Choice Theory and Choices Made:

The Effect of Economics Education on Risky Behavior in Young Adults

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I. Introduction

Oreopoulos, in his analysis of returns to schooling (2009), shows that education results in benefits beyond those at the monetary level. He reasons that schooling increases to what degree one enjoys their employment, as well as improves patience, trust, and social interactions. Most importantly, he postulates that more education leads to better decision making, and thus a tendency to avoid risky behavior.

Given such benefits, it stands to reason that by increasing levels of education, the government might be able to help the population make less risky decisions. This prescription does beg the nontrivial question of whether it is the government's responsibility to try to affect individual behavior. This question will not be answered in either way during this research—we will simply seek to find out if an attempt at this proves successful. However, with respect to the conclusions of this research, this question is crucial if one intends to extend those conclusions into policy prescription.

In this research, I seek to find out whether or not economics education specifically helps stop individuals from making irrational risky decisions. Economics, even at the most basic level, deals with choices—often, at the basic level, framed in the world of business and politics, but still choices. Students have the opportunity to analyze the choices made, and, if their

microeconomics class covers game theory topics, discuss behavior on an even finer individual level. Eventually, the students should have the tools to analyze any decision on a basic level, including their own—understanding that a decision, in economic terms, is made taking into account all possibilities and factors. This should allow them to analyze their own behavior and decisions and, in turn, make better ones. In this research, I will explore whether this process occurs in high school students.

II. Literature Review

There is very little research that has been done on the effect of economics education, and the measured outcomes tend to be very narrow. There is some literature, for one, on how well economic courses transmit information about economics. Burnett and La Croix (2010) used the institution of an economics test for high schools in Hawaii as a way of distinguishing how taking an economics course affects economic knowledge. Using a diagnostic test testing certain factors of economic knowledge, they found that education in a factor was reflected in higher scores in that factor on the test. Gratton-Lavoie and Gill (2009) performed a similar experiment in California using the Test of Economic Literacy (TEL) and measured differences between the pretest and post-test, and found that a semester of high school economics education increased scores by 12.3%. Walstad also used the TEL in an experiment with Soper (1989) and found that high school economics education increased scores on average.

The literature that does focus on the tangible outcomes of economics coursework and exposure to economic information tends to focus on the effect on behavior in the financial realm. Hilgert (2003) finds that increases in knowledge about financial behavior, for one, led to increases in participation in recommended financial practices regarding saving and investing. Peng and Bartholomae (2007) tested 1039 alumni from a university, and found that those that

had participated in a personal finance course had higher levels of future investment knowledge and savings rates. However, some of the variance in their findings was explained by previous experience with financial tools. Christiansen (2008) found that economists (who should thus have the largest amount of economic knowledge) were significantly more likely to hold stocks than investors with any other kind of education. Grimes (2010) similarly used a survey and found that those who had taken economics courses were more likely to have a bank account. These studies all employ the concept that economic education gave these individuals the ability to better analyze their financial situation, and make the smarter choice with their money.

I seek to fuse this literature with literature regarding general education's effect on risky behavior.

There exists a section of literature directed specifically towards education's effect on risky behaviors. Dupas (2009) performed a field experiment in Kenya to test the effect of education about HIV risks on the incidence of unprotected sex. Using both pregnancy rates and self-reported data as measures, Dupas found that the group that had received HIV education had significant differences in the rate of unprotected sex. de Walque found that (college) education was strongly correlated with lower smoking rates. In a later study (2010), he also found that, as information about the risks of smoking spread out across the population, there is evidence that those that were more well-educated were more responsive to this information, decreasing their smoking behavior by more than their less-educated peers. More generally, Berger and Leigh (1989) found evidence that schooling had a significant direct effect (as opposed to an effect created from known lurking variables) on improving health outcomes of individuals.

The typical methodology for these studies has been experimental, testing the difference in measured outcomes between groups who received education and groups who did not. This

methodology was not used out of a lack of faith in its results, but rather a lack of means. The usage of data on the aggregate level may also be more relevant to discussing policy implications.

