.	1	3
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1809.	1	3
1810.	1	3
1811.	1	3
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1960.	1	3
1965.	1	3

1969.	1	3
1975.	1	3
1982.	1	3
1986.	1	3
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2223.	1	3
2224.	1	3
2226.	1	3
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2285.	1	3
2291.	1	3
2336.	1	3
2356.	1	3
2360.	1	3
2379.	1	3
2380.	1	3



User: Suraj Anandalwar (sda37)
Project: Empirical Project

```
1 . list denied s7 if denied==0
```

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6.	0	1
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15.	0	1
16.	0	1
17.	0	1
18.	0	1
19.	0	1
20.	0	1
22.	0	1
23.	0	1
24.	0	1
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27.	0	1
28.	0	1
29.	0	1
30.	0	1
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32.	0	1
33.	0	1
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1705.	0	1
1706.	0	1
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1712.	0	1
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1714.	0	1
1715.	0	1
1716.	0	1
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1770.	0	1

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1998.	0	1

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2112.	0	1

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2200.	0	1
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2205.	0	1
2206.	0	1
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2213.	0	2
2214.	0	1
2215.	0	1
2216.	0	1
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2220.	0	1
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2237.	0	2
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2245.	0	1
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2302.	0	1

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2320.	0	1
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2322.	0	1
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2324.	0	1
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2328.	0	1
2329.	0	1
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2339.	0	1
2340.	0	1
2341.	0	1
2342.	0	1
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2351.	0	1
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2355.	0	1
2357.	0	1

2358.	0	2
2359.	0	1
2361.	0	1
2362.	0	2
2363.	0	1
2364.	0	1
2365.	0	1
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2367.	0	1
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2369.	0	1
2370.	0	1
2371.	0	2
2372.	0	1
2373.	0	1
2374.	0	1
2375.	0	1
2376.	0	1
2377.	0	1
2378.	0	1

```

2 . gen black = 999999.4

3 . replace black = 1 if s13==3
   (339 real changes made)

4 . replace black = 0 if s13==5
   (2,041 real changes made)

5 .

```


3. About 28.3% of black applicants in the sample were denied while about 9.26% of white applicants were denied. For the equation

$$denied_i = \beta_0 + \beta_1 black_i + u_i$$

we can estimate $(\hat{\beta}_0, \hat{\beta}_1)$ using the sample values previously mentioned as estimators for population conditional probabilities.

$$P(denied_i = 1 | black_i = 1) = \beta_0 + \beta_1(1) + u_i$$

$$P(denied_i = 1 | black_i = 0) = \beta_0 + \beta_1(0) + u_i = \beta_0 + u_i$$

$$\frac{96}{339} = \hat{\beta}_0 + \hat{\beta}_1$$

$$\frac{189}{2041} = \hat{\beta}_0 \Rightarrow \hat{\beta}_0 \approx 0.0926$$

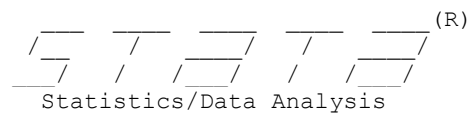
$$\frac{96}{339} = \frac{189}{2041} + \hat{\beta}_1 \Rightarrow \hat{\beta}_1 \approx 0.190584$$

So, $(\hat{\beta}_0, \hat{\beta}_1) \approx (0.0926, 0.190)$

The Stata regression provided the following estimators:

$$(\hat{\beta}_0, \hat{\beta}_1) \approx (0.0926, 0.1905842)$$

Which are virtually the same as the estimators calculated before running the Stata regression.



User: Suraj Anandalwar (sda37)
Project: Empirical Project

1 . tab denied black

denied	black		Total
	0	1	
0	1,852	243	2,095
1	189	96	285
Total	2,041	339	2,380

2 . display 96/339
.28318584

3 . display 189/2041
.09260167

4 . regress denied black

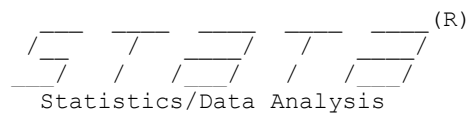
Source	SS	df	MS	Number of obs	=	2,380
Model	10.5594043	1	10.5594043	F(1, 2378)	=	104.49
Residual	240.312444	2,378	.101056537	Prob > F	=	0.0000
				R-squared	=	0.0421
				Adj R-squared	=	0.0417
Total	250.871849	2,379	.105452648	Root MSE	=	.31789

denied	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
black	.1905842	.0186444	10.22	0.000	.1540231	.2271452
_cons	.0926017	.0070366	13.16	0.000	.0788032	.1064001

5 . save "\\rschfs1x\usercl\sda37_ECON3140\Desktop\Replicate_crunching.dta", replace
file "\\rschfs1x\usercl\sda37_ECON3140\Desktop\Replicate_crunching.dta" saved

6 .

