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A Cross-Sectional Study of Risk Aversion and Life Insurance Demand at the Country Level

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Abstract: This study measured the risk aversion of nineteen selected countries using Szpiro's approach and analyzed its effect on life insurance demand. Additionally, income and education were included as control variables and tested for their effects on life insurance demand and risk aversion. The results show a positive effect of risk aversion on life insurance demand, while income has a positive effect and education has a negative effect. We also find that income positively affects risk aversion, while education negatively affects it. These findings support the increasing relative risk aversion hypothesis and have significant implications for life insurance demand and pricing analysis.

Keywords: cross-sectional; income; education; life insurance demand; risk aversion

1. Introduction

Life insurance plays a fundamental role in reducing risk and protecting people against contingencies such as premature death or various degrees of disability. Life insurance works by pooling risks and sharing them efficiently among the members of the risk-sharing pool. This mechanism helps to alleviate bad fortunes and enhance social welfare.

In 2022, the global life insurance market reached USD 2813 billion (Figure 1), increasing by 66% over the last two decades (Sigma Re Institute, 2024). Greater growth has been observed in emerging markets, which rose by 524% to reach USD 1586 billion, while the developed market grew by 35% to reach USD 2140 billion.

The existence of this trillion-dollar life insurance industry demonstrates humanity's great effort to avoid risk. Risk-averse consumers face uncertain lifetimes, leading them to purchase life insurance in preparation for bequests (Yaari, 1965). There are other reasons people buy insurance, such as legal compulsion and contractual obligation (Thoyts, 2010), but risk aversion should be the primary reason for life insurance purchases (Heo, 2020).

Given the fact that risk aversion is an important predictor of consumers' financial decisions, some studies developed measurements of risk aversion (Bokern et al., 2021). However, Conine et al. (2017) found a wide range of risk aversion coefficients from previous studies of risk aversion measurement. Moreover, some studies also find different results regarding the effect of risk aversion on insurance demand. Mossin (1968) argues that individuals become less risk averse as income increases, leading to an increase in the demand for risky assets or a decrease in the purchase of insurance. Meanwhile, Arrow (1970) shows that people become more risk averse as income rises, resulting in an increase in insurance demand.

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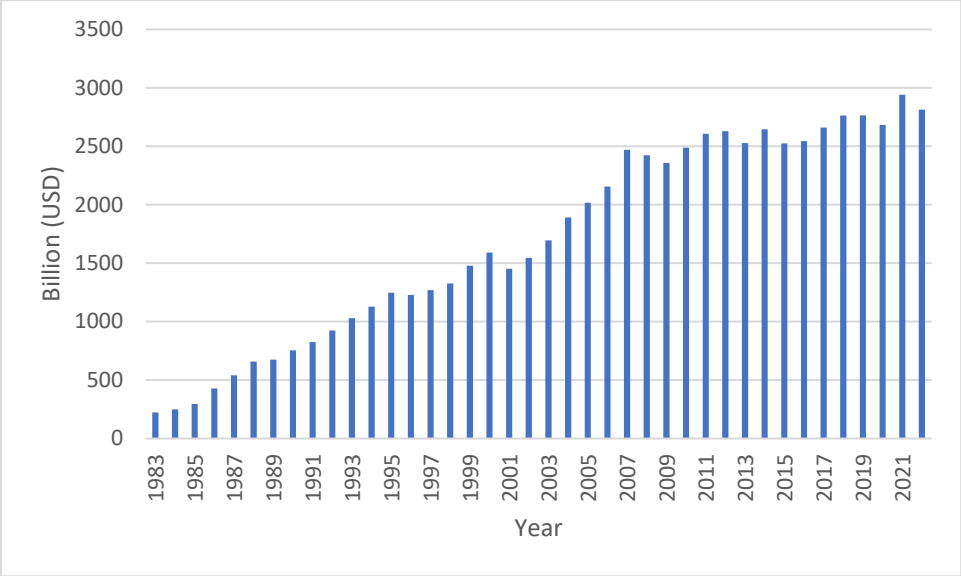

Figure 1. World's life insurance premium for the last forty years.

