IS THE EXPECTED VALUE OF LIFE EQUAL ACROSS PROVINCES? – RESULTS USING HEDONIC WAGE INFORMATION*

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I. Introduction

Hedonic estimates of the value of a statistical life fo back some 30 years or more [see Thaler and Rosen (1973) for the seminal work]. Hedonic estimates of this type are now well-established in the literature. In cost-benefit analysis (especially health and transport studies),

forensic economics (in tort cases where lives are lost), the literature emphasizes quantifying loss of life (or lives saved), or the statistical valuation of a year of life decreased (or extended). The literature discussing issues on the statistical value of life varies widely, from discussions of valuations of future lives saved [see Frederic(2003)], to the value of an additional year of left prolonged [Johannesson and Johansson (1996)], to estimates of children, future generations, and retired persons not in the labour force [see Jenkins et. al. (2002),, and Johannesson and Johansson (1996a) and (1996b)].

In this paper, we raise the question as to whether, in a multi-state of province federation, the estimated value of life differs across states or provinces. Although raising this question might at first glance appear unseemly, the very nature of hedonic price estimates in life valuation, and thier used in cost-benefit calculus, suggest that in theory statistical values of lives could differ across regions. Evans and Viscussi (1993), for example, argue that valuations of risk typically rise with income – and using consumer valuations of product safety they estimate income elasticities of between .18 and .39.

Indeed in the development economics literature, Miller (2000) found that the value of a statistical life did in fact vary across 13 countries, with an income elasticity of life values ranging from .85 to 1.00 . Since average personal incomes vary across provinces, in an analogous fashion to that of countries, one could hypothesize that average valuations of risk might in fact vary across provinces. In this paper, following the approach of Thaler and Rosen (1973) and Meng and Smith (1990), we investigate whether or not the expected value of life differs across provinces. We might expect that individuals in richer provinces might value life more highly than individuals in poorer provinces, if risk aversion is a normal good. To explore this, we interact provincial dummy variables with risk to find whether or not there exists a difference in value of life across the provinces in Canada. Whether or not cross-province differences exist has interesting applications for (1) cross-province federal projects, and (2) provincial government decision making.

The paper is organized as follows: Section 2 describes the model methodology and the data. Section 3 presents empirical results and Section 4 concludes.

II. The Model and Methodology

The method

data, we calculate Canada's value of life by estimating the income differences compared by the workers in risky jobs relative to those in safe jobs. In particular, we explore differences in the expected value of life at the provincial level, compare the differences and find the possible reasons and policy implications. Unfortunately, specific provincial data as to occupational risk are not available. To circumvent the lack of provincial specific occupational risk data, we include provincial dummy variables and the interaction between these province variables and risk to capture the difference among provinces. This procedure will be explored in more detail below.

2.1 Hedonic Method of Value of life Estimation

Consumption goods differ as to size and quality. Similarly jobs in the labour market differ as to "quality", such as safety and risk. Such characteristics in the latter market do not have an explicit market price. The total compensation of a certain occupation shows a weighted average of the positive and negative characteristics associated with it. As explained in the previous chapter, the "hedonic method", as applied to the labour market, generates valuations of different occupational characteristics, including risk. Generally speaking, if all occupations pay the same wage rate, workers prefer those that are more pleasant (in this essay's context, less risky). Thus, more risky jobs will attract fewer workers at the same wage and therefore will pay more to attract sufficient workers. The value of life is then calculated by examining the size of the wage premiums that workers receive for accepting more risk.

As shown by Meng and Smith (1990), to use this approach, the following conditions have to be fulfilled:

1. Workers value not only the wage rate but also the quality of their jobs, such as the working environment, the amount of stress or the exposure to risk of injury or death and so on.
2. Workers have enough information and understand the different characteristics of the occupations. They are aware of the risks associated with a given occupation.
3. Since a compensating differential for risk of death can only occur if workers are able

to choose from a range of safe and risky jobs, there have to be a variety of jobs and workers are free to choose the one that maximizes their utility.

2.2 Data

Two data sets are used in this project. One is a cross-sectional data set, which was collected as part of the 1990 Labour Market Activity Survey (LMAS), the other is the Occupational Surveillance in Canada. The LMAS was conducted by the Statistics Canada, whereby the primary objectives are to provide measures of the dynamic nature of the Canadian labour market and to provide information on the characteristics of paid jobs. The Occupational Surveillance in Canada was conducted by Labour Canada from 1965 to 1991[1], to determine the associations between job titles and specific causes of death for both women and men.