4. I initially interpreted PI as the s45 variable, which represented the bank's calculation of housing expense divided by income. An alternate interpretation of PI may lead to using the s46 variable, which represents the bank's calculation of total obligations divided by income. Because the question defined PI as payments over income, I made the interpretation that the question sought analysis with regards to mortgage payments specifically. Just to be sure, however, I ran heteroskedastic robust regressions of denied on both s45/100 and s46/100. I divided by 100 because it seems from Munnell et al. that s45 and s46 are recorded in percentage form, and the provided scatterplot, against which I am hoping to compare my results, seems to have PI in decimal form. After comparing my resultant scatterplots to the scatterplot provided in the project outline, I found that use of the s46 variable yielded the closest match. So, I generated the PI variable by dividing s46 by 100. The economic effect of β_1 is the following: for a given change in PI (ΔPI), there will be a resultant change in the probability of denial of $\beta_1 * \Delta PI$. I prefer the heteroskedastic robust standard errors because of the binary nature of the dependent variable (denied). Considering PI can take on an uncountable variety of particular values, the error term (u) will have to take on whatever value necessary to bring $\beta_0 + \beta_1 PI_i + u_i$ to 1 or 0. This implies the variance of u_i must depend on the realization of PI, resulting in heteroscedasticity. The coefficient $\hat{\beta}_1 = 0.604$ is significantly positive with a t-value of 6.13, implying a significance at a <1% significance level. These results do make sense economically considering a high PI probably leads to less ability to save, which makes it less likely that payments will continue if future income falls, for one reason or another. An "eyeball" check of the provided scatterplot and generating my own scatterplot shows my numbers are consistent with the provided scatterplot.



User: Suraj Anandalwar (sda37)
Project: Empirical Project

```
1 . gen PIs45 = s45/100
2 . gen PIs46 = s46/100
3 . reg denied PIs45, robust
```

Linear regression

Number of obs	=	2,380
F(1, 2378)	=	29.81
Prob > F	=	0.0000
R-squared	=	0.0177
Root MSE	=	.32191

denied	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
PIs45	.4470974	.0818825	5.46	0.000	.2865289	.6076658
_cons	.0055833	.0210396	0.27	0.791	-.0356746	.0468412

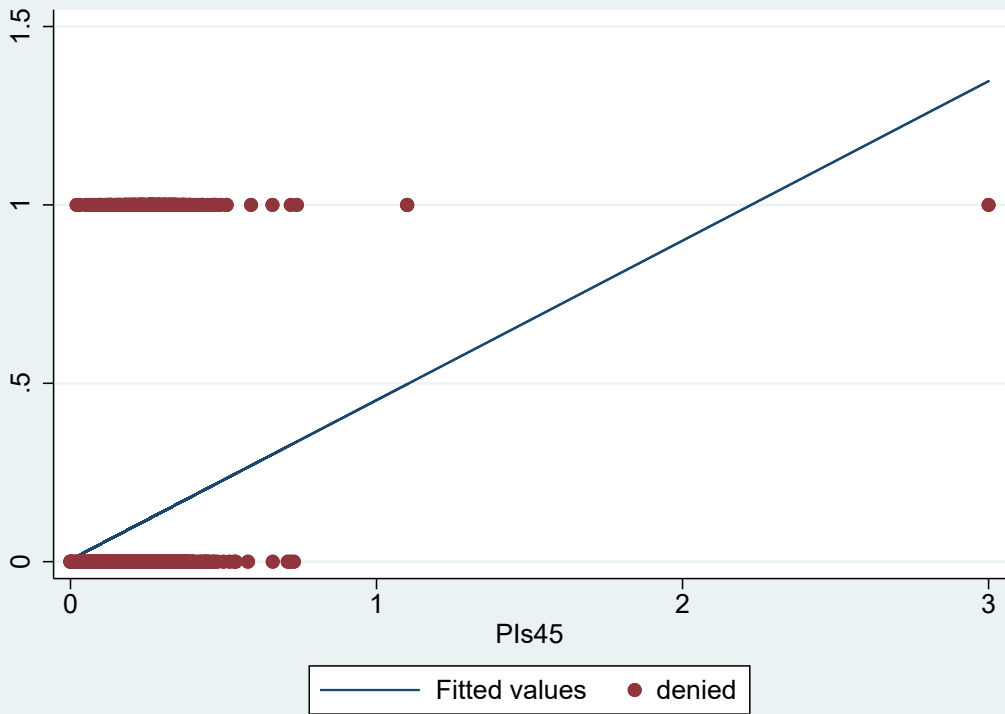
```
4 . predict fittedDeniedPIs45
   (option xb assumed; fitted values)
5 . twoway (line fittedDeniedPIs45 PIs45) (scatter denied PIs45)
6 . graph export "\\rschfs1x\usercl\sda37_ECON3140\Desktop\Q3_graph_denied_v_PIs45.pdf", as(pdf) replace
   (file "\\rschfs1x\usercl\sda37_ECON3140\Desktop\Q3_graph_denied_v_PIs45.pdf" written in PDF format)
7 . reg denied PIs46, robust
```