Past studies often measure risk aversion using survey data (Holt & Laury, 2002), but Andersson et al. (2016) argue that people are plausibly affected by framing and make inconsistent choices when facing multiple options in a questionnaire. Furthermore, risk aversion time series are likely non-stationary, so applying standard linear regression without verifying stationarity can lead to spurious regression results. Spurious regressions are a well-documented pitfall in econometrics (Granger & Newbold, 1974).

Therefore, it is appropriate to reexamine the measurement of risk aversion and analyze its effect on life insurance demand. Furthermore, it is necessary to understand factors that are associated with risk aversion because different behaviors of individuals when facing similar risky situations can be explained by certain factors (Outreville, 2013).

How has risk aversion contributed to life insurance demand? And what factors determine risk-averse behavior? Answering these questions will provide significant contributions to predicting life insurance demand and improving the adoption of life insurance. Life insurance has contributed significantly to the social and economic sectors; thus, its adoption should be supported, especially in developing countries (United Nations Conference on Trade and Development (UNCTAD), 1982).

Given the nature of the study, cross-sectional regression with a unit root test using insurance market data seems more appropriate for answering research questions. This approach would avoid issues related to non-stationary time series and provide more robust insights into cross-country differences. The risk aversion measurement method developed by Szpiro (1986) is arguably an appropriate model to use because this approach addresses multicollinearity problems (Szpiro, 1988), and has been employed to estimate risk aversion in various countries (Szpiro & Outreville, 1988) to analyze the determinants of risk aversion (Outreville, 2015).

Therefore, this study fills the gap by employing Szpiro's (1986) approach to measuring risk aversion in various countries and then demonstrates how it affects life insurance demand. Additionally, this study adds control variables, such as income and education, then examines their effect on risk aversion.

The rest of the article is structured as follows: the next section will review previous research on risk aversion and life insurance demand, and we will develop hypotheses. In the third section, the empirical model will be explained, and the following section will

present the results. Then, we will discuss the results and limitations, and conclude the study.

2. Literature Review and Hypothesis Development

It has been almost three centuries since Bernoulli (1954) solved the St. Petersburg paradox, which demonstrates the existence of a concave utility function, where utility for wealth increases at a decreasing rate, in explaining individuals' behavior under uncertainty. Two centuries later, Von Neumann and Morgenstern (1944) formulated the expected utility theory, which posited that individuals will choose alternatives that maximize their expected utility. Then, Pratt (1964) and Arrow (1965) independently developed the measure of risk aversion under expected utility.

Decision under uncertainty is a pivotal theory in financial analysis (Machina, 1987). Most individuals' decisions are made under risk or uncertainty; thus, eliciting individuals' risk preferences will help predict many of their behaviors. One behavior that can be predicted from risk-averse individuals is their preference for purchasinginsurance when facing uncertain conditions, while risk lovers prefer gambling (Friedman & Savage, 1948).

Risk aversion can be interpreted as the situation where consumers prefer receiving a guaranteed payoff to take a gamble (Seog, 2010). The purchase of life insurance is a rational choice for risk-averse consumers because they have diminishing utility as income increases, so that the decision to purchase insurance under uncertainty maximizes their utility.

Some studies have used survey data to examine risk aversion (Conine et al., 2017). Harrison and Rutström (2008) and Charness et al. (2013) reviewed the literature on risk aversion measurements using survey methods, where the multiple price list (MPL) design from Holt and Laury (2002) became one of the most popular methods. Asuming and Gaisie (2022) and Senapati (2024) elicited risk aversion by modifying the MPL, subsequently showing that risk-averse individuals are more likely to purchase insurance.

Andersen et al. (2006) argue that eliciting risk aversion in the laboratory or using survey data has the advantage of data transparency and clear incentives in revealing preferences. However, Charness et al. (2020) showed that measures of risk attitude in the laboratory are not related to risk behavior in the field. Moreover, Csermely and Rabas (2016) demonstrated that arbitrary selection in conducting experiments can lead to different results and misleadingly revealed preferences.