In both of the two data sets mentioned above, jobs are broken into 21 categories[2] based on the 1971 occupation code. Wages and salaries, the crucial left-hand dependent variable, is from the LMAS survey and is total wages and salaries earned in a year. With the Occupational Surveillance in Canada, we calculate the death rate associated with a certain job category based on $ = D/N where D is the number of deaths in a particular

occupation; N is the total number of people in this occupation. *$* is the occupational risk.

Then, we link the two data sets. To do this, we assign a given person in the LMAS set a given 'risk of death', given the stated occupation of that person as calculated in (3.1) above. In this way, in one data set, we have not only the detailed information about a person, such as age, sex, education and so on, but also the characteristics associated with a specific job, such as the job risk, indexed by the death rate of a job.

1 [1]The survey is conducted from 1965 to 1991, but there is only one data set.

2.3 Models and Variables:

In this project, three regression models are estimated. The dependent variable, expressed by *logwage*, is the natural log of annual earnings in 1990 for each worker in the sample. The difference between the three models are in the set of explanatory variables used. The first model uses only control variables such as age, sex, education, marital status and provincial dummies. In model II, in addition to the identical control variables, we include an occupation risk variable at the national level. Model III includes all of the exact explanatory variables in Model II plus the interaction between province and risk to capture the difference in job related risk among province. The first model is estimated to test if the parameter of occupational risk and provincial interaction dummies of model III are statistically significant taken as a group. The second model is estimated to test if the parameters of interaction provincial/risk dummies are statistically significant taken as a group.

(A) Control variables:

The control variables for the three models are:

Weeks employed: Total weeks employed. The relationship between wage rate and working time is expected to be positive. The wage rate is the annual wage per person, so working more weeks would therefore increase annual earings.

Age dummies: In this project, the working age population is broken into four age groups:16 to 24, 25 to 44, 45 to 54 and 55 to 64 years of age. In order to measure the relationship between age and wage rate, we include age dummy variables. Using the population aged between 25 to 44 as the

2 [2] The 21 job categories and the associated death rate are shown in section IV.

reference, parameters of the age dummies show, keeping other factors constant, the difference in wages between persons aged 25 to 44 and those of other age group. Generally speaking, older people are paid more because they have more work experience.

Education: In this project, population are broken into three groups based on education level: less than high school, high school graduate and university degree. To find the effect of education on wage rate, we use people with high school graduate as reference and include two dummies indicating other educational level. We should expect that higher educations raises wages, given higher human-capital industrial productivity.

Marital Status: This dummy states whether the person is married or not. The value is set 1 if yes, and 0 otherwise. Marriage has positive effect on a person's wage rate, since typically, married persons have more dependents, and are accordingly more responsible and more productive.

Union: This dummy states whether the person belongs to a union or not. The value is set to 1 if yes, and 0 otherwise. The coefficient is expected to be positive, since unionised collective bargaining typically results in higher wages for union worker.

Skills: People are broken into three groups based on skills: unskilled worker, semi-skilled worker and skilled workers. We use the semi-skilled workers as reference and include two dummies indicating different skill levels. We expect that more skilled workers are better paid, given higher human capital endowments.

Sex: This dummy states the sex of an individual. The value is set to 1 if male, and 0 otherwise. This dummy variable indicates, keeping other factors constant, the difference in wage between male and female. Males are considered to be better paid, given possible gender discrimination or some other theory explaining gender-based wage differences.

Country of Birth: This dummy states whether the person is born in Canada or not. The value is set to 1 if yes, and 0 otherwise. The coefficient on the dummy is indeterminate. Newly-arrived immigrants are generally poorer paid than nature-born Canadians, but well-established immigrants might be better paid than native-born Canadians.

(B) Occupational Risk and Provincial Dummies:

Occupational risk: The risk associated with a specific job, expressed by *OCCURISK*. The parameter is expected to be positive, as shown by Thaler and Rosen (1975), because firms needs to offer higher wages to attract workers to do jobs with more risk.