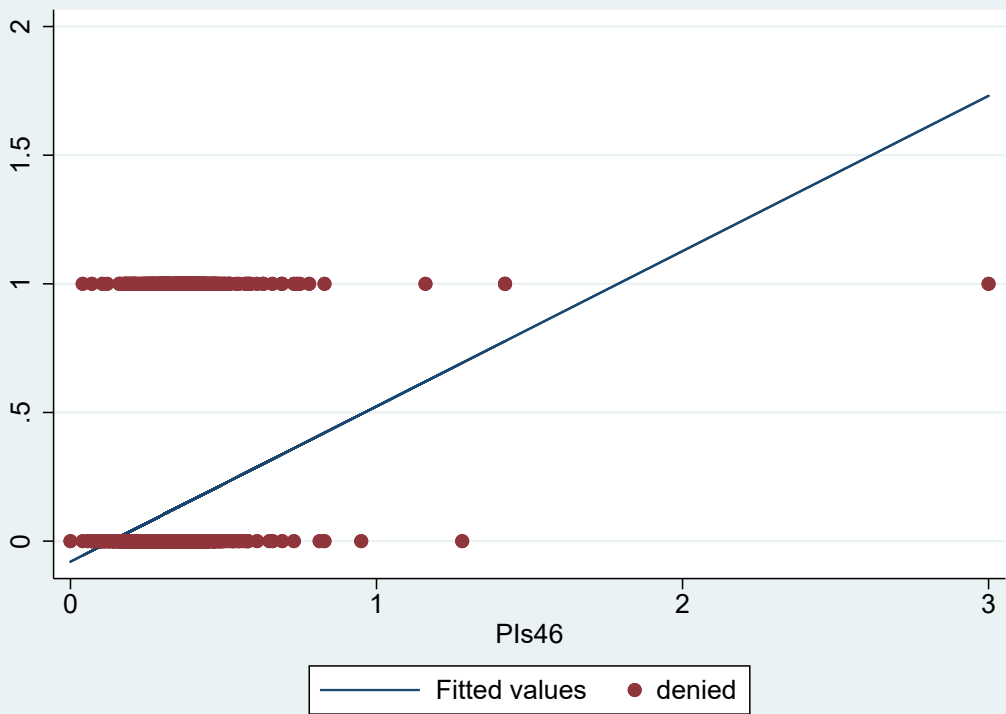
Linear regression

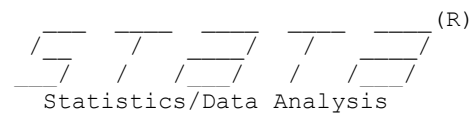
Number of obs	=	2,380
F(1, 2378)	=	37.56
Prob > F	=	0.0000
R-squared	=	0.0397
Root MSE	=	.31828

denied	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
PIs46	.6035349	.0984826	6.13	0.000	.4104144	.7966555
_cons	-.0799096	.0319666	-2.50	0.012	-.1425949	-.0172243

```
8 . predict fittedDeniedPIs46
   (option xb assumed; fitted values)
9 . twoway (line fittedDeniedPIs46 PIs46) (scatter denied PIs46)
10 . graph export "\\rschfs1x\usercl\sda37_ECON3140\Desktop\Q3_graph_denied_v_PIs46.pdf", as(pdf) replace
    (file "\\rschfs1x\usercl\sda37_ECON3140\Desktop\Q3_graph_denied_v_PIs46.pdf" written in PDF format)
11 .
```







User: Suraj Anandalwar (sda37)
Project: Empirical Project

1 . gen PI = s46/100

2 . reg denied PI, robust

Linear regression	Number of obs	=	2,380
	F(1, 2378)	=	37.56
	Prob > F	=	0.0000
	R-squared	=	0.0397
	Root MSE	=	.31828

denied	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
PI	.6035349	.0984826	6.13	0.000	.4104144	.7966555
_cons	-.0799096	.0319666	-2.50	0.012	-.1425949	-.0172243

3 .

5.

$$\widehat{denied}_i = \hat{\beta}_0 + \hat{\beta}_1 PI_i$$

$$\widehat{denied} = (-0.0799) + (0.604)(0.2)$$

$$\widehat{denied} = 0.0408$$

Considering the binary nature of the denied variable, the above calculated predicted value for denied being 0.0408 implies the probability of denial is 0.0408 or 4.08%.

$$\widehat{denied} = (-0.0799) + (0.604)(0.1)$$

$$\widehat{denied} = -0.0196$$

This value does not make sense considering the interpretation discussed above. Because probability cannot be negative, the predicted denied value also cannot be negative.

One solution is to utilize a logit model.

$$denied_i = \Lambda(\beta_0 + \beta_1 PI_i) + u_i \quad \text{where } \Lambda(z) = \frac{e^z}{1 + e^z}$$

$$E[denied_i | PI] = P(denied_i = 1 | PI) = \Lambda(\beta_0 + \beta_1 PI_i)$$

Because $\Lambda : \mathbb{R} \rightarrow (0,1)$, $P(denied_i = 1 | PI)$ will always be between 0 and 1, a necessity for a probability value.

