ESTIMATING THE RISK PREMIUM OF LAW ENFORCEMENT OFFICERS

Brandon Payne
East Carolina University
Department of Economics
Thesis Paper
November 27, 2002

Abstract

This paper is an empirical study to estimate the risk premium or compensating differential for law enforcement officers. First, we use the human capital model to form a baseline regression using data from the Current Population Survey from 1989 to 1999. The second regression includes crime rates from around the United States to determine how the risk premium of officers' change as crime rates rise and fall. A third regression includes only MSA sizes to show how the size of area affects officers' wages. Last, we estimate regressions based on splitting up the different types of officers: police officers, supervisors, and sheriffs. The results indicate that controlling for crime rates and MSA sizes do help explain the risk premium of law enforcement officers, but more day to day on the job characteristics are needed to make more accurate estimations.

The author would like to thank Dr. DeSimone and Dr. Schumacher for their help, advice, and guidance through all phases of this paper.

INTRODUCTION

Society has a number of jobs that are unpleasant or risky and would be costly to make safe and pleasant, such as coal mining and police work. There are two ways to recruit the necessary labor for such jobs. One is to compel people to do these jobs, such as the military draft. The other way is to induce people to do the jobs voluntarily. Compensating wage differentials are used to recruit labor to unpleasant jobs voluntarily. A compensating wage differential is the additional wage paid to individuals for working in undesirable working conditions. Similarly, those who choose more pleasant conditions have to "buy" them by accepting lower wages.

Our prediction about the existence of compensating wage differentials grows out of the reasonable assumption that if an informed worker has a choice between a job with good working conditions and a job of equal pay with bad working conditions, he or she will choose the good job. The predicted outcome of our theory of job choice is not that employees working under bad conditions receive more than those working under good conditions do. The prediction is that, holding worker characteristics constant, employees in bad jobs receive higher wages than those working under more pleasant conditions do because employers have to pay a premium to these workers. The characteristics that must be held constant include all the other things that influence wages: skill level, age, experience, race, gender, union status, region of the country, etc. There are three assumptions that have been used to arrive at this prediction. First, workers seek to maximize their utility, not their income. This explains why compensating wage differentials exist because some people do not choose the highest paid job offered, but prefer instead a lower paying but more pleasant job. Wages do not equalize in this case.

Workers net utility equalizes for the marginal worker from overall utility from pay and the psychic aspects of the type of job worked. Second, workers are aware of job characteristics of potential importance to them. A company offering a bad job with no compensating wage differential would have trouble recruiting or retaining workers, enough trouble that would eventually force it to raise its wage. Third, workers have a range of job offers from which to choose. With this range of offers, workers would not be able to select the combination of job characteristics they desired or avoid the ones to which they did not wish experience. A compensating wage differential for risk of injury would not arise if workers were able to obtain only dangerous jobs. It is the act of choosing safe jobs over dangerous ones that forces employers offering dangerous work to raise wages.

This report is an empirical study using the human capital model to estimate the risk premium or compensating differential for law enforcement officers. First, we analyze a baseline regression model with log wage as the dependent variable and independent variables such as human capital, region, and year to see the risk premium for law enforcement officers. The results are consistent with economic theory in that males, being married and union workers all earn a premium over their counterparts. Also, returns to education are about 8 percent and there is a risk premium for law enforcement officers. We then see how the risk premium is affected when we control for MSA size, and more importantly, crime rates within the MSA. We attempt to examine how much influence the outside factor of the amount of crime within an MSA determines the wages of law enforcement officers.

Second, this paper compares the risk premiums for law enforcement officers as they are broken up into the three occupation categories that made them up. The categories are working as a sheriff, police officer, and superintendent (detective or chief). We then control for MSA size and the crime rates within MSA to see how this affects the risk premiums.