Before we can analyze the effect of economics education on risky behavior, it is important to understand what the general determinants of risky behavior are. Dohmen, et al., in a study undertaken in The Netherlands (2009), used a survey to try to enumerate how characteristics were correlated with risk tolerance. They found that age, for example, was negatively correlated with risks of all kinds. Feenstra et al., studying youth cycling behavior (2010), found the same effect. In addition, they found that even previous bad outcomes did not actually result in less risky behavior. This, in their eyes, justifies the need for proper education about safe behaviors, since it seems that when individuals are made aware of their risks by experience, this does not change their behavior.

A final note on the literature is that the concept of 'risky behavior' is not entirely clear in the existing literature concerning risky behavior. Oreopolous does not define it, although he gives teen fertility and criminal activity as examples. de Paula, Shapira, and Todd (2010), analyzing what they call "risky sexual behavior" in Malawi, measure risky behavior as the propensity to engage in extramarital affairs, but do not define what risky behavior actually is. Dupas (2009) classifies "unsafe sex" as his risky behavior of measure, instead. The most illustrative example is Milne, analyzing the purchasing behavior of online consumers, who says "risky behaviors are…actions that put people at risk" (George R. Milne et al., 2009). It is such a lack of a strong definition in the applied literature that necessitates creating my own definition for what risky behavior entails.

Thus, when the term "risky behavior" is used, we will use it to refer to actions taken that have at least two possible outcomes (in this research, this is generally going to be simplified

down to two), each of which have a nonzero possibility of occurring, and one cannot predict with certainty which outcome will occur until after it is observed. However, there must exist methods to estimate what the probability of a given outcome is. It is also necessary that each outcome will have an associated utility, where at least one has positive utility, and at least one has disutility. For example, smoking is considered a risky behavior because there exist possible outcomes with disutility (lung cancer and other effects) that will occasionally occur, but smoking also carries positive utilities (social effects, for example).

III. Economic Model

I simplify the previously-defined concept of "risky behavior" down to actions with two outcomes—B, the outcome with some level of negative utility (which will be referred to as the "bad outcome"), and G, the outcome with some level of positive utility (which will be referred to as the "good outcome").

It stands to reason that, given that an individual has a utility function of various states of the world, different outcomes of risky behavior will result in different expected levels of utility. Thus, the expected utility after a risky action is performed should be:

$$(1-p)U(G)+pU(B)$$

The individual also has the choice to not engage in any risky behavior. In that case, their expected utility should simply be, choosing N as the null outcome (that is, the outcome of not engaging in risky behavior):

$$U(N)$$

Thus, a rational individual will choose to engage in risky behavior when their expected utility is higher than it would be if they did not engage in risky behavior. That is, if this inequality holds:

$$U(N) < (1-p)U(G)+pU(B)$$

A visual representation of the model is given in figure 2. This model is based off of one used by Viscusi (1990) used to analyze the decision to smoke.

The red line represents the individual's utility as a function of outcome. It is not necessary that this be a convex function. It has been represented as such here due to familiarity, since this model is adapted from the theory of expected utility of wealth.

The actual expected value of risky behavior will be a point on the blue line. Where that point is will depend on the probability of a bad outcome occurring—with a higher probability, the expected value will be lower. If the individual's probability corresponds to the dark blue part of the line, then the expected value of risky behavior will be higher than the expected value of inaction, and they will rationally choose to engage in risky behavior.

Note that, for the purposes of our analysis, it is necessary to assume that $U(B) < U(N) < U(G)$. If N is a strictly better outcome than G or B, or a strictly worse outcome than G or B, then our inequality is trivial, since an individual will then rationally choose whether or not to engage in risky behavior regardless of expected probabilities.

However, until this point, a fundamental axiom has been assumed—that the individual is acutely aware of what the likelihood is that they will have a bad outcome. But in the real world, this may not be true. People may not have access to the information. Thus, they make their decisions based on their expected probability of a bad outcome, which they arrive at through some sort of heuristic. We will call this expected probability p_E.