6. In spite of utilizing a logit model, the model will still be heteroskedastic because for a binary variable such as denied,

$$Var(denied_i | PI) = [P(denied_i = 1 | PI)] * [1 - P(denied_i = 1 | PI)]$$

This implies the variance of denied conditioned on PI is still dependent on the particular realization of PI. So, I will use heteroskedastic robust standard errors.

$$P(\widehat{denied}_i = 1 | PI) = \Lambda(\hat{\beta}_0 + \hat{\beta}_1 PI_i)$$

$$P(denied_i = 1 | PI) = \Lambda(-4.03 + 5.88 * PI_i)$$

[0.359] [1.00]

The predicted probability of denial for someone with a PI of 20% is as follows:

$$P(\text{denied}_i = 1 | PI = 0.2) = \Lambda(-4.03 + 5.88 * (0.2))$$

$$P(\text{denied}_i = 1 | PI = 0.2) = \Lambda(-2.85) = \frac{e^{-2.85}}{1 + e^{-2.85}}$$

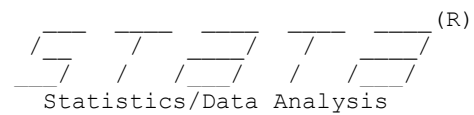
$$P(\text{denied}_i = 1 | PI = 0.2) = 0.0546 \text{ or } 5.46\%$$

The predicted probability of denial for someone with a PI of 10% is as follows:

$$P(\text{denied}_i = 1 | PI = 0.1) = \Lambda(-4.03 + 5.88 * (0.1))$$

$$P(\text{denied}_i = 1 | PI = 0.1) = \Lambda(-3.44) = \frac{e^{-3.44}}{1 + e^{-3.44}}$$

$$P(\text{denied}_i = 1 | PI = 0.1) = 0.0311 \text{ or } 3.11\%$$



User: Suraj Anandalwar (sda37)
Project: Empirical Project

1 . logit denied PI, robust

Iteration 0: log pseudolikelihood = **-872.0853**
 Iteration 1: log pseudolikelihood = **-830.96071**
 Iteration 2: log pseudolikelihood = **-830.09497**
 Iteration 3: log pseudolikelihood = **-830.09403**
 Iteration 4: log pseudolikelihood = **-830.09403**

Logistic regression Number of obs = **2,380**
 Wald chi2(1) = **34.63**
 Prob > chi2 = **0.0000**
 Log pseudolikelihood = **-830.09403** Pseudo R2 = **0.0482**

denied	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
PI	5.884498	.9999333	5.88	0.000	3.924664	7.844331
_cons	-4.028432	.3589036	-11.22	0.000	-4.73187	-3.324994

2 .

7. The following is the OLS estimation:

$$denied_i = \beta_0 + \beta_1 PI_i + \beta_2 black_i + u_i$$

$$\widehat{denied}_i = \hat{\beta}_0 + \hat{\beta}_1 PI_i + \hat{\beta}_2 black_i$$

$$P(\widehat{denied}_i = 1|PI) = \hat{\beta}_0 + \hat{\beta}_1 PI_i + \hat{\beta}_2 black_i$$

$$P(\widehat{denied}_i = 1|PI) = -0.0905 + 0.0559 * PI_i + 0.177 * black_i$$

[0.0296] [0.0887] [0.0249]

The following is the logit model estimation:

$$denied_i = \Lambda(\beta_0 + \beta_1 PI_i + \beta_2 black_i) + u_i$$

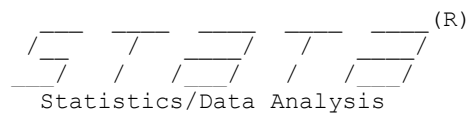
$$\widehat{denied}_i = \Lambda(\beta_0 + \beta_1 PI_i + \beta_2 black_i)$$

$$P(\widehat{denied}_i = 1|PI) = \Lambda(\hat{\beta}_0 + \hat{\beta}_1 PI_i + \hat{\beta}_2 black_i)$$

$$P(\widehat{denied}_i = 1|PI) = \Lambda(-4.13 + 5.37 * PI_i + 1.27 * black_i)$$

[0.346] [0.963] [0.146]

β_2 in the OLS regression is the difference in probability of denial between a white applicant and a black applicant with the same total obligations to income ratio (PI). The interpretation of β_2 in the Logit model is much less straightforward; however, the sign of $\hat{\beta}_2$ will indicate the direction of change in the probability of denial when moving from a white applicant to a black applicant with the same total obligations to income ratio (PI). For the Logit model estimation provided above, $\hat{\beta}_2 = 1.27 > 0$ implies, keeping PI equal, that being black raises the probability of denial. If $\hat{\beta}_2$ were negative, then, keeping PI equal, being black would decrease the probability of denial. The effect is statistically significant at a significance level of <1% for both the OLS and Logit estimations, as the t-values from both the OLS and Logit estimations, 7.11 and 8.71, respectively, are greater than 2.58, implying the critical t-value for significance at 1%. It is difficult to judge the magnitude of $\hat{\beta}_2$ in the Logit model considering the general difficulty in precisely interpreting Logit model coefficients. However, the $\hat{\beta}_2$ from the OLS estimation is 0.177, indicating that a black applicant has a probability of denial 0.177 greater than a white applicant with the same PI, which seems pretty large and considerable.