Regional Dummies: Using Atlantic provinces as the reference, we include four provincial dummies to control for differences between people in the Atlantic region and those in British Columbia, Quebec, the Prairie region (Alberta, Saskatchewan and Manitoba), and Ontario when other factors are held constant. We group provinces that are geographically close, and which share many characteristic, together

(C) Interaction Provincial Dummies

In this report, we want to explore the value of life at provincial levels, compare the differences, find the possible reasons and discuss policy implications. Unfortunately, the provincial data are not available. We include the interaction between province and job risk to capture the difference among provinces. As such, in addition to the exact explanatory variables listed above, model III includes interaction dummy variables between province and job risk, with the interaction between Ontario and job risk being the reference variable. Regarding pure provincial dummies, instead of using Atlantic region as reference, we use Ontario as the base in this case, to be consistent with the interaction dummy variables' reference category. The interaction dummy variables show the difference in wage rate of jobs with the same risk level between provinces.

2.4. Tests

In this paper, T-tests and F-tests are used to test the null hypothesis of a specific or a set of parameters. The results are compared with the critical values using the significance levels 1%, 5% and 10%.

2.5 Calculating the Value of Life.

The approach for using the results of our wage regression equation to infer required compensation for exposure to risk is relatively straightforward. The risk variable that we used is the death rate *$* form 1965 to 1991 taken as one time period. The regression results of the wage function indicates the wage premium received by workers in the more risky jobs, holding other factors constant. Assume that we find that workers in jobs with a risk factor of one death per year are paid $ 3,000 annually more than comparable workers in risk-free jobs, then, if information is complete in the labour market, workers in this risk category will be compensated by $3,000 to accept the risk of one death. This monetary value is termed a statistical value of life. The wage regression functions stated above are used to estimate the risk premium that exists in the Canadian labour market. The coefficient of occupation risk is the key parameter in our estimates of the value of life for Canada.

III. Empirical Results

This section presents our estimates of the occupational risk and the regression results of the two models based on the methodology described above.

3.1 Occupational Risk

Table 3.1 shows the sample occupations and risks of death from 1965 to 1991, where 1.0 would mean certain death. Based on the1971 occupation codes from the Occupational Surveillance In Canada: 1965-1991, occupations are broken into 21 classifications, including managerial, administrative and related occupation; occupations in natural sciences, engineering and mathematics; occupations in social sciences and related fields; occupations in religion; teaching and related occupations; occupations in medicine and health; artistic, literary, recreational and related occupations; clerical and related occupations and so on.

Occupational risk is the risk of dying on the job, from 1965 to 1991. As shown in the table 4.1, the occupational fatality rate for managers and administrators is a 7.88 chance out of 100 of dying between 1965 and 1991. For the occupations in social sciences and related fields, the occupational fatality rate is 0.0501, which means that there are about 5 in 100 chance of dying in that time interval. Compared with the former occupation, the latter

Table 3.1: Sample Occupations and Risks of Death on Job, between 1965 and 1991.

OCCUPATION	RISK	OCCUPATION	RISK
MANAGERIAL, ADMINISTRATIVE AND RELATED OCCUPATIONS	0.08	FISHING, HUNTING, TRAPPING AND RELATED OCCUPATIONS	0.045
OCCUPATIONS IN NATURAL SCIENCES, ENGINEERING AND MATHEMATICS	0.06	FORESTRY AND LOGGING OCCUPATIONS	0.074
OCCUPATIONS IN SOCIAL SCIENCES AND RELATED FIELDS	0.05	MINING AND QUARRYING INCLUDING OIL AND GAS FIELD OCCUPATIONS	0.082
OCCUPATIONS IN RELIGION	0.09	PROCESSING OCCUPATIONS	0.069
TEACHING AND RELATED OCCUPATIONS	0.04	MACHINING AND RELATED OCCUPATIONS	0.068
OCCUPATIONS IN MEDICINE AND HEALTH	0.05	PRODUCT FABRICATING, ASSEMBLING AND REPAIRING OCCUPATIONS	0.058
ARTISTIC, LITERARY, RECREATIONAL AND RELATED OCCUPATIONS	0.08	CONSTRUCTION TRADES OCCUPATIONS	0.084
CLERICAL AND RELATED OCCUPATIONS	0.04	TRANSPORT EQUIPMENT OPERATING OCCUPATIONS	0.087
SALES OCCUPATIONS	0.06	MATERIALS HANDLING AND RELATED OCCUPATIONS	0.054
SERVICE OCCUPATIONS	0.06	OTHER CRAFTS AND EQUIPMENT OPERATING OCCUPATIONS	0.059
FARMING, HORTICULTURAL AND ANIMAL HUSBANDRY OCCUPATIONS	0.06		

Source: Author's Calculation Based on Data from the Occupational Surveillance In Canada: 1965- 1991.

has less occupational fatality, in other words, less risk. The reason is that those working in the managerial and administrative occupations have more stress and more challenges, which is harmful for a person's health.

