Amy Kim
Professor Italo Garcia Lopez
Econ 318 Empirical Project
9 December 2023

Responses to Risks: Reality or Perception?

Abstract

People make risk management decisions every day. Some people decide to take more risks for greater rewards while others decide that the rewards are not worth the risk. This threshold is different for everyone, but we want to establish patterns in what factors determine these threshold levels.

Method: Using Wooldridge data regressions, we examine what factors make people more prone to making risk-taking decisions in various situations involving crimes, violent crimes, affairs, injuries, etc.

Results: Although most people generally followed risk-aversive patterns, in extreme cases like murder and violent crime, they tend to diverge from the norms.

Conclusion: Perception of risks has a greater influence than real-world deterrence. What is considered a great risk also differs for everyone, which is what makes it so difficult to create effective prevention and deterrence of crime risky actions that create negative externalities.

Introduction

What attributes and situations motivate risky behavior? Is it certain demographics of people or people in different conditions? I think it is worth defining what risk means in our research, and what counts as excessive risk-taking. What people shouldn't typically do if they're following cost-benefit analysis. Risky behaviors often put people's health, financial stability, relationships, and careers in jeopardy, but people are sometimes more tolerating of such risks.

Foster, Shenesey, and Goff (2009) confirmed the existing literature, that narcissists are more likely to engage in risky behaviors. A more precedent study modeled a function of motive, expectancy, and incentive and that performance levels should significantly improve when uncertainty is greatest, while non-risk-takers avoid the most difficult cases (Atkinson, 1957). Shefrin and Statman (1985) claim that risk-taking may be a quest for pride because closing a stock account at a loss creates a sense of regret while closing with creates pride. They also argue that the tendency to avoid regret is generally stronger than the drive for pride, making investors prefer inaction over action (Shefrin & Statman, 1985).

Methods

In this paper, I will run various regress various risky behaviors on factors that I suspect are encouraging or discouraging that particulate behavior. Some of the independent (responsive) variables are smoking cigarettes, being hospitalized (this may be a direct result of being risky), having affairs outside of marriage, crime rates, murder rates, and more. Some of these data are cross-sectional and some are panel.

Results

Using the Wooldridge data, we first regress cigarettes on restaurant, white, age, and age squared. Restaurant = 1 if smoking in restaurants is prohibited, and white = 1 if the respondent is white. As people age, they generally realize their increased health risks, and the knowledge of smoking in restaurants being prohibited should increase their perceived risks of smoking–getting fined. We know that minority groups—especially blacks—are disproportionately convicted and often unfairly. At the same time, it tells us that majority groups may get away with the same risky behavior or crime.

I hypothesize that: RiskyBehavior (whites) ≥ Riskybehavior (blacks).

VARIABLES	(1) Model 1
restaurn	-2.952***
	(1.107)
white	-0.559
	(1.462)
age	0.742***
	(0.152)
agesq	-0.00855***
	(0.00164)
Constant	-3.678
	(3.379)
Observations	807
R-squared	0.042

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

We see outputs conflicting each other with my hypothesis. The variable "white" is statistically insignificant, while restaurant, age, and agesq are. We cannot conclude that white is a significant factor in smoking. Instead, age contributes greatly to changes in smoking behavior. We see that people are generally less likely to smoke as they age, which is standard behavior in avoiding risks.

Then we will look at another risky behavior: injury.

	(1)
VARIABLES	Model 2
(real $ value)	
benefit	0.000413***
	(0.000107)
(=1 if) male	0.0246*
	(0.0137)
(=1 if) married	0.0205*
	(0.0120)
(=1 if high earner) highearn	0.0277**
	(0.0140)
Constant	0.152***
	(0.0187)
Observations	6,846
R-squared	0.009

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

According to the regression, with 1 more dollar of insurance "benefit" (real dollar value of the benefit received), people are 0.04126% more likely to be hospitalized with 1% level significance. In theory, having more coverage in insurance reduces risks (or opportunity costs), but in the long run, the risks may be greater as the physical damage may reoccur in a worse condition as people age. This speaks to how people are blind or do not respond rationally when the damages seem far away in time. Discounting for the present value isn't the most intuitive process, so this is understandable. Smoking and frequent drinking also fall under the same logic category. They undermine the future value of their health and prioritize immediate pleasure. You may wonder how addiction plays into this. A study by Asaoka et al. (2020) outlines how behavioral addiction inhibits the probability of judgment and encourages risk-taking due to weakening prefrontal activity.