User: Suraj Anandalwar (sda37)
Project: Empirical Project

1 . reg denied PI black, robust

Linear regression

Number of obs	=	2,380
F(2, 2377)	=	49.39
Prob > F	=	0.0000
R-squared	=	0.0760
Root MSE	=	.31228

denied	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
PI	.5591946	.0886663	6.31	0.000	.3853233	.7330658
black	.1774282	.0249463	7.11	0.000	.1285096	.2263469
_cons	-.0905136	.0285996	-3.16	0.002	-.1465963	-.0344309

2 . logit denied PI black, robust

Iteration 0: log pseudolikelihood = -872.0853
Iteration 1: log pseudolikelihood = -806.3571
Iteration 2: log pseudolikelihood = -795.72934
Iteration 3: log pseudolikelihood = -795.69521
Iteration 4: log pseudolikelihood = -795.69521

Logistic regression

Number of obs	=	2,380
Wald chi2(2)	=	117.75
Prob > chi2	=	0.0000
Pseudo R2	=	0.0876

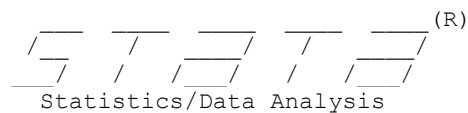
Log pseudolikelihood = -795.69521

denied	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
PI	5.370362	.9633435	5.57	0.000	3.482244	7.258481
black	1.272782	.1460986	8.71	0.000	.9864339	1.55913
_cons	-4.125558	.345825	-11.93	0.000	-4.803362	-3.447753

3 .

8. It is difficult to argue that $\hat{\beta}_2$ should be considered as a measure of the causal effect of being black on the probability of denial because of the credible arguments concerning the potential violation of MLR-4 ($E[u_i|x] = 0$). There are many variables that probably have an effect on an applicant's probability of being denied (and thus, hidden inside of u_i) and are also correlated with being black. One example is credit history, which is definitely considered by lending institutions when evaluating mortgage applications and is very likely to be correlated with income, which itself is correlated with race. Munnell et al. further discusses the difficulty in deriving causal relationships from equations with similar problems as the equation provided in Question 7. These equations, from which estimations and causal arguments were put forth, pervaded earlier literature, motivating Munnell et al. to correct those mistakes by incorporating enough data such that a credible argument could be made while satisfying MLR-4.

9. For both regressions, all coefficients; except those for HI, LV, and LV²; are significant at the 5% level. All of the significant coefficients are positive, which does make economic sense. A higher total obligations to income ratio (PI) probably gives lenders less confidence in the applicant's ability to survive an economic shock, raising the perceived chance of default. A higher value for CCS indicates a bad credit history with consumer purchases, which will also reduce lenders' confidence in the applicant's ability to pay back the loan, considering previous debts have been either late or completely delinquent. Likewise, a higher value for MCS indicates a bad credit history specifically with regards to mortgages, which definitely lowers lenders' confidence in a potentially approved mortgage being paid back on time. The positive value for the NoMI coefficient is also sensible considering lender and private mortgage insurers issue denials in similar circumstances. Finally, lenders may be wary of lending to those who are self-employed, considering small companies are usually much less able to handle economic shocks than large companies. Results are generally consistent between models, especially with both models deeming the same variables significant at 5%. However, among those variables deemed significant at 5%, except for PI and NoMI, the Logit model produces lower p-values.



User: Suraj Anandalwar (sda37)
Project: Empirical Project

```
1 . gen HI = s45
2 . gen LV = s6/s50
3 . gen squaredLV = LV^2
4 . gen CCS = s43
5 . gen MCS = s42
6 . gen NoMI = s53
7 . gen self = s27a
8 . reg denied black PI HI LV squaredLV CCS MCS NoMI self, robust
```

Linear regression	Number of obs	=	2,380
	F(9, 2370)	=	76.87
	Prob > F	=	0.0000
	R-squared	=	0.2350
	Root MSE	=	.28457

denied	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
black	.1024729	.0229488	4.47	0.000	.0574711	.1474747
PI	.5042901	.1168057	4.32	0.000	.2752383	.733342
HI	-.0006241	.0011526	-0.54	0.588	-.0028842	.0016361
LV	-.0499137	.2268218	-0.22	0.826	-.4947034	.394876
squaredLV	.1130414	.1796688	0.63	0.529	-.2392828	.4653657
CCS	.0391006	.0047636	8.21	0.000	.0297593	.0484418
MCS	.022906	.0115843	1.98	0.048	.0001895	.0456225
NoMI	.7275353	.0417773	17.41	0.000	.6456114	.8094592
self	.065897	.020973	3.14	0.002	.0247698	.1070243
_cons	-.2185699	.074551	-2.93	0.003	-.3647619	-.072378

```
9 . logit denied black PI HI LV squaredLV CCS MCS NoMI self, robust
```

```
Iteration 0: log pseudolikelihood = -872.0853
Iteration 1: log pseudolikelihood = -684.41427
Iteration 2: log pseudolikelihood = -669.91372
Iteration 3: log pseudolikelihood = -657.88559
Iteration 4: log pseudolikelihood = -657.77809
Iteration 5: log pseudolikelihood = -657.77798
Iteration 6: log pseudolikelihood = -657.77798
```