DATA

The data for the baseline model comes from a sample of the Current Population Survey for the years, 1989 through 1999, which yields 144,325 observations. The survey includes all relevant variables such as geographic size and location, personal, educational, and occupational characteristics. These variables allow us to see how they affect individual wages, primarily law enforcement officers. We use the log wage in our models because human capital theory estimates the returns to schooling, gender, union membership, marriage status, race, experience, and age. Our sample has approximately 8 percent of law enforcement officers. Our control group is the average worker taken from the average occupation. Our control group is important in explaining how law enforcement officers' wages are affected when we take other variables into account.

In order to estimate the effect of the crime rates on the risk premium of law enforcement officers we need to merge crime rates from 1989 to 1999. This data is held by the National Archive of Criminal Justice Data, through the US Department of Justice (Federal Bureau of Investigation). The data comes from the Uniform Crime Reporting Program Data US: County-Level Detailed Arrest Data. The data contain relevant arrest figures for all crimes such as murder, arson, rape to burglary, robbery, and destruction of property. These figures were merged into two groups: violent and property crimes; these numbers are then divided by MSA population. County-level arrest data are aggregated to the MSA level and then merged with the CPS data.

DESCRIPTIVE STATISTICS

Table 1 shows some descriptive statistics for law enforcement officers. Column 1 shows us the average hourly real wage of officers within the ten largest MSAs, school levels and over the years of 1989 through 1999. Column 2 shows us the average violent crime rates per capita within MSAs and over the years of 1989 through 1999. These statistics show that everything is consistent with economic theory in that within larger MSAs the average wage and violent crime rates are higher than smaller MSAs.

Table 1

Descriptive Statistics (Means) for Law Enforcement Officers

Variable	Real Wage Column 1	Violent Crime Rate Column 2
Non - MSA	15.56	184333
MSA1	21.63	114578
MSA2	24.36	115506
MSA3	19.55	57717
MSA4	18.78	40144
MSA5	24.13	36546
MSA6	19.57	35342
MSA7	18.56	17997
MSA8	16.78	31857
MSA9	20.04	22456
MSA10	17.77	30899
HS Dropout	12.01	
HS Graduate	15.98	
Some post-HS	17.68	
College Degree	19.76	
Graduate Degree	22.67	

The statistics also show that law enforcement officers also earn higher wages with the more education they possess.

BASELINE REGRESSION

The baseline regression model is formed using the log wage as the dependent variable and independent variables such as schooling, experience, region, year, and dummy variable for law enforcement occupation variable to see the risk premium for law enforcement officers. The regression yields the following equation:

$$\text{lnwage} = b(\textit{leo}) + c(\textit{school}) + d(\textit{exp.}) + e(\textit{exp.2}) + f(\textit{female}) + g(\textit{union}) + h(\textit{married}) + i(\textit{race}) + j(\textit{part-time}) + k(\textit{region}) + l(\textit{year}) + x.$$

Here *leo* is the dummy variable for being a law enforcement officer and b is the respective coefficient. This gives the unexplained wage difference between law enforcement officers and the control group. Given that law enforcement officers take on an increased amount of risk, we estimate this unexplained difference to be approximately 8 to 12 percent. *School* is a continuous variable for the school level completed and c is the respective coefficient. *Exp.* is a continuous variable for the amount of experience in the labor force and *exp.2* is the square of experience to show the diminishing returns to experience and d and e are their respective coefficients. *Female* is a dummy variable to show the difference in wages earned between men and women and f is the respective coefficient. *Union* is a dummy variable to show the difference in wages earned between union and non-union workers and g is the respective coefficient. *Married* is a vector of marriage status and h is their respective coefficient. *Race* is a vector of individual race and i is their respective coefficients. *Part-time* is a dummy variable for part-time working status and j is the respective coefficient. *Region* is a vector of the region lived in the country and k is the respective coefficient. *Year* is a vector of the years 1989 to 1999 to see how wages have changed over the decade and l is their respective coefficients. X is the error coefficient.