In contrast, the Balloon Analogue Risk Task (BART) made respondents incredibly risk-aversive (Dahne et al., 2013). Respondents are asked to click on a button to inflate the balloon, which adds money to their temporary winnings, and all of the balloons have different points of explosion. They can either choose to collect their winnings or keep inflating the balloon for a greater winning, but risk popping the balloon and losing all of their winnings. In this scenario, they are immediately faced with the visual representation of the consequences. This is the logic behind why anti-tobacco campaigns often use gross visuals. But how does the BART compare with real-life risks? Growing research on risk-taking is leaning towards the idea that these experiments/tasks can be used as proxies for risk-taking (Dahne et al., 2013). This means that despite slight iterations, people will show similar patterns of risk-taking in real life and the BART test.

Something that I did not expect was the "highearn" variable. It has a low significance of 5% but high-income earners are 2.77% more likely to be hospitalized. I suspect this is due to how high earners have highly stressful jobs, long work hours, and therefore less leisure time. Now we shift to other variables that may be contributing to injuries.

	(1)
VARIABLES	Model 2
=1 if after change	-0.0117
	(0.0104)
=1 if manufacturing	-0.0272**
	(0.0120)
=1 construcion	0.0555***
	(0.0153)
Age at time of injury	0.00106**
	(0.000413)
Constant	0.230***
	(0.0166)
Observations	7,121
R-squared	0.005

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

From the results, we can’t say that people are changing their insurance policies and getting injured on purpose to receive more insurance benefits. It is highly likely that people in the construction industry are getting hospitalized more. They are hospitalized 5.55% more with 1% significance. As people age 1 more year, they're 0.106% more likely to get hospitalized, which makes sense as they get older, they generally have more health complications. This example also follows the standard risk-aversive behavior.

Now we look at affairs and various variables affecting it.

	(1)
VARIABLES	Model 2
male	0.0583
	(0.0392)
age	-0.00730**

	(0.00311)
educ	0.000953
	(0.00795)
kids	0.0660
	(0.0474)
yrsmarr	0.0171***
	(0.00563)
Constant	0.256*
	(0.139)
Observations	601
R-squared	0.035

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

This time, we regressed twice using two different dependent variables (affairs and affair) as they are different indicators of behavior; affairs refer to the number of affairs they have, while affair is the chances of a person having an affair at all. The only statistically significant factors were age and years in marriage. In both regressions, an increase in age slightly decreased the likelihood of affairs, and years in marriage increased it. However, these two variables may introduce multicollinearity as an increase in age would generally be equivalent to an increase in years in marriage. Therefore, I tried the combination of regressions each, it seems that the most significant one is naffairs and yrsmarr. So we ran the following regression again:

	(1)
VARIABLES	Model 1
yrsmarr	0.111***
	(0.0238)
Constant	0.551**
	(0.235)
Observations	601
R-squared	0.035

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

One more year in marriage increases the likelihood of having another affair by 11.1%, whereas the $\beta yrsmarr$ for affair was 0.0109, or a 1% increase in chances of having an affair for the first time. This could mean that people who engage in affairs believe that the consequences of getting caught get smaller as their marriage and themselves age, or they could be becoming more risk-taking. However, we do not have the evidence to say which one of them (or any of them) is true.

Now we move on to crime. I regress crmrte (crimes committed per person) on log(crmrte), polpc (police per capita), urban (=1 if SMSA; standard metropolitan statistical area), prbarr (probability of arrest), prbconv (p of conviction), and prbpris (p of prision sentence).

	(1)
VARIABLES	Model 1
polpc	2.673***
	(0.221)
urban	0.0293***
	(0.00184)
prbarr	-0.0400***
	(0.00320)
prbconv	-0.00264***
	(0.000342)
prbpris	0.0153***
	(0.00589)
Constant	0.0315***
	(0.00279)
Observations	630
R-squared	0.506