As shown in table 3.1, in the 21 occupations, the one with the least fatality rate is the teaching and related occupations, which is 0.0363; while the occupation with the most fatality rate is the transport equipment operating occupations. Generally speaking, persons in teaching and related occupations have less pressure and comparatively more pleasant work environment. Thus, it is understandable that the fatality rate for this occupation is least of all. From the calculation results, the transport equipment operating occupations are the riskiest jobs of all.

3.2 A Description of the Sample Data

Before undertaking the statistical tests, it is often useful to look at the raw data to draw at some interesting facts. Table 3.2 shows occupation concentration by gender. For men -- who have a slightly higher level of labour force participation than women -- the 1.0497 in "artistic, literary and recreational" occupation says that this occupation men (and women) are represented at approximately qual proportions. Comparing Table 3.1 and 3.2, it is seen that men are in the most dangerous occupations (managerial, construction, transport and equipment operating).

Table 3.3 shows occupation concentration by province. The data points were calculated analogously to those in Table 3.2. A province with a data point considerably higher than 1 means that province has a high concentration of that occupation (e.g. mining in Alberta). We do note that Alberta and British Columbia are highly represented in the .

Table 3.2: Occupational Concentration by Gender

	Male	Female
Teaching	0.6644	1.4026
Clerical	0.3152	1.8216
Fishing, Hunting, Trapping	1.5196	0.3765
Social Science	0.6781	1.3862
Medicine & Health	0.3175	1.8188
Material Handling	1.4896	0.4126
Natural Sciences, Engineering & Maths	1.5054	0.3936
Product Fabricating, Assembling & Repairing	1.5101	0.3880
Crafts & Equipment Operating	0.9247	1.0903
Farming, Horticulture & Animal Husbandry	1.3266	0.6081
Service	0.6702	1.3957

Machining	1.7573	0.0914
Processing	1.2001	0.7599
Forestry & Logging	1.7029	0.1566
Managerial & Administrative	1.0976	0.8829
Artistic, Literary& Recreational	1.0497	0.9404
Mining & Quarrying	1.7925	0.0492
Construction Trades	1.7621	0.0857
Religion	1.5174	0.3793
Transport & Equipment Operating	1.6732	0.1923

"dangerous occupations", such as farming, construction, and transportation and equipment operation

3.3 Regression Results.

Table 3.4 and 3.5 show the regression result of OLS based on the Models I, II and III. As pointed out by Thaler and Rosen (1975) and similar studies, the theory requires the wage-risk function to be positively sloped, with a significant coefficient as the risk variable using a one-tailed test of significance, while the statistic analysis of the other variables will be based on two-tailed test. In table 3.4, the dependent variable for the three models is the log of wage. One star indicates that this variable is 10% statistically significant. Two stars and three stars represent the 5% and 1% significance level, respectively.

As shown in the table, accords with our expectation, the sign of the estimated coefficient for occupational risk is positive. The estimated parameter for occupation risk is 0.451 in Model II, which means that, holding other factors constant, a 1 percent increase in the death rate will cause a 0.451 percent increase in wage compensation.. From table 3.4, after we include the interaction dummies into the regression model, the estimated coefficient becomes 0.273, which means that, holding other factors constant, a 1 percent increase in the fatality rate will increase wages by 0.273 percent in Ontario only (given the presence of nine interaction dummies with Ontario the reference province). From tables 4.4 and 4.5, the positive relationship between occupational risk and the related wage rate is statistically significant at 1% significance level for Model II and 5% for Model III.

The estimated parameter for weeks employed is similar in the three models. It is 0.004 in Model I, which means that, keeping other factors fixed, working an extra week will increase the wage rate by about 0.4 percent. As shown in the tables 3.4 and 3.5, the relationship between wage rate and weeks employed is statistically significant.