Thus, our conditions for risky behavior have changed for an individual with imperfect information. Now, the condition for risky behavior is if this new inequality holds:

$$U(N) < (1 - p_E)U(G) + p_E U(B)$$

The difference between this new inequality and the previous one is that the new probability may cause some individuals to rationally choose to engage in risky behavior when, if they knew what the true probability of a bad outcome was, they would normally not. It is quite possible that heuristics will often cause an individual to underestimate risks. Indeed, Viscusi found that a great deal of smokers have lower expected probabilities of a negative return from smoking than nonsmokers do.

Through economics education, individuals will learn more about good decision-making, leading to two possible effects: First, that these individuals may construct better heuristics for approximating unknown probabilities; and second, that these individuals may be more likely to seek out information providing them the true probability. These two effects will help to bring such individuals' expected probabilities closer to the true probability, which, for some, will lead them to not engage in risky behavior, as their new expected probability will not satisfy the given inequality.

IV. Empirical Strategy

There are a few possible ways to measure such an effect. It would be possible to take an experimental group and control group, give the experimental group economics education, and follow their lives to see if they engage in risky behavior. However, the limited time and means of this research made this method impossible.

Because of the No Child Left Behind Act, each state is required under federal law to have minimum requirements for education in the state. Some states mandate economics in some way, and some do not. By taking dummy variables that reflect levels of risky behavior amongst older teens (who would have already taken economics), we can measure how a mandate of economics education impacts levels of risky behavior by state.

The econometric model being used to estimate risky behavior is as follows:

$$risk_i = \beta_1 offer_i + \beta_2 etest_i + \beta_3 etest_i \times offer_i + \beta_4 \ln(income_i) + \beta_5 \ln(childpov_i) + \beta_6 minority_i + \beta_7 youth_i + \beta_8 crime_i + \beta_9 unemployment_i + \varepsilon_i$$

Each variable is indexed by state i.

risk is the respective proxy variable for risk taken by youths. In our model, for these variables, I substitute the proportion of high school seniors who regularly smoke cigarettes (*cigarettes*), the proportion of high school seniors who did not use a condom during their last sexual activity (*condoms*), and the proportion of high school seniors who have driven drunk (*drunkdrive*). All of these variables are proxies for actions with well-known bad outcomes of nonzero probability.

offer and *etest* are dummy variables indicating if state i has standards requiring schools to offer high school economics courses or standards requiring economics to be tested as a prerequisite to high school graduation, respectively. The reason for including both of these as two separate variables is that not all states that require economics to be offered as a class necessarily require testing for it, and not all states that require it to be tested actually require schools to offer the class. I also use a dummy variable for the situation that a state has both requirements, which is represented by *testoffer*.

income is the median household income for state i, the logarithm taken to provide a better fit, as is standard. Income is controlled for because it is positively correlated with risk-taking, such as in Dohmen, et al. (2009). This seems reasonable, as individuals with higher income will be better able to deal with losses from risk. For example, if unprotected sex results in unexpected pregnancy, an individual with higher income will be able to afford an abortion, so the disutility from a bad outcome may not be as severe for them. However, those without income may not

have access to nonrisky behaviors—for example, condoms may not be accessible. *childpov* is the proportion of students in state i who live in poverty. This is included as a second measure of household wealth, but is more specific to young adults.

minority is the proportion of people in state i who reported their race as anything other than non-Hispanic white in the U.S. Census. *youth* is the proportion of the population between the ages of 18 and 24 in state i. This is included because a higher rate of young people may create peer effects, which would lead to additional positive utility to risky behavior.

crime is the crime rate in state i as a proportion. *unemployment* is the unemployment rate of state i among young adults between 20 and 25 as a proportion. It is possible that the presence of high crime rates or high unemployment rates will also create social or peer effects which may affect the incidence of risky behavior.

In addition, each state is given a variable that corresponds to its region, defined by the Census Bureau as one of four—West, Midwest, Northeast, and South. Dummies are named *r1* through *r4*. The inclusion of these should account for variation in state laws which may change the rate of risky behavior, as well as control for cultural differences between different regions.