Thus, the existing literature shows the importance of risk aversion and the difficulty of its measurement. Moreover, to the best of the author's knowledge, there is still little attention being paid to risk aversion at the country level. Gandelman and Hernández-Murillo (2015) used the methodology developed by Layard et al. (2008) to measure risk aversion for 80 countries, but this approach uses happiness data. Eisenhauer and Halek (1999) used insurance market data at the household level; thus, it is extremely hard to compare this data with other countries.

Outreville (2015) argues that the only exception for risk aversion measurements across countries using insurance market data is the approach used by Szpiro (1986). Szpiro has measured risk aversion levels using non-life insurance data in America, and they show that the degree of risk aversion is between 1.2 and 1.8.

Szpiro's approach has the task of finding h optimum (h^*), p_0, and p_1, from the equation $P = p_0 W + p_1\left(\lambda W^h\right)$, where P is premium, W is income, λ is loading, h is power of income, and p_0 and p_1 are parameters. Szpiro denotes the risk aversion function by $R(W)$, which is $R(W) = \frac{c}{W^h}$, where c is the coefficient of risk aversion. It is known that $\lambda = \frac{Premium}{Claim} - 1$, $p_0 = p$, and $p_1 = -p\frac{1}{c}$. Thus, we obtain the coefficient and function of risk aversion.

Then, Szpiro and Outreville (1988) implemented the approach in thirty-one countries. Szpiro (1988) shows that this approach can also help insurers in pricing and performance

analysis. Szpiro addresses the multicollinearity problem by using constant relative risk aversion (CRRA), which is a risk aversion function with $h = 1$. Pratt (1964) shows that the risk aversion function, $R(W) = \frac{c_p}{W}$, is one of the alternative functional forms for $R(W)$. The CRRA condition is also widely used in research studies (Levy, 2024) and cannot be rejected in Szpiro's (1988) study.

Moreover, despite the theoretical application from Pratt (1964) exhibiting a decreasing risk aversion as income rises, there is little consensus on the empirical study. Szpiro (1983) has supported the increasing relative risk aversion (IRRA) hypothesis, but the latter did not reject CRRA (Szpiro, 1986). Eisenhauer and Halek (1999) also support IRRA, but they found ambiguity in their results when wealth was measured by human capital.

In life insurance demand theory, risk aversion is seen as the basic assumption of individuals who purchase life insurance when facing uncertain lifetimes (Yaari, 1965). Karni and Zilcha (1985) developed Yaari's theory by incorporating risk aversion into the model. They then argued that risk aversion increases with income and has a positive effect on the demand for life insurance. Thus, it is expected that risk aversion is a life insurance determinant that positively affects life insurance demand.

H_1: *Risk aversion has a positive effect on life insurance demand*.

Past studies often used education as a proxy for risk aversion (Ward & Zurbruegg, 2002; Lee & Chiu, 2012). The decision to purchase insurance is based on maximizing utility, so that consumers make educational decisions that involve expected benefits and costs (Outreville, 2015). Thus, education is expected to have the same effect on life insurance demand with risk aversion.

Browne and Kim (1993) argue that as individuals become more educated, they gain better knowledge to purchase insurance in the face of uncertainty. Moreover, families also need an education fund, so that the need for life insurance will rise. Empirical studies also show the positive effect of education (Srinivasan & Mitra, 2024; Buric et al., 2017). Thus, life insurance demand is expected to increase as education improves.

H_2: *Education has a positive effect on life insurance demand*.

In addition to risk aversion, income is often viewed as the main determinant of life insurance demand (Beck & Webb, 2003). As people have more income, more assets should be covered by insurance, leading to an increase in life insurance demand (Li et al., 2007). The life insurance demand model from Yaari (1965) and Hakansson (1969) also posits income as a determinant of life insurance demand.

Outreville (1985) tested the theory, and then showed a positive effect of income on life insurance demand. After more than fifty years of study, numerous empirical research studies also show the positive effect of income (Hammond et al., 1967; Enz, 2000; Dragota et al., 2023). Therefore, income is expected to have a positive effect on life insurance demand.

H_3: *Income has a positive effect on life insurance demand*.