As shown in the table, in the three models, age effect on wage rate is significant at 1% significance level for age group 16-24. The estimated result is similar, which is -0.146, -0.148, and -0.147, respectively. For age group 45-54, its positive effect on wage rate is 10% statistically significant for Model I and Model II, respectively. In model III, this relationship is even more significant, which is 5%. Holding other factors constant, compared with those aged between 25-44, wage rate for people aged 16-24 is about 15 percent less, while for people aged 45-54 is about 1 percent higher. As shown in tables 4.4 and 4.5, there is no significant difference in wage rate between people aged 25-44 and people aged 55-64, when other factors are equal.

The relationship between marriage and wage rate accords with our assumption. In Model III, keeping other factors constant, the wage rate for the married people is 16.7 percent higher than those have not married. The positive effect is statistically significant.

Table 3.4: Regression Estimates.

Explanatory Variables	Model I	Model II	Model III

OCCURISK	--	0.451^{***}	$0 .273^{**}$
WEEKEMPLOY	0.004^{***}	0.003^{***}	0.003^{***}
AGE1624	-0.146^{***}	-0.148^{***}	-0.147^{***}
AGE4554	0.012^{*}	0.011^{*}	0.012^{**}
AGE5564	0.005	-0.002	0
MARRIED	0.161^{***}	0.166^{***}	0.167^{***}
NONHIGH	-0.194^{***}	-0.182^{***}	-0.179^{***}
UNIVERSI	0.126^{***}	0.139^{***}	0.141^{***}
UNIONJOB	0.321^{***}	0.319^{***}	0.322^{***}
SKIJOB	0.231^{***}	0.225^{***}	0.224^{***}
USKIJOB	0.041^{***}	0.040^{***}	0.04^{***}
CANABORN	-0.023^{***}	0.006	0.0098
MALE	0.255^{***}	0.246^{***}	0.245^{***}
ATLANTIC	--	-0.178^{***}	-0.188^{***}
QUBEC	--	-0.05^{***}	-0.04
MTSKAB	--	-0.085^{***}	-0.113^{***}
BC	--	0.013^{*}	0.096^{***}
NFRISK	--	--	-0.131
PEIRISK	--	--	-0.054
NSRISK	--	--	0.088
NBRISK	--	--	0.296
QURISK	--	--	-0.091
MTRISK	--	--	-0.099
SARISK	--	--	-0.176
ABRISK	--	--	0.603^{*}
BCRISK	--	--	0.887^{*}

Explanatory Variables	Model I	Model II	Model III
OCCURISK	--	6.151	1.82
WEEKEMPLOY	32.87	31.54	31.46
AGE1624	-29.68	-30.45	-30.38
AGE4554	1.85	1.826	1.97
AGE5564	0.57	-0.249	-0.03
MARRIED	37.68	39.129	39.56
NONHIGH	-42.45	-40.163	-39.44
UNIVERSI	24.29	27.081	27.36
UNIONJOB	74.58	74.462	75.07
SKIJOB	47.58	46.424	46.41
USKIJOB	8.2	7.902	7.86
CANABORN	-3.73	0.928	1.57
MALE	64.41	59.157	58.97
ATLANTIC	--	-31.197	-7.67
QUBEC	--	-7.724	-1.42
MTSKAB	--	-16	-4.87
BC	--	1.849	-3.11
NFRISK	--	--	-0.325
PEIRISK	--	--	-0.13
NSRISK	--	--	0.22
NBRISK	--	--	0.735
QURISK	--	--	-0.195
MTRISK	--	--	-0.255

SARISK	--	--	-0.46
ABRISK	--	--	1.605
BCRISK	--	--	1.805

As shown in the table 3.4, in Model III, the wage rate for persons without a high school degree is about 17.9 percent less than persons with highschool graduate degree, when other factors constant. The wage rate for persons with university degree is

mated to be 14.1 percent higher. These results square with our assumptions.

Contrary to our expectations, the parameter for the dummy variable unskilled worker is positive and significant in all of the three models. It means that the wage rate for unskilled worker is about 4% higher than semi-skilled worker, with other factors held constant. This differs from stated labour market theory. The result may due to the data quality or the classification of semi-skilled worker and unskilled worker.