Observing figure 2, note that *cigarettes,condoms,* and *drunkdrive* were obtained by the Youth Risk Behavior Surveillance System, run by the Center for Disease Prevention and Control. *offer* and *etest* were obtained by the Council for Economic Education's Survey of the States. c*hildpov* was obtained by the Annie E. Casey Foundation. *minority, youth,* and *crime* were obtained by the 2010 Census. Finally, *unemployment* was obtained by the Bureau of Labor Statistics.

One can see for the results of the regression for *cigarettes, condoms,* and *drunkdrive*, respectively, in figures 3 through 5.

Thus we have that

$$cigarettes = .0079offer - .011etest - .0038testoffer + .0016\ln(income) + .0052minority - 1.675youth + .0584\ln(childpov) - .8669unemployment - .0097r1 + .0326r2 + .0089r3 + .5897 + \varepsilon_i$$

$$condoms = -.0145offer - .0218etest - .0017testoffer + .1163\ln(income) + .0432minority - 2.439youth - .0164\ln(childpov) - .8827unemployment - .0673r1 - .0482r2 - .0630r3 - .4507 + \varepsilon_i$$

$$drunkdrive = -.0015offer - .0184etest - .0147testoffer - .0845\ln(income) + .0462minority + .2604youth + .0052\ln(childpov) - .6523unemployment - .0202r1 + .0147r2 - .0081r3 - .4507 + \varepsilon_i$$

The coefficients given for the independent variables *offer* and *etest* reflect the differences in proportion of young adults who engage in these risky behaviors between states that impose requirements to offer or test economics in high school and states that do not. *testoffer* measures the added effect of imposing both requirements.

Assuming that the population follows the model given, and that economics education is the sole source of these differences, without any lurking effects, then these coefficients reflect the net proportion of the population that moves across the "indifference point" from not engaging in risky behavior to engaging in it. The negative coefficients on the majority of independent variables make sense, given our model. This would mean that imposing economics education requirements results in a net movement of some amount of people from engaging in risky behavior to not engaging, thus reducing the proportion of youths who smoke, engage in unprotected sex, and drive drunk.

This is true in every case except the relationship between offering economics in high schools and smoking rates, where the coefficient is positive. This implies that offering economics education is correlated with higher teen smoking rates, which does not fit neatly into the model.

Overall, I have found that putting a mandate for schools to offer economics education is correlated with an increase in the proportion of teens who smoke cigarettes by .79 percentage points, a reduction in the proportion of condom nonusage by 1.45 percentage points, and a reduction in the proportion of drunk driving by .15 percentage points. Requiring that economics education be tested is correlated with a reduction in the proportion of teens who smoke cigarettes by 1.1 percentage points, condom nonusage by 2.2 percentage points, and drunk driving by 1.8 percentage points. Having both requirements in place lead to a total reduction in smoking teens by .69 percentage points, in condom nonusage among teens by 3.8 percentage points, and in drunk driving among teens by 3.5 percentage points.

The t-values on the coefficients on the independent variables (*offer, etest, testoffer*), however, are too low, so we cannot infer a significant relationship between mandating economics education and changes in rates of young adults engaging in risky behavior.

This lack of significance may be the result of a lack of precision. The data I used was measured on the state level, but I was attempting to infer conclusions about individual behavior. The data used is only capable of measuring how a mandate for economics education affects aggregated statistics. It may be true that economics education does have a significant impact, but that it is not observable at the aggregate level.

This may occur because, although minimum requirements may exist, not all youths may end up receiving economics education. There are a few ways this could happen. It could be that

these youths just drop out of high school before this could happen. It could also be that the student is too far behind in their coursework to be able to take the course.

An ideal method for fixing this in the future may be to use the high school dropout rate in each state as a control. This may be able to explain some of the variation within the subgroups of states that do or do not mandate economics education.

This may be exacerbated by the fact that it is also possible that students who are more prone to dropping out or failing out have differently-structured utility functions from students who are not. It may be true that such students' utility function makes them also more prone to engaging in risky behavior, due to the same external effects which lead them to drop out or fail out.