It has been argued that a higher level of education leads to greater awareness and a greater degree of risk aversion (Browne & Kim, 1993). Hwang and Gao (2003) argue that higher education has an impact on people's perception of risk, from the traditional view of using savings as an economic security achievement for modern financial instruments like life insurance.

Jianakoplos and Bernasek (1998) show that a higher education level makes individuals hold fewer risky assets or become more risk averse. Hersch (1996) also finds similar results, showing that a more educated person has more to choose from. Thus, education is expected to positively affect risk aversion.

H_4: *Education has a positive effect on risk aversion*.

Finally, risk aversion is a function of income (Arrow, 1970; Deschamps, 1973). Chesney and Loubergé (1986) find ambiguity regarding the relationship between income and life insurance; however, this study argues that risk aversion will increase as income grows. This view is consistent with the previous framework in this study, which posits that income has a positive effect on life insurance demand and that risk aversion is the main reason for insurance demand. Therefore, as income grows, consumers are expected to become more risk averse, leading to an increase in life insurance purchases. In other words, this study is expected to support the IRRA hypothesis.

H_5: *Income has a positive effect on risk aversion*.

3. Methodology

This study uses secondary data from the Organisation for Economic Co-operation and Development (OECD) Statistics and World Bank (WB) metadata, with annual frequency. Premium and claims data are sourced from OECD statistics, while GDP, population, and education data are obtained from World Bank metadata. Software Eviews 10 is utilized to estimate and portray the data.

Following Szpiro (1986), this study uses premium, claim, and GDP on a per capita basis; thus, premium and claim data use a 5-year average. This study also follows Outreville (2015) to identify factors, such as sociodemographic and economic factors, that are associated with risk aversion behavior. The analysis can explain the different risk behaviors in similar risky situations. There are other determinants of risk aversion, such as residence, assets, and occupation (Lim et al., 2023). But, due to the limitation of the data, this study only analyzes income and education.

The unit of observation is the country that meets the following requirements: the country must be included in OECD statistics from 1993 to 2022 and have complete data for at least 10 years. Thus, we will obtain country data from various years.

There are three phases of this research. First, we examine the risk aversion of each country. Second, we analyze the effect of risk aversion, income, and education on life insurance demand using cross-sectional data from selected countries in 2022 with ordinary least squares (OLS). Third, we analyze the effect of income and education on risk aversion, using data from selected countries, with the same method used in the previous step.

A critical assumption in time series data analysis is that the variables are stationary, meaning that the variables have means and variances that do not change over time (Hill et al., 2018). Thus, in the first phase of this study, following Juanda (2012), we begin by verifying stationarity using the Augmented Dickey–Fuller (ADF) test. The null hypothesis of the ADF test is that the data have a unit root; therefore, the variable is stationary if the p-value from the ADF test is less than 10% at the level or first differences.

Szpiro's approach in this study is estimated by using ordinary least squares (OLS). OLS is a method for estimating linear regression model parameters by minimizing the sum of the squared deviations between actual and estimated data. Previous studies in life insurance demand analysis have also applied OLS (Hwang & Gao, 2003; Lenten & Rulli, 2006).

The formula of Szpiro's approach in the previous section is rewritten as follows:

$$P_t = p_0 W_t + p_1 \left(\lambda_t W_t^{h_t} \right) + \varepsilon \quad (1)$$

where t is the year—t, P_t is the premium per capita in the year t, W_t is the GDP per capita in the year t, h_t is the power in the year t, λ_t is loading in the year t, and ε is the error term.

Model 1 is estimated by using OLS. This study restricts h to the range of $\{-5, +5\}$ with a step size of 0.1; then, it searches for the optimum h (h^*) or the model with minimum Sum of Squared Resid (SSR). The results are converted to obtain the risk aversion coefficient, $c = -\frac{p_0}{p_1}$. Finally, we add GDP per capita in 2022 to the risk aversion function and find the relative risk aversion of the selected country.