Logistic regression	Number of obs	=	2,380
	Wald chi2(9)	=	241.08
	Prob > chi2	=	0.0000
Log pseudolikelihood = -657.77798	Pseudo R2	=	0.2457

denied	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
black	.8008418	.1717947	4.66	0.000	.4641304	1.137553
PI	4.990338	1.334321	3.74	0.000	2.375117	7.605559
HI	-.0026471	.0129535	-0.20	0.838	-.0280355	.0227413
LV	2.582211	3.24215	0.80	0.426	-3.772287	8.936709
squaredLV	-.4293693	2.084154	-0.21	0.837	-4.514236	3.655498
CCS	.3462494	.0370033	9.36	0.000	.2737242	.4187746
MCS	.3173436	.1362448	2.33	0.020	.0503087	.5843785
NoMI	4.505393	.5608385	8.03	0.000	3.40617	5.604616
self	.719261	.210948	3.41	0.001	.3058106	1.132711
_cons	-7.284695	1.360324	-5.36	0.000	-9.950882	-4.618509

10. The predicted effect of race on the probability of denial is 0.102 or 10.2%. This implies that when comparing a white applicant and black applicant with the same total obligations to income ratio, housing expense to income ratio, loan to value ratio, characterized consumer and mortgage credit histories, outcomes concerning the possible acquisition of private mortgage insurance, and employment status in regards to being self-employed or not; the black applicant's probability of being denied is 0.102 higher, or 10.2% higher, than that of the white applicant.
11. I cannot generate a similarly precise interpretation of the estimated coefficient for the black variable in the Logit model. This is because the Logit model is non-linear with respect to that coefficient.
12. Inserting a hypothetical applicant whose attributes are the average of each attribute (except race) in the sample into the OLS estimation yields the same predicted race effect as found in Question 10. This is completely sensible considering:

$$P\left(\widehat{denied}_i = 1 \left| \begin{array}{l} black_i = 1, PI_i = \overline{PI}, HI_i = \overline{HI}, LV_i = \overline{LV}, LV^2_i = \overline{LV^2}, \\ CCS_i = \overline{CCS}, MCS_i = \overline{MCS}, NoMI_i = \overline{NoMI}, self_i = \overline{self} \end{array} \right. \right) \\ = \hat{\beta}_0 + \hat{\beta}_1(1) + \hat{\beta}_2\overline{PI} + \hat{\beta}_3\overline{HI} + \hat{\beta}_4\overline{LV} + \hat{\beta}_5\overline{LV^2} + \hat{\beta}_6\overline{CCS} + \hat{\beta}_7\overline{MCS} + \hat{\beta}_8\overline{NoMI} \\ + \hat{\beta}_9\overline{self}$$

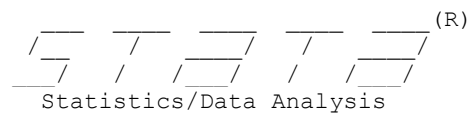
$$P\left(\widehat{denied}_i = 1 \left| \begin{array}{l} black_i = 0, PI_i = \overline{PI}, HI_i = \overline{HI}, LV_i = \overline{LV}, LV^2_i = \overline{LV^2}, \\ CCS_i = \overline{CCS}, MCS_i = \overline{MCS}, NoMI_i = \overline{NoMI}, self_i = \overline{self} \end{array} \right. \right) \\ = \hat{\beta}_0 + \hat{\beta}_1(0) + \hat{\beta}_2\overline{PI} + \hat{\beta}_3\overline{HI} + \hat{\beta}_4\overline{LV} + \hat{\beta}_5\overline{LV^2} + \hat{\beta}_6\overline{CCS} + \hat{\beta}_7\overline{MCS} + \hat{\beta}_8\overline{NoMI} \\ + \hat{\beta}_9\overline{self}$$

$$P\left(\widehat{denied}_i = 1 \left| \begin{array}{l} black_i = 1, PI_i = \overline{PI}, HI_i = \overline{HI}, \\ LV_i = \overline{LV}, LV^2_i = \overline{LV^2}, CCS_i = \overline{CCS}, \\ MCS_i = \overline{MCS}, NoMI_i = \overline{NoMI}, \\ self_i = \overline{self} \end{array} \right. \right) - P\left(\widehat{denied}_i = 1 \left| \begin{array}{l} black_i = 0, PI_i = \overline{PI}, HI_i = \overline{HI}, \\ LV_i = \overline{LV}, LV^2_i = \overline{LV^2}, CCS_i = \overline{CCS}, \\ MCS_i = \overline{MCS}, NoMI_i = \overline{NoMI}, \\ self_i = \overline{self} \end{array} \right. \right)$$

$$(\hat{\beta}_0 + \hat{\beta}_1(1) + \hat{\beta}_2\overline{PI} + \hat{\beta}_3\overline{HI} + \hat{\beta}_4\overline{LV} + \hat{\beta}_5\overline{LV^2} + \hat{\beta}_6\overline{CCS} + \hat{\beta}_7\overline{MCS} + \hat{\beta}_8\overline{NoMI} + \hat{\beta}_9\overline{self}) - \\ (\hat{\beta}_0 + \hat{\beta}_1(0) + \hat{\beta}_2\overline{PI} + \hat{\beta}_3\overline{HI} + \hat{\beta}_4\overline{LV} + \hat{\beta}_5\overline{LV^2} + \hat{\beta}_6\overline{CCS} + \hat{\beta}_7\overline{MCS} + \hat{\beta}_8\overline{NoMI} + \hat{\beta}_9\overline{self}) = \hat{\beta}_1$$