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Police per capita is very high (2.7673)*** but this is a case of reverse causality. It would be reasonable to believe that the police per capita is high due to the high crime rate, rather than the other way around. The dummy variable for urban is also significant at 1%. We can say with confidence that being in an urban area increases the crime rate by 2.93%. But we need more information about what these crimes are. We know that some postindustrial cities–that used to thrive with manufacturing but have declined–like Baltimore, Cleveland, Detroit, Philadelphia, Pittsburg, and St. Louis, are urban metro centers but have high violent crime rates including homicide. The U.S. is a country where the city centers are poor and have big homeless populations, and where the rich reside in the suburbs where they can avoid the negative public externalities. Therefore, we will investigate murder in our next set of regression. Probability of arrest and conviction also each decrease the crime rates by 4.00% and 0.264%, respectively. It is rational for people to not commit crimes if they know the consequences are more severe. Most people know black and minority ethnic groups get disproportionately arrested, convicted, and face police brutality. For that reason, minority groups, especially Hispanics and Blacks are more likely to fear police confrontation. A good example of this in the media depiction is in the film Blindspotting (2018), where the black main character is first very evasive towards police encounters, but then becomes very agitated when forced to confront. This type of serious risk typically makes people evasive. Then there is the probability of imprisonment. At this point, I decided to take the log variables of crime rate, rates of arrest, conviction, and prison conviction.

	(1)
VARIABLES	Model 2
polpc	65.41***
	(6.351)
urban	0.342***
	(0.0574)
ln_prbarr	-0.697***
	(0.0386)
ln_prbconv	-0.557***
	(0.0298)
ln_prbpris	0.193***
	(0.0653)
Constant	-4.870***
	(0.0883)
Observations	630
R-squared	0.581

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The beta for log(prison sentence) has been increased from 0.0153*** to 0.193***. However, since we are using a double log variable, it means that a 1% increase in prison sentences would lead to a 0.193% increase in crime rates. Again, reverse causality may be at play here; the city having a high imprisonment rate proves that this area is unsafe and high in crime, attracting more criminals, drug addicts, and poor people who are drawn to the cheaper rents.

Finally, we look at the murder rates. Referring to what we did in lab 11, we regress cmrdrte (change in murder rate from the previous year; mrdrte - mrdrte[n-1]) on cexec (change in the number of executions), and cunem (change in unemployment rate), excluding outliers (Texas) and accounting for robustness:

	(1)
VARIABLES	Model 2

cexec	-0.0675
	(0.0791)
cunem	-0.0700
	(0.146)
Constant	0.413**
	(0.200)
Observations	50
R-squared	0.013

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

So as common literature suggests, execution has no significant or positive effect on murder rates. This is contrary to my hypothesis.

Conclusion

I hypothesized that people will be less likely to take risks when the risks are greater and the benefits are not big enough. However, a lot of research and many of my regressions show that this is not necessarily true. We cannot say murders are deterred by executions or that crimes are deterred by high imprisonment rates. I want to argue that the perception of risks has a greater influence than real-world deterrences. From the BART responses, we can infer the imagery of the balloon popping provides an extreme impression of risk, preventing people from behaving overly risky. But as we can see with how ineffective the offensive illustrations on cigaret packaging are, something that is too on the nose may not work. What is considered a great risk also differs for everyone, which is what makes it so difficult to create effective prevention and deterrence of crime risky actions that create negative externalities.

References

Asaoka, Y., Won, M., Morita, T., Ishikawa, E., & Goto, Y. (2020). Higher risk taking and impaired probability judgment in behavioral addiction. *International Journal of Neuropsychopharmacology*, *23*(10), 662-672.

Atkinson, J. W. (1957). Motivational determinants of risk-taking behavior. *Psychological review*, *64*(6p1), 359.

Blindspotting. (2018). [Film]. USA: Lionsgate Films.

Dahne, J., Richards, J. M., Ernst, M., MacPherson, L., & Lejuez, C. W. (2013). Assessment of risk taking in addiction research. *The Wiley‐Blackwell handbook of addiction psychopharmacology*, 209-231.

Foster, J. D., Shenesey, J. W., & Goff, J. S. (2009). Why do narcissists take more risks? Testing the roles of perceived risks and benefits of risky behaviors. *Personality and Individual Differences*, *47*(8), 885-889.

Shefrin, H., & Statman, M. (1985). The disposition to sell winners too early and ride losers too long: Theory and evidence. *The Journal of finance*, *40*(3), 777-790.

Wooldridge, J. M. (2022). Retrieved from http://fmwww.bc.edu/ec-p/data/wooldridge/datasets.list.html