Szpiro uses conditions of constant relative risk aversion (CRRA) that are using $h = 1$, as denoted by h^1, to address the multicollinearity problem or the existence of more than one linear relationship. This study follows Wahyudi (2020) to test for multicollinearity by calculating the variance inflation factors (VIFs). The formulation of VIF is $VIF = \frac{1}{(1-R^2)}$, where R^2 is R squared. A severe multicollinearity problem exists if the auxiliary model has a VIF greater than 10. If the model of h^* exhibits severe multicollinearity, this study follows Szpiro and uses h^1. However, if h^1 also has a severe multicollinearity problem, the country is excluded from further analysis.

After performing the same steps for other countries, we will have the risk aversion value data of the selected countries in 2022. This means that the data of this study are cross-sectional. Subsequently, we tested hypothesis 1 by estimating model 2 using OLS. Cross-sectional studies in life insurance demand also use OLS to estimate data (Mare et al., 2019; Celik & Kayali, 2017). The result is significant if the probability < α = 1%, 5%, and 10%. When the criteria are met, the values are marked by ***, **, and *, respectively.

Then, we developed model 3 and added education and income as control variables to test hypotheses 2 and 3. All variables in models 2 and 3 utilize data from the year 2022. Models 2 and 3 are written as follows:

$$Log(Y_i) = \alpha_0 + \alpha_1 R_i + \varepsilon \tag{2}$$

$$Log(Y_i) = \beta_0 + \beta_1 R_i + \beta_2 Log(W_i) + \beta_3 Log(E_i) + \varepsilon \tag{3}$$

where i represents the country based on Appendix A, Y_i is the life insurance penetration in country i, R_i is the risk aversion in country i, W_i is the GDP per capita in the country i, E_t is education in country i, and ε is the error term.

After that, we test hypotheses 4 and 5 regarding the analysis of risk aversion determinants using model 4. All variables in model 4 also utilize data from the year 2022.

$$R_i = \gamma_0 + \gamma_1 W_i + \gamma_2 E_i + \varepsilon \tag{4}$$

where i represents the country based on Appendix A, R_i is the risk aversion in country i, W_i is GDP per capita in country i, E_t is education in country i, and ε is error term.

Table 1 summarizes operational variables in this study.

Table 1. Operational variable.

Variable	Code	Measurement	Data Source
Dependent variable			
Penetration	Y	$Y = \frac{Premium}{GDP}$	• *Premium* : OECD
Risk aversion	R	$R = Szpiro$ (1986)	• *GDP*: WB
Independent variable			
Premium per capita	P	$P = \frac{Premium}{Population}$	• *Premium*: OECD
Claim per capita	Q	$Q = \frac{Claim}{Population}$	• *Claim*: OECD
GDP per capita	W	$W = \frac{GDP}{Population}$	• *GDP*: WB
Loading	L	$L = \lambda = \frac{P}{Q} - 1$	• *Population*: WB
Risk aversion	R	$R = Szpiro$ (1986)	• *Education*: WB
Education	E	School enrollment, tertiary (% gross)	

4. Results

There are 29 countries that meet the requirements of this study. The ADF test was used to verify stationarity. There are 19 countries that passed the test at the level or first differences (Appendix A). Among these, there are sixteen high-income countries and three non-high-income countries, with only two countries, Peru and Singapore, not being OECD members. Thus, the majority of the data in this study are high-income and OECD countries.

Table 2 presents the descriptive statistics for all variable data of the 19 countries selected. Variables Y, L, and E are expressed in percentage (%), while variables P, Q, and W are measured in thousands of dollars (USD 000). The selected countries have an average GDP per capita of USD 38,519. The averages of premium per capita and claim per capita in this study are USD 1946 and USD 1319, respectively. The averages of life insurance penetration, loading, and education are 4.352%, 188.5%, and 82.952%, respectively. Education has the fewest data observations since this study only uses education data in 2022 from the selected countries. All variable data, except income, exhibit high kurtosis, while claims and loading show high data variation.

Table 2. Descriptive statistics of all operational variables for 19 selected countries.