From the result, whether a person belongs to union or not has positive and significant effect his/her wage rate. Holding other factors fixed, in Model III, wage rate for person in a union is 32 percent more than those not in a union. This result is in accordance with our expectation. As shown in the two tables, the males' wage rate is about 24.5 percent higher than the females' in Model III, when other characteristics of the two are equal. This result squares with our assumptions on this variable. This gender effect on wage rate is statistically significant at 1% significance level.

From tables 3.4 and 3.5, the directionality of the estimated coefficients for control variables are similar in the three models except for variable CANABORN. In model I, it has a negative but significant effect on wage, but when we comes to Model II and III, this effect is positive and statistically insignificant. In model I, the negative significant finding may capture the fact that well-established immigrants tend to earn more than native-born Canadians, other factors held constant.

As shown in the table, in Model III, wage disparity statistically significant except for Quebec. Holding other factors constant, compared with individuals in Ontario, those

earn 9.6 percent more, while people in Saskatchewan, Alberta or Manitoba earn 11.3 percent less. Thus, compared with the Ontario, the job opportunities in Atlantic region are not that attractive, since the wage rate is lower.

Model III accounts for the interaction between province and risk to capture the difference in job related risk among provinces. The coefficients for the interaction provincial dummy variables are significant only for Alberta and British Columbia. The interpretation of the coefficients on the interaction dummies is as follows. Consider the estimated coefficient on the Alberta interaction dummy ABRISK. This says that the coefficient for risk, wage for Alberta would be 0.876 (=0.603+0.273). The *W($)* line for Alberta, is other words, becomes steeper, indicating a statistically-derived higher value of life for individuals in that province. Analogous calculations could be made for British Columbia.

3.4 Testing for Heteroskedasticity

In this report, we use cross-sectional data. Since cross-sectional estimates may reveal heteroskedasticity, testing if it exists or not is important. We could, for example, hypothesize that the size of the error terms (for Models I, II and III) increase with income. We could imagine, for example, that rich people may be in both risky and unrisky jobs, more so than lower income people. If so, the error terms may not be randomly distributed.

In this project, to test for heteroskedasticity we do the following:

1. Get the squared OLS residuals of the estimated regression equation.
2. Run a regression of the residuals on all of the explanatory in the original model.

3. Form the t statistics. If it is sufficiently big, we reject the null hypothesis of homoskedasticity, otherwise, we conclude there is no heteroskedasticity.

As shown in table A-1 in the appendix, the relationship between the estimated residual and the explanatory variables are insignificant. Thus, we accept the null hypothesis and conclude that heteroskedasticity does not exist.

In this report, we run an F test to examine the overall effect of occupational risk. We redo the regression of Model III, excluding occupational risk and the nine provincial interaction dummies. The estimated F statistics is 18.6982, which is greater than the critical value of any historically used level of significance. Thus, we reject the null hypothesis and conclude that the coefficients of the set of risk variables are statistically different from zero.

3.5 The Value of Life

As shown in table 4.7, the average wage rate is 11.67 dollars per hour. If we assume that a full-time worker works for 40 hours a week and 52 weeks a year, the average annual income per full-time worker is 24,287.32 dollars.

When calculating the value of life from the wage equation, we have to first calculate the partial derivative of personal wage with respect to the occupational risk. From the estimation of Model II, the coefficient of occupational risk is 0.451. We can calculate,

noting that Y is income between 1965 and 1991, Y =$24,287.32*26=$631,470. So, substituting $631,470 into equation 4.1, we have W/ R = .451*Y or

W/ R = .451*$6t31470 = $284,793 .

Clearly, in contrast to other estimates in the literature, our value of life estimate os too low. One problem could be with the "risk of death" data used. It may be that the 23-occupation definitions are to broad, or have too low a variance to pick of risk of death differences properly. Or it may be that the quality of the occupation/risk survey is poor.

IV. Conclusions

In this report, we caclulate differences in the value of life at provincial levels, compare the differences and find the possible reasons for the differences. To do so we include the interaction between province and job risk. We find that in the case of Alberta and British Columbia, there is a statistically higher value of life. This makes intuitive sense, since these two provinces have higher per-capita provincial incomes. But for the remaining eight provinces, the estimated value of life is not statistically different from the national estimate.