It could also be that the school might not enforce such requirements (that is, if the requirement is simply taking the course, rather than testing it) in a real way. There is also the possibility that, although economics instruction is required, schools may not have a qualified teacher to teach it, so students will not realize the full effect of instruction, if any.

All of these effects are problems with the transmission of economics education—the structure of the schools may dampen the positive effects. This is best reflected in the fact that the effects of the two different ways to create a requirement for economics to be taught are quite different. If transmission were perfect, then both should have roughly the same coefficient, as both efforts to require economics classes would result in it being taught to every student.

In addition, there may be some students in the states where economics education is not mandated who take the class anyway. The fact that these students are counted under states with no mandates will cause our econometric model to treat them as if they had not taken an economics course when they had. If it is true that economics education causes students to engage

in less risky behavior, then states with no economics education mandates would have lower proportions of risky behavior than would be expected, and this would lead the econometric model to not see a difference in requiring economics education.

It is a nontrivial possibility that students choosing to take economics in these states are different from other students. Peterson (1992) finds that there are real differences between students who elect to take economics and those who do not. For example, he finds that female students are less likely to choose to take economics. This is important because females may have significantly different utility functions from males (especially for the decision whether or not to use a condom, where the disutility of unexpected pregnancy is often much worse for the woman), so we will see a confounding effect on these choices due to the presence of students taking economics courses in these states.

A way to correct for this might be to use, if such were available, the proportion of students who take economics during high school as an independent variable. Using this alongside the dummy variables for education requirements would not only measure more precisely the effect of taking education on risky behavior, but would also allow the measurement of how well an economics mandate actually gets people to take economics courses, as well as what effects are observed when both interact together. This may also correct for some of the transmission error previously stated, as well, since I would not have to take into account the uncertainty of whether the mandate actually brings economics education to the students.

Another way to correct for these problems would be to redesign the study around a different form of data. One possibility is to do a survey, asking individuals both if they have received economics education, as well as what risky actions they take. A question measuring outcomes of risky actions would also be useful. By testing this sort of data instead, and surveying

over a large number of people, regression analysis can do the aggregation itself, rather than rely on previously aggregated data.

The other type of data to use would be experimental data. If there was enough time, I could have a group of some students in a high school go through economics instruction, and another group not go through it. Then, over time, the lives of these students could be observed to find out which ones had higher incidence of risky behavior. This incidence could again be measured both by surveying the students, as well as measuring outcomes (such as pregnancy).

Forgoing data problems, there may have also been issues with the model used. Assuming that an individual's economics education does indeed impact their expected probability of a bad outcome, the model does not provide the magnitude of that effect. It is possible that the insignificance of the regression coefficients is because the effect of economics education is so small as to be negligible.

It is also possible that economics education does not actually have any effect on an individual's expected probability of bad outcomes of risky actions. Although the education may lead students to think about their own behavior, it may not improve the heuristics by which they estimate probabilities, nor push them to seek out true probabilities. In this case, there are still some possible mechanisms by which economics instruction could improve their behavior. If they reconsider their behavior, it may lead them to change the utility they associate with outcomes of risky behavior. For example, an individual may stop discounting the possibility of future health complications that may arise from smoking, which would lead the magnitude of their associated disutility to increase. This, in turn, would lower the expected utility of smoking, which will then lead the individual to rationally go away from risky behavior.

In this model, there has also been the assumption that the individuals in question are rational actors. If this assumption is dropped, then it is possible (and likely) that the students are making their decisions irrationally. In an economics course, the student will learn about rationality, which may lead them to evaluate their own decisions in a more rational manner, which, again, might shift their behavior.

These mechanisms are both ways to explain the difference between those states that had economics requirements and those that did not. However, the results of statistical analysis found that the effect of economics requirements was not statistically significant. This still leaves the possibility that none of these mechanisms are happening, or that if any are happening, it is not at a noticeable level.

In this final situation, economics education has no effect on whether an individual engages in risky behavior or not. However, this still leaves an open question. Previous research does show that those with more schooling are less likely to engage in risky behavior. Thus, if not economics, there must be some factor of schooling that influences such decisions.