Variable	Y	P	Q	W	L	E
Mean	4.352	1.946	1.319	38.519	1.885	82.852
Median	3.465	1.412	0.862	40.477	0.573	80.150
Maximum	19.268	10.488	7.595	103.983	22.857	127.580
Minimum	0.121	0.004	0.001	3.099	−0.414	46.410
Std. Dev.	3.411	1.941	1.526	20.362	3.327	19.352
Skewness	1.379	1.833	1.778	0.291	2.999	0.282
Kurtosis	5.450	7.092	6.107	2.930	12.782	3.116
Jarque–Bera	231.37	513.14	379.09	5.84	2238.43	0.261
Probability	0.00	0.00	0.00	0.05	0.00	0.877
Observations	408	408	408	408	408	19

Szpiro's approach begins with the search for h^*. We measure countries' risk aversion in alphabetical order, as listed in Appendix B. For example, the estimation of model 1 in Australia found that h^* is 0.2 (Figure 2), with the coefficient of risk aversion, c, being −0.0235. The multicollinearity test shows that the VIF value for Australia in this model is 1.487 less than 10. Therefore, this model does not have a multicollinearity problem. Then, we found that the risk aversion function for Australia using data from the period of 2000 to 2022 is $R = \frac{-0.0235}{W^{0.2}}$. Thus, the risk aversion of Australia in 2022 is −0.0102.

The same step was taken for all 19 selected countries. All these selected countries did not have a severe multicollinearity problem, as shown in Appendix B. Thus, there were 19 cross-section data points used for further analysis. Also, all variables for models 2, 3, and 4 have no unit root at the level or first difference; thus, all data can be used.

Table 3 presents the results for the 19 selected countries using data from 2022. The selected countries had an average income of USD 47,347, with an average life insurance penetration of 3.803% and an education level of 82.85%. The range of countries' risk aversion in this study is between −2.21 (Peru) and 0.33 (United Kingdom), with an average risk aversion of −0.3528. There are 13 out of the 19 countries (68%) that had a negative value of risk aversion; therefore, the majority of countries in this study show a lower risk behavior. Appendix C portrays the relationship between risk aversion and SSR in all the selected countries.

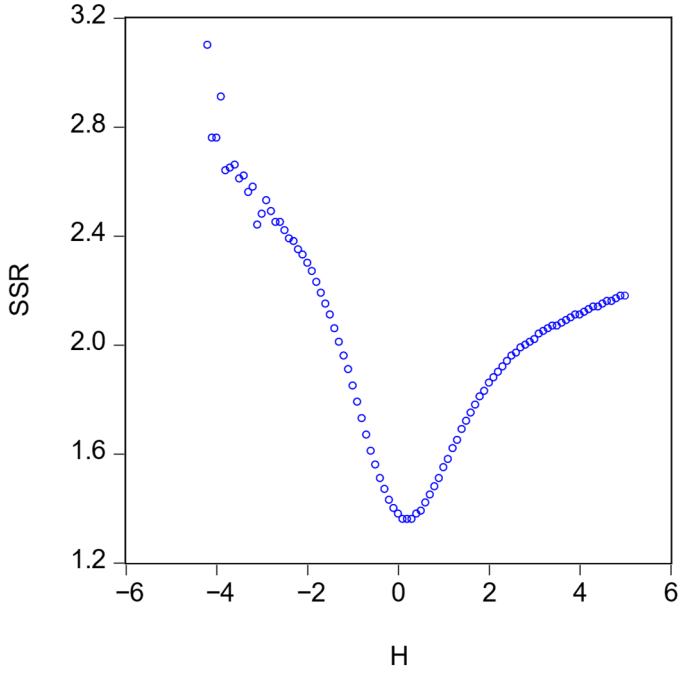

Figure 2. Scatter plot showing the relationship between the value of h (H) and Sum of Squared Resid (SSR) in Australia.

Table 3. Descriptive statistics of income, risk aversion, penetration, and education in 2022 for the 19 selected countries.