Table 2 shows the results of the baseline regression. We see that the results are consistent with economic theory in that males, being married and union workers all earn a premium over their counterparts. Also, returns to education are about 8 percent. Of important interest to us is the risk premium of law enforcement officers. The premium for officers is approximately 9.4 percent higher than the average worker. This is not

Table 2

Baseline Regression

Variable	Parameter Estimate	Standard Errors
law enforcement	0.09377 **	0.00450
school	0.07913 **	0.00044
exp.	0.03180 **	0.00037
exp.2	-0.000484 **	0.00001
female	-0.06184 **	0.01203
male	deleted	
union	0.06949 **	0.00262
married	0.09080 **	0.00352
divorced	0.05900 **	0.00475
single	deleted	
black	-0.11800 **	0.00389
hispanic	-0.02120 **	0.00532
other	-0.04979 **	0.00546
white	deleted	
part-time	-0.33623 **	0.00458
region dummies	yes	
year dummies	yes	
adjusted r-squared	0.3650	

** significant at the 1% level.
*   significant at the 5% level.

surprising given how dangerous it is to be an officer. Under the detailed occupation tabulations, which shows characteristics of occupations, the percent of hazards for law enforcement officers is high. The percent of hazards, such as exposure to bodily harm and other exposure to dangerous conditions, for law enforcement officers are approximately 86 percent. Also, a category that shows the years required for occupational proficiency called SVP is approximately 4.5 years, which is high for most jobs and supports officers' higher wages.

Table 3 shows the baseline regression model with three different sets of variables added. Column 1 shows the model with crime rates added. Our point of interest is to

Table 3

Variable	With Crime Rates Parameter Estimate	With MSA Size Parameter Estimate	With Both Parameter Estimate
violent crime	0.00000 **	deleted	0.00000
property crime	-0.00000 **	deleted	-0.00000
law enforcement	0.08917 **	0.08635 **	0.09028 **
school	0.07814 **	0.07561 **	0.07646 **
exp.	0.03224 **	0.03169 **	0.03197 **
exp.2	-0.000500 **	-0.00048 **	-0.00050 **
female	-0.06569 **	-0.06836 **	-0.06960 **
male	deleted	deleted	deleted
union	0.05695 **	0.05522 **	0.05138 **
married	0.10085 **	0.11238 **	0.11324 **
divorced	0.06264 **	0.07282 **	0.07104 **
single	deleted	deleted	deleted
black	-0.14491 **	-0.16399 **	-0.16538 **
hispanic	-0.05841 **	-0.05024 **	-0.05601 **
other	-0.05495 **	-0.05998 **	-0.07074 **
white	deleted	deleted	deleted
part-time	-0.33148 **	-0.32692 **	-0.32463 **
region dummies	yes	yes	yes
year dummies	yes	yes	yes
msa dummies	no	yes	yes
adjusted r-squared	0.3644	0.3655	0.3650

** significant at the 1% level.
* significant at the 5% level.

examine how the crime rates within MSA size change the risk premium for law enforcement officers. The model with crime rates included yields a risk premium of 8.917 percent and compared to the baseline model, we see that the risk premium for officers decreases by approximately 0.5 percent. This tells us that by including crime rates, we can help explain 0.5 percent of the risk premium of officers. This reinforces our assumption that crime rates help determine the wages of our law enforcement officers.

Column 2 shows the baseline model with the MSA dummy variables added to see how the risk premium for law enforcement officers changes. This is done to take into account the theory that bigger cities pay higher wages than smaller cities. The risk premium with MSA size dummy variable included is 8.635 percent. Compared to the baseline model with crime rates included, we see that the risk premium decreases by approximately 0.3 percent. Compared to the baseline model only, we see that the risk premium decreases by 0.8 percent. This tells us that by including MSA size only, we can help explain approximately 0.8 percent of the risk premium of law enforcement officers.