The Logit model, however, provides a predicted effect of race of 7.34%, which is lower than that from the OLS. This is also understandable, considering the OLS predicted effect is meant to estimate the effect of race between a black applicant and white applicant with the same attributes, while the Logit model's 7.34% value is meant to estimate the effect of race between a black applicant and white applicant with a particular set of identical attributes, namely, each attribute's average in the sample. The larger OLS predicted effect is likely indicative of a skew as black and white applicants with attributes, though still equivalent, of magnitude larger than average probably display larger differences in denial probability.

The average predicted effect of race was about 19.1% for both the Logit and OLS estimations, which is sensible considering conditional averages are invariant to the Logit transformation. It is larger than the 10.2% described in Question 10, which is also sensible considering the average black applicant in the sample had larger attribute values, in magnitude, than those of the average white applicant. Considering the positive coefficients of all of the statistically significant attributes, larger attribute values imply a larger denial rate.



User: Suraj Anandalwar (sda37)
Project: Empirical Project

1 . logit denied black PI HI LV squaredLV CCS MCS NoMI self, robust

```
Iteration 0: log pseudolikelihood = -872.0853
Iteration 1: log pseudolikelihood = -684.41427
Iteration 2: log pseudolikelihood = -669.91372
Iteration 3: log pseudolikelihood = -657.88559
Iteration 4: log pseudolikelihood = -657.77809
Iteration 5: log pseudolikelihood = -657.77798
Iteration 6: log pseudolikelihood = -657.77798
```

```
Logistic regression      Number of obs      =      2,380
                        Wald chi2(    9)      =      241.08
                        Prob > chi2          =      0.0000
Log pseudolikelihood = -657.77798      Pseudo R2          =      0.2457
```

denied	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
black	.8008418	.1717947	4.66	0.000	.4641304	1.137553
PI	4.990338	1.334321	3.74	0.000	2.375117	7.605559
HI	-.0026471	.0129535	-0.20	0.838	-.0280355	.0227413
LV	2.582211	3.24215	0.80	0.426	-3.772287	8.936709
squaredLV	-.4293693	2.084154	-0.21	0.837	-4.514236	3.655498
CCS	.3462494	.0370033	9.36	0.000	.2737242	.4187746
MCS	.3173436	.1362448	2.33	0.020	.0503087	.5843785
NoMI	4.505393	.5608385	8.03	0.000	3.40617	5.604616
self	.719261	.210948	3.41	0.001	.3058106	1.132711
_cons	-7.284695	1.360324	-5.36	0.000	-9.950882	-4.618509

2 . use "\\rschfs1x\usercl\sda37_ECON3140\Downloads\mean_except_race.dta"

3 . predict fittedMeanDenied
(option **pr** assumed; Pr(denied))

4 . list fittedMeanDenied if black==0 in 1/5

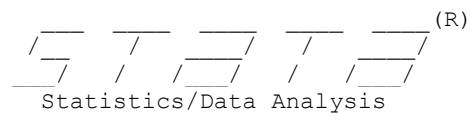
	fitted~d
1.	.0697703
2.	.0697703
3.	.0697703
4.	.0697703
5.	.0697703

5 . list fittedMeanDenied if black==1 in 1/50

	fitted~d
30.	.1431486
38.	.1431486
48.	.1431486

6 . display fittedMeanDenied[30] - fittedMeanDenied[1]
.0733783

7 .



User: Suraj Anandalwar (sda37)
Project: Empirical Project

```
1 . reg denied black PI HI LV squaredLV CCS MCS NoMI self, robust
```

Linear regression	Number of obs	=	2,380
	F(9, 2370)	=	76.87
	Prob > F	=	0.0000
	R-squared	=	0.2350
	Root MSE	=	.28457

denied	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
black	.1024729	.0229488	4.47	0.000	.0574711	.1474747
PI	.5042901	.1168057	4.32	0.000	.2752383	.733342
HI	-.0006241	.0011526	-0.54	0.588	-.0028842	.0016361
LV	-.0499137	.2268218	-0.22	0.826	-.4947034	.394876
squaredLV	.1130414	.1796688	0.63	0.529	-.2392828	.4653657
CCS	.0391006	.0047636	8.21	0.000	.0297593	.0484418
MCS	.022906	.0115843	1.98	0.048	.0001895	.0456225
NoMI	.7275353	.0417773	17.41	0.000	.6456114	.8094592
self	.065897	.020973	3.14	0.002	.0247698	.1070243
_cons	-.2185699	.074551	-2.93	0.003	-.3647619	-.072378

```
2 . use "\\rschfs1x\usercl\sda37_ECON3140\Downloads\mean_except_race.dta"
```

```
3 . predict fittedMeanDenied
(option xb assumed; fitted values)
```

```
4 . list fittedMeanDenied if black==0 in 1/5
```