Country	Years	W	h^*	R	Y	E
Peru	2015–2022	7126	−0.80	−2.2099	1.025	72.29
Turkiye	1997–2022	10,675	2.70	−0.1788	0.211	127.58
Mexico	1997–2022	11,497	−0.80	−1.6738	1.065	46.41
Chile	2013–2022	15,355	−3.70	−0.1442	2.609	99.34
Slovak Republic	2001–2022	21,257	−0.10	−0.8640	1.026	52.50
Japan	2004–2022	34,017	−3.70	0.1455	6.028	64.63
Italy	1997–2022	34,776	4.60	−0.1625	4.875	73.90
France	1997–2022	40,886	−1.00	−0.3711	5.768	71.42
United Kingdom	2000–2022	46,125	−3.70	0.3346	7.677	80.15
Germany	1997–2022	48,718	5.00	0.0316	2.407	77.37
Finland	2000–2022	50,872	5.00	−0.0269	1.636	104.94
Austria	2000–2022	52,085	−4.20	−1.6895	1.738	94.51
Sweden	2007–2022	56,424	0.80	−0.0176	9.144	83.90
The Netherlands	1999–2022	57,025	2.10	−0.0175	1.156	85.65
Australia	2000–2022	65,100	0.20	−0.0102	1.050	106.24
Denmark	2000–2022	67,790	0.50	0.0200	7.723	84.59
Singapore	2015–2022	82,808	0.50	0.1480	7.872	98.02
Switzerland	2000–2022	93,260	−0.30	−0.0224	2.986	74.15
Ireland	1997–2022	103,983	5.00	0.0055	6.257	76.60
Average in 2022		47,357	0.43	−0.3528	3.803	82.85

Figure 3 portrays the relationship between risk aversion (R) and life insurance penetration (Y). The Figure shows that risk aversion has a positive effect on life insurance penetration. The results of model 2 (Table 4) show that risk aversion has a positive and significant effect on life insurance penetration, with $R^2 = 0.1922$. Model 3 shows that risk aversion has a positive but not significant effect on life insurance penetration, while income

has a positive and significant effect on life insurance penetration, and education has a negative effect.

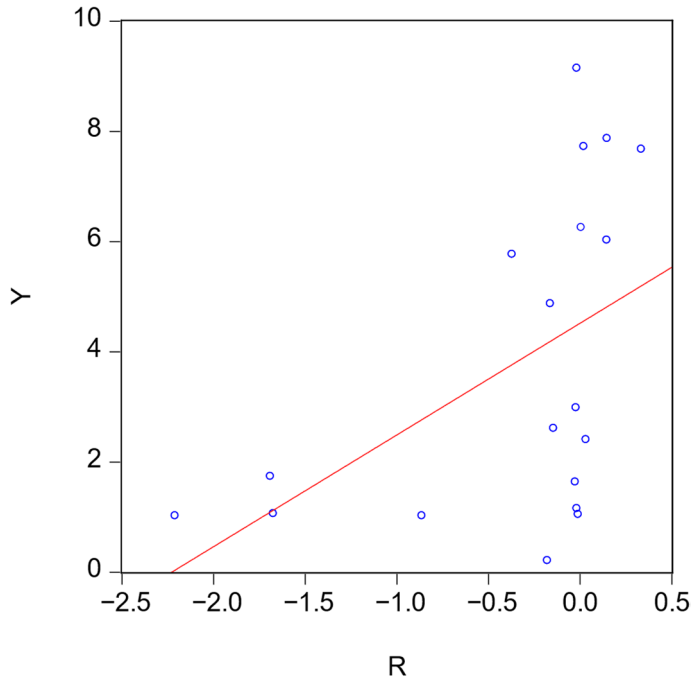

Figure 3. Linear regression line between risk aversion (R) and life insurance penetration (Y) of the 19 selected countries.

Table 4. The results of models 2 and 3.

Variable	2	3
α	1.17 ***	
β		0.88
Risk aversion	0.62 ***	0.38
log(Income)		0.67 *
log(Education)		−1.56
R-squared	0.1922	0.4838
Adjusted R-squared	0.1447	0.3805
F-statistic	4.0459	−20.3687
Prob(F-statistic)	0.0604	4.6853

Note: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.\ 1$.

Then, Table 5 shows the results for model 4, which indicate that income has a positive and significant effect on risk aversion, while education has a positive but not significant effect. Therefore, this study provides evidence for hypotheses 1, 3, 4, and 5, while education presents a different result, as expected in hypothesis 2.

Table 5. The results of model 4.

Coefficient			R-Sqrd	Adj R-Sqrd	F-Stat	Prob (F-Stat)
C	log(W)	log(E)				
−9.32 **	0.52 ***	0.79	0.4454	0.3761	6.4250	0.0089

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Moreover, Figure 4, utilizing the "Kernel Fit" feature in EViews 10, demonstrates that relative risk aversion (R) increases as income (W) increases. There are countries that show

an anomaly, such as Austria, which has an income of USD 50,872 and a risk aversion of −1.69, that are far from the red line in the graph; however, most of the countries show that risk aversion tends to increase in diminishing fashion as income grows. Thus, this study also supports the increasing relative risk aversion (IRRA) hypothesis, as evidenced by the positive effect of income on risk aversion and the graph in Figure 4.

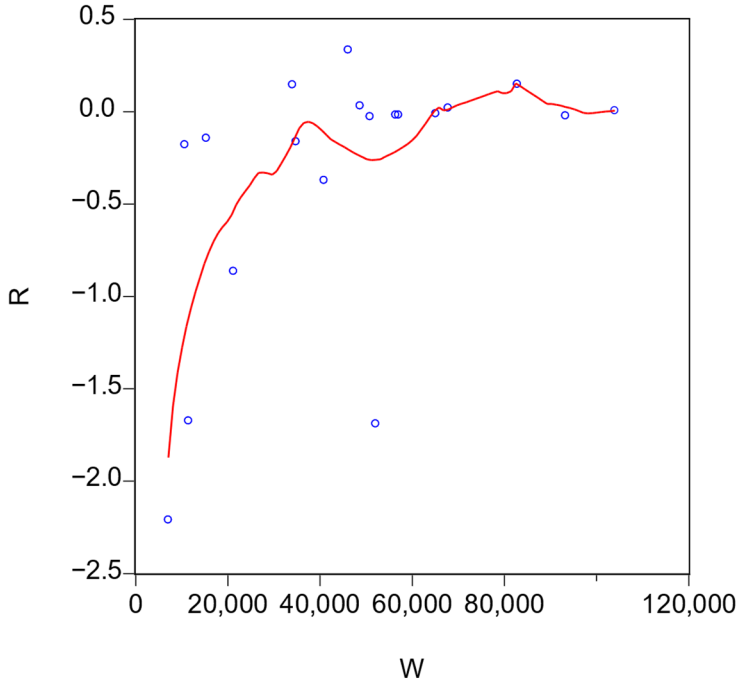

Figure 4. Kernel regression fit between Income (W) and risk aversion (R) of the 19 selected countries.

5. Discussion

This study uses the cross-section data of the 19 selected countries, and shows that risk aversion has a positive and significant effect on life insurance demand, with income and education having a positive effect on risk aversion. This finding indicates that the target consumers of life insurance should be risk averse; consumers and insurers can predict this type of consumer by analyzing their income and education level.

Are the results still the same using the CRRA condition? Further analysis (Appendix D) shows that the CRRA condition results for the models remain similar, that risk aversion and income show a positive effect on insurance demand, while education shows a negative effect. Income and education exhibit a positive effect on risk aversion. Moreover, as shown in Figure 5, the horizontal axis is the number i of the country, as indicated in Appendix A, and the vertical is the risk aversion, which shows that the majority of h^1 has a lower risk aversion than that of h^*.

This study finds different results from the expectation about the effect of education on life insurance demand. The negative effect of education on life insurance demand was also found by Rapi et al. (2025) using panel data from forty-one countries. This phenomenon arguably occurs because people seek other financial products as substitutes for life insurance as they become more educated. Kabrt (2022) also found a negative effect of education and argued that educated consumers are better able to find low-cost and high-yield products. Millo and Carmeci (2012) also identified a negative relationship between both factors, asserting that better educated consumers are capable of diversifying their portfolios.