Column 3 shows the baseline model with crime rates and MSA size dummy variables included. The risk premium for officers is 9.028 percent. Compared to the baseline model, we see that the risk premium decreases by 0.4 percent. This tells us that by including both the crime rates and the MSA size dummy variables, we can help explain approximately 0.4 percent of the risk premium of law enforcement officers. This change is only half the change with the baseline model with only MSA size dummies included. This leads us to believe that including the MSA size dummies have more explanatory power in the wages of law enforcement officers than using a baseline model with crime rate variables or even using a baseline model with both crime rate and MSA size dummy variables included. More importantly, we see that the violent and property crime variables become not significantly different than zero. Also, not shown are the MSA size dummies, which are also not significantly different than zero. The insignificant crime rate and MSA size variables are most likely due to multicollinearity because the MSA size dummies are explaining the same things that the crime rates are explaining. This is not surprising because the larger the MSA, the more crime is prevalent and vice versa.

LAW ENFORCEMENT OFFICER CATEGORIES

Table 4 shows the baseline regression model with one exception. The law

Table 4

	Baseline Regression	
Variable	Parameter Estimate	Standard Errors
supervisors	0.13699 **	0.01124
police officers	0.11814 **	0.00519
sheriffs	deleted	
school	0.07910 **	0.00044
exp.	0.03181 **	0.00037
exp.2	-0.000483 **	0.00001
female	-0.05952 **	0.01178
male	deleted	
union	0.06796 **	0.00262
married	0.09027 **	0.00351
divorced	0.05854 **	0.00475
single	deleted	
black	-0.11771 **	0.00389
hispanic	-0.02147 **	0.00532
other	-0.04974 **	0.00546
white	deleted	
part-time	-0.33592 **	0.00458
region dummies	yes	
year dummies	yes	
adjusted r-squared	0.3658	

** significant at the 1% level.
*   significant at the 5% level.

enforcement officer variable has been split up by the occupational categories that made them up. The categories are sheriffs, police officers, and supervisors or detectives. These variables are made into dummy variables for the regression model with the sheriff category deleted. The estimates of interest are the supervisors and police officers. We see that supervisors and police officers earn approximately 13.7 and 11.8 percent respectively higher wages than sheriffs earnings. This is understandable because supervisors are appointed after years of experience and police officers are on the streets all the time where their hazards are higher than sheriffs' hazards.

Similar to table 3, table 5 shows the baseline model with law enforcement officers split in their categories and three different sets of variables added. Again, our point of interest is looking at how the supervisor and police officer variables change when crime rates and MSA size dummy variables are included. Column 1 shows the model with the crime rates added to the model and yields a risk premium for 12.4 and 11.1 percent for supervisors and police officers respectively higher than sheriffs. Compared to the baseline model, we see that the risk premium for supervisors and police officers decreases by approximately 1.3 and 0.7 percent respectively. This tells us that by including crime rates, we can help explain 1.3 and 0.7 percent of the risk premium for supervisors and police officers respectively. This reinforces our assumption that crime rates help determine the wages of our law enforcement officers.

Column 2 shows the baseline model with the MSA size dummy variables added to see how the risk premium for supervisors and police officers change. The risk premium with MSA size dummy variable included is 13 and 10.5 percent for supervisors