We can discuss shortcomings in the analysis. First, life expectancy differs across provinces, and such differences might not be captured by the regional dummies introduced in the three models above. Some of the non-risk variation may turn up in the province/risk interaction dummies. Second, the quality of data is suspect, particularly with the Occupational Surveillance Survey. Third, the analysis above neglects the fact the risky/stressful occupations might see workers out-migrating to other occupations (instead of dying on the job). This bias would understate risk, and thus estimated value of life. Finally, actual mortality/occupation data is not available, and as such other, more accurate values of life could be estimated.

Nevertheless, the results presented in this report have important policy implications. Since there are provincial differences in the effect of occupational risk on wage, the provincial government may want to use the provincial “value of life”for cost-benefit policy considerations. We can say that, in the case of Alberta and British Columbia, these provinces would for provincially-funded projects consider a higher valued benefit for “lives saved”, than would be the case of the remaining eight provinces. Analogously, in development economics, poor countries would, given their own funding of health and transportation projects, consider “benefits of lives saved” at a lower value than would be the case of richer countries. Here all we are claiming is that the income elasticity of life-saving (risk- reduction) projects is greater than zero.

We submit that such analysis introduces a equity rationale for federal government intervention, in the case of provinces having unequal “statistical value of lives” in a multi-province federation. We hypothesize that egalitarian principles suggest that a federal government consider the statistical value of life as being equal across provinces. The federal government for example – in undertaking a multi-province highway project – would use a nationally-derived statistical value of life, instead of separate provincial ones. But in doing so, such an analysis would technically-speaking inflate the benefits in poor provinces. But that would imply greater spending at the margin in poorer provinces. The federal government, in other words, could argue for additional transportation spending (or, analogously, life-saving health spending) in poorer provinces, to compensate for underspending by provincial governments, given their lower intra-provincial estimates of value of life. Consequently, contrary to the belief that differential “values of life” across provinces or countries are in some way antiegalitarian, one could argue that having such differences provides an equity argument for federal government intervention.

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Appendix: **Table A-1: Results of Heteroskedasticity Test**

Explanatory Variables	Model I	Model II	Model III
OCCURISK	--	8.160E-05 (0.001)	0.000 (0.001)
WEEKEMPLOY	3.6E-05 (0.334)	2.7E-05 (0.246)	2.7E-05 (0.246)
AGE1624	6.732E-05 (0.014)	2.116E-05 (0.004)	0.001 (0.140)
AGE4554	0.000 (-0.078)	0.000 (0.040)	0.000 (0.020)
AGE5564	0.000 (-0.039)	-2.977E-05 (-0.004)	0.001 (0.089)
MARRIED	0.000 (0.054)	0.000 (-0.096)	9.082E-05 (0.022)
NONHIGH	0.000 (0.080)	4.449E-05 (0.010)	0.000 (0.098)
UNIVERSI	0.000 (-0.024)	0.000 (0.072)	0.000 (-0.035)
UNIONJOB	0.000 (-0.067)	0.000 (0.041)	0.000 (-0.116)
SKIJOB	0.000 (-0.094)	0.000 (-0.091)	0.000 (0.047)
USKIJOB	-9.872E-05 (-0.020)	0.000 (-0.032)	0.000 (-0.086)
CANABORN	0.000 (-0.040)	0.000 (-0.035)	0.000 (-0.034)
MALE	0.000 (0.55)	6.761E-05 (0.016)	0.000 (-0.040)
ATLANTIC	--	2.903E-06 (0.001)	0.000 (-0.007)
QUBEC	--	0.000 (-0.074)	0.010 (0.334)

MTSKAB	--	-8.328E-05 (-0.016)	1.282E-05 (0.001)
BC	--	0. 0013 (0.1849)	-0.0096(0.3111)
NFRISK	--	--	0.000 (-0.001)
PEIRISK	--	--	0.000 (-0.001)
NSRISK	--	--	0.000 (0.001)
NBRISK	--	--	0.000 (-0.002)
QURISK	--	--	-1.187E-05 (0.000)
MTRISK	--	--	0.000 (0.001)
SARISK	--	--	0.000 (0.001)
ABRISK	--	--	-5.584E-05 (-0.000)
BCRISK	--	--	-3.102E-05 (-0.000)

(The dependent variable are the estimated residual of Model I, Model II and Model III, respectively. Numbers in the bracket shows the t statistics.)