V. Conclusion and Directions for Future Research

This opens up a new line of potential research, to find out which part of education is the one that improves decision making. Mathematics education seems like a good choice to begin with—out of all subjects, it deals most with both probabilities and calculations, making a strong case for the possibility of improving heuristics. More specifically, statistics education focuses even more attention on these topics. A potential continuation of this research would be to do the same sort of analysis on how math education affects risky behavior. After this, other subjects could be tested in the same way. A possibility is that none of these tests would show significant results, which would lead to an interesting quandary. Berger and Leigh's study (1989) showed

that there was evidence that even while controlling for the effect of potential lurking variables, schooling did show some direct effect on health outcomes, including those outcomes which would be a result of risky health behavior. If both of these studies are accurate, it would mean that there are benefits to decision-making that arise directly from schooling but do not arise from the actual coursework done in school.

In conclusion, I did not find any significant relationship between a mandate for economics education and incidence of risky behavior. However, given the weaknesses of this method of analysis, there is no reason why a more precise study should not be done. In addition, considering which subjects contribute to which of the benefits of schooling may be a fruitful line of research to better understand the mechanism by which education improves the lives of students. It would also allow us to better choose what subjects high school should cover, using a non-ideological method of analysis. Future research should make this much clearer.

VI. References

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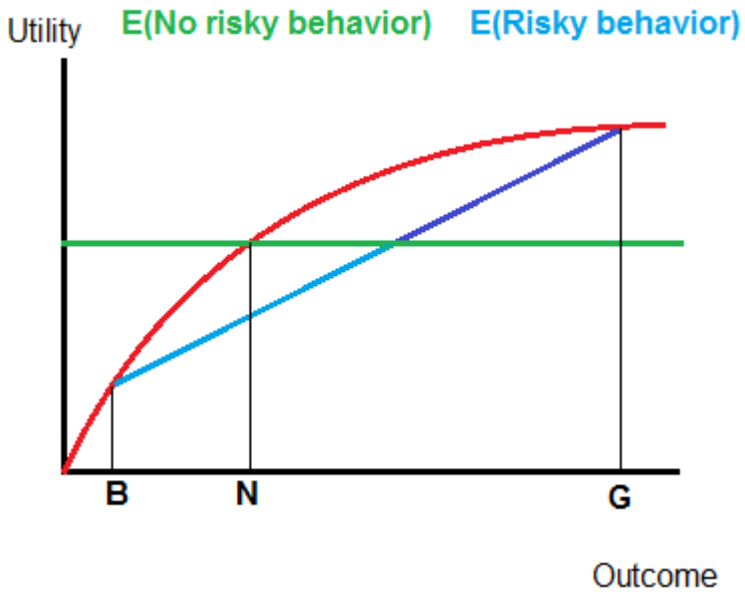
VII. Figures

1.



2.

Variable	Obs	Mean	Std. Dev.	Min	Max
offer	51	.4117647	.4970501	0	1
etest	51	.372549	.4882944	0	1
cigarettes	42	.2350952	.0452267	.115	.314
condoms	32	.5601562	.0499265	.455	.645
drunkdrive	40	.1546	.0333504	.089	.25
drugabuse	50	551.32	263.1968	204	1843
income	51	50859.81	7468.175	36650.06	66654.02
minority	51	.2869451	.1665849	.0489	.7905
youth	51	.0986961	.0091016	.0817	.1288
crime	50	3277.196	781.014	1619.6	4653.8
childpov	51	.1731373	.0485588	.09	.3
unemployment	51	.084549	.020111	.043	.136
region	51	2.588235	1.202938	1	4
testoffer	51	.2156863	.4153902	0	1

3.