Table 5

Variable	With Crime Rates Parameter Estimate	MSA Size Parameter Estimate	With Both Parameter Estimate
violent crime	0.00000 **	deleted	0.00001
property crime	-0.00000 **	deleted	-0.00000
supervisors	0.12439 **	0.13009 **	0.12570 **
police officers	0.11052 **	0.10486 **	0.10826 **
sheriffs	deleted	deleted	deleted
school	0.07810 **	0.07558 **	0.07640 **
exp.	0.03226 **	0.03167 **	0.03197 **
exp.2	-0.000500 **	-0.00049 **	-0.00050 **
female	-0.06274 **	-0.06439 **	-0.06454 **
male	deleted	deleted	deleted
union	0.05547 **	0.05407 **	0.05011 **
married	0.10034 **	0.11191 **	0.11280 **
divorced	0.06220 **	0.07244 **	0.07068 **
single	deleted	deleted	deleted
black	-0.14442 **	-0.16357 **	-0.16493 **
hispanic	-0.05839 **	-0.05026 **	-0.05593 **
other	-0.05487 **	-0.05982 **	-0.07052 **
white	deleted	deleted	deleted
part-time	-0.33131 **	-0.32686 **	-0.32467 **
region dummies	yes	yes	yes
year dummies	yes	yes	yes
msa dummies	no	yes	yes
adjusted r-squared	0.3651	0.3660	0.3654

** significant at the 1% level.
*   significant at the 5% level.

and police officers higher than sheriffs' wages respectively. Compared to the baseline model with crime rates included, we see that the risk premium decreases by approximately 0.6 percent for both supervisors and police officers. Compared to the baseline model only, we see that the risk premium decreases by 0.7 and 1.3 percent for supervisors and police officers respectively. This tells us that by including MSA size only, we can help explain approximately 0.7 and 1.3 percent of the risk premium of supervisors and police officers respectively.

Column 3 shows the baseline model with both crime rates and MSA size dummy variables included. The risk premium for supervisors and police officers is 12.6 and 10.8 percent higher than sheriffs' wages respectively. Compared to the baseline model, we see that the risk premium decreases by 1.1 and 1.0 percent for supervisors and police officers respectively. This tells us that by including both the crime rates and the MSA size dummy variables, we can help explain approximately 1.1 and 1.0 percent of the risk premium of supervisors and police officers. This change is mixed for including either crime rates and MSA size dummy variables and does not lead us to choose adding either crime rates or MSA size dummies. More importantly, we see that the violent and property crime variables become not significantly different than zero. Also, not shown are the MSA size dummies, which are also not significantly different than zero. The insignificant crime rate and MSA size variables are most likely due to multicollinearity because the MSA size dummies are explaining the same things that the crime rates are explaining. This is not surprising because the larger the MSA, the more crime is prevalent and vice versa.

CONCLUSION

The purpose of this study is to determine the risk premium or compensating differential for law enforcement officers. First, we analyze a baseline regression model with human capital, region, and year to see the risk premium for law enforcement officers. The results are consistent with economic theory. We then see how the risk premium is affected when we control for MSA size, and more importantly, crime rates within the MSA. We see with the inclusion of MSA size and the crime rates within MSA explain some of the risk premium of law enforcement officers, but not with an alarming large change.

Second, this paper compares the risk premiums for law enforcement officers as they are broken up into the three occupation categories that made them up. The categories are working as a sheriff, police officer, and superintendent (detective or chief). We then control for MSA size and the crime rates within MSA to see how this affects the risk premiums. Again, there is a significant change in explaining the risk premium for law enforcement officers, but none too large.

We have attempted to explain the risk premium of law enforcement officers by controlling for MSA size and crime rates, but we cannot control for the actual risks faced by law enforcement officers. With more detailed information on the more personal risks officers face such as, shootings, death rates, and the number of fights that they have encountered then we could further explain the risk premium.

REFERENCES

Ehrenberg, Ronald and Robert Smith. *Modern Labor Economics: Theory and Public Policy*, 7 ed., 2000.

Glaeser, E. and D. Mare. "Cities and Skills," *Journal of Labor Economics*, Vol 19, No.2, April 2001.

Gottschalk, Peter. "Inequality, Income Growth, and Mobility: The Basic Facts," *Journal of Economic Perspectives*, Spring 1997.

Schumacher, Edward and Barry Hirsh, "Private Sector Union Density and the Wage Premium: Past, Present, and Future," *Journal of Labor Research*, Summer 2001.