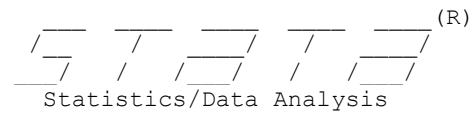
	fitted~d
1.	.105152
2.	.105152
3.	.105152
4.	.105152
5.	.105152

```
5 . list fittedMeanDenied if black==1 in 1/50
```

	fitted~d
30.	.2076249
38.	.2076249
48.	.2076249

```
6 . display fittedMeanDenied[30] - fittedMeanDenied[1]
.10247293
```

```
7 .
```



User: Suraj Anandalwar (sda37)
Project: Empirical Project

1 . logit denied black PI HI LV squaredLV CCS MCS NoMI self, robust

Iteration 0: log pseudolikelihood = **-872.0853**
 Iteration 1: log pseudolikelihood = **-684.41427**
 Iteration 2: log pseudolikelihood = **-669.91372**
 Iteration 3: log pseudolikelihood = **-657.88559**
 Iteration 4: log pseudolikelihood = **-657.77809**
 Iteration 5: log pseudolikelihood = **-657.77798**
 Iteration 6: log pseudolikelihood = **-657.77798**

Logistic regression Number of obs = **2,380**
 Wald chi2(9) = **241.08**
 Prob > chi2 = **0.0000**
 Log pseudolikelihood = **-657.77798** Pseudo R2 = **0.2457**

denied	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
black	.8008418	.1717947	4.66	0.000	.4641304	1.137553
PI	4.990338	1.334321	3.74	0.000	2.375117	7.605559
HI	-.0026471	.0129535	-0.20	0.838	-.0280355	.0227413
LV	2.582211	3.24215	0.80	0.426	-3.772287	8.936709
squaredLV	-.4293693	2.084154	-0.21	0.837	-4.514236	3.655498
CCS	.3462494	.0370033	9.36	0.000	.2737242	.4187746
MCS	.3173436	.1362448	2.33	0.020	.0503087	.5843785
NoMI	4.505393	.5608385	8.03	0.000	3.40617	5.604616
self	.719261	.210948	3.41	0.001	.3058106	1.132711
_cons	-7.284695	1.360324	-5.36	0.000	-9.950882	-4.618509

2 . predict fitDenied
 (option **pr** assumed; Pr(denied))

3 . sum fitDenied if black==0

Variable	Obs	Mean	Std. Dev.	Min	Max
fitDenied	2,041	.0926017	.1318716	.0025696	.9999645

4 . gen fitWhiteDenied = r(mean)

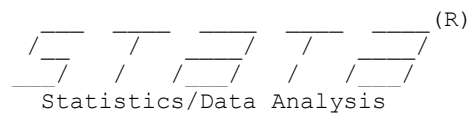
5 . sum fitDenied if black==1

Variable	Obs	Mean	Std. Dev.	Min	Max
fitDenied	339	.2831858	.2287096	.0154565	.9912374

6 . gen fitBlackDenied = r(mean)

7 . display fitBlackDenied - fitWhiteDenied
.19058418

8 .



User: Suraj Anandalwar (sda37)
Project: Empirical Project

```
1 . reg denied black PI HI LV squaredLV CCS MCS NoMI self, robust
```

Linear regression	Number of obs	=	2,380
	F(9, 2370)	=	76.87
	Prob > F	=	0.0000
	R-squared	=	0.2350
	Root MSE	=	.28457

denied	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
black	.1024729	.0229488	4.47	0.000	.0574711	.1474747
PI	.5042901	.1168057	4.32	0.000	.2752383	.733342
HI	-.0006241	.0011526	-0.54	0.588	-.0028842	.0016361
LV	-.0499137	.2268218	-0.22	0.826	-.4947034	.394876
squaredLV	.1130414	.1796688	0.63	0.529	-.2392828	.4653657
CCS	.0391006	.0047636	8.21	0.000	.0297593	.0484418
MCS	.022906	.0115843	1.98	0.048	.0001895	.0456225
NoMI	.7275353	.0417773	17.41	0.000	.6456114	.8094592
self	.065897	.020973	3.14	0.002	.0247698	.1070243
_cons	-.2185699	.074551	-2.93	0.003	-.3647619	-.072378

```
2 . predict fitDenied
(option xb assumed; fitted values)
```

```
3 . sum fitDenied if black==0
```

Variable	Obs	Mean	Std. Dev.	Min	Max
fitDenied	2,041	.0926017	.1313914	-.1612871	1.289188

```
4 . gen fitWhiteDenied = r(mean)
```

```
5 . sum fitDenied if black==1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
fitDenied	339	.2831858	.1973906	.0255535	1.14414

```
6 . gen fitBlackDenied = r(mean)
```

```
7 . display fitBlackDenied - fitWhiteDenied
.19058418
```

```
8 .
```