Source	SS	df	MS
Model	.021631139	12	.001802595
Residual	.062232484	29	.002145948
Total	.083863623	41	.002045454

Number of obs = 42
F(12, 29) = 0.84
Prob > F = 0.6112
R-squared = 0.2579
Adj R-squared = -0.0491
Root MSE = .04632

cigarettes	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
offer	.0079219	.0232257	0.34	0.736	-.0395799	.0554237
etest	-.0109696	.0284884	-0.39	0.703	-.0692349	.0472957
testoffer	-.0037859	.0381151	-0.10	0.922	-.08174	.0741682
lnincome	.0015727	.1453134	0.01	0.991	-.2956265	.2987719
minority	.0051911	.0637554	0.08	0.936	-.1252034	.1355855
youth	-1.675401	1.080234	-1.55	0.132	-3.884727	.5339244
crime	-.0000106	.0000114	-0.92	0.363	-.000034	.0000128
lnchildpov	.0584149	.0711846	0.82	0.419	-.087174	.2040038
unemployment	-.8669389	.4932999	-1.76	0.089	-1.875851	.1419727
r1	-.0096652	.0266503	-0.36	0.719	-.0641712	.0448408
r2	.0326228	.0247054	1.32	0.197	-.0179054	.083151
r3	.0088667	.0307825	0.29	0.775	-.0540905	.0718239
_cons	.5896861	1.457433	0.40	0.689	-2.3911	3.570472

4. .

Source	SS	df	MS		
Model	.033809071	12	.002817423		
Residual	.043463114	19	.002287532		
Total	.077272185	31	.002492651		

Number of obs	32
F(12, 19)	1.23
Prob > F	0.3317
R-squared	0.4375
Adj R-squared	0.0823
Root MSE	.04783

condoms	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
offer	-.0145049	.0275246	-0.53	0.604	-.0721144	.0431047
etest	-.0217739	.0328326	-0.66	0.515	-.0904934	.0469456
testoffer	-.0016727	.0451722	-0.04	0.971	-.0962192	.0928739
lnincome	.1163327	.2085682	0.56	0.584	-.3202056	.552871
minority	.0431841	.08248	0.52	0.607	-.1294484	.2158167
youth	-2.439183	1.705471	-1.43	0.169	-6.008775	1.13041
crime	-.0000118	.0000135	-0.87	0.395	-.00004	.0000165
lnchildpov	-.0163705	.0888302	-0.18	0.856	-.2022943	.1695533
unemployment	-.8826557	.6033901	-1.46	0.160	-2.145566	.3802543
r1	-.0673313	.0340367	-1.98	0.063	-.1385709	.0039083
r2	-.0482005	.0312264	-1.54	0.139	-.113558	.0171571
r3	-.0630115	.0422819	-1.49	0.153	-.1515086	.0254856
_cons	-.450651	2.138946	-0.21	0.835	-4.927516	4.026214

5. .

Source	SS	df	MS
Model	.014936253	12	.001244688
Residual	.028441346	27	.001053383
Total	.043377599	39	.001112246

Number of obs = 40
F(12, 27) = 1.18
Prob > F = 0.3437
R-squared = 0.3443
Adj R-squared = 0.0529
Root MSE = .03246

drunkdrive	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
offer	-.0015371	.0168549	-0.09	0.928	-.0361205	.0330463
etest	-.0184484	.0204728	-0.90	0.375	-.0604551	.0235583
testoffer	-.0147117	.0272808	-0.54	0.594	-.0706873	.041264
lnincome	-.0845223	.1054246	-0.80	0.430	-.3008357	.1317911
minority	.046248	.0455817	1.01	0.319	-.0472779	.139774
youth	.2604412	.800162	0.33	0.747	-1.381356	1.902238
crime	-.0000139	8.45e-06	-1.64	0.113	-.0000312	3.49e-06
lnchildpov	.0052143	.0519443	0.10	0.921	-.1013666	.1117953
unemployment	-.652253	.3530054	-1.85	0.076	-1.37656	.0720543
r1	-.0202217	.0193035	-1.05	0.304	-.0598291	.0193858
r2	.0147298	.0173868	0.85	0.404	-.0209449	.0504046
r3	-.0080592	.0221736	-0.36	0.719	-.0535557	.0374372
_cons	1.155408	1.060528	1.09	0.286	-1.020616	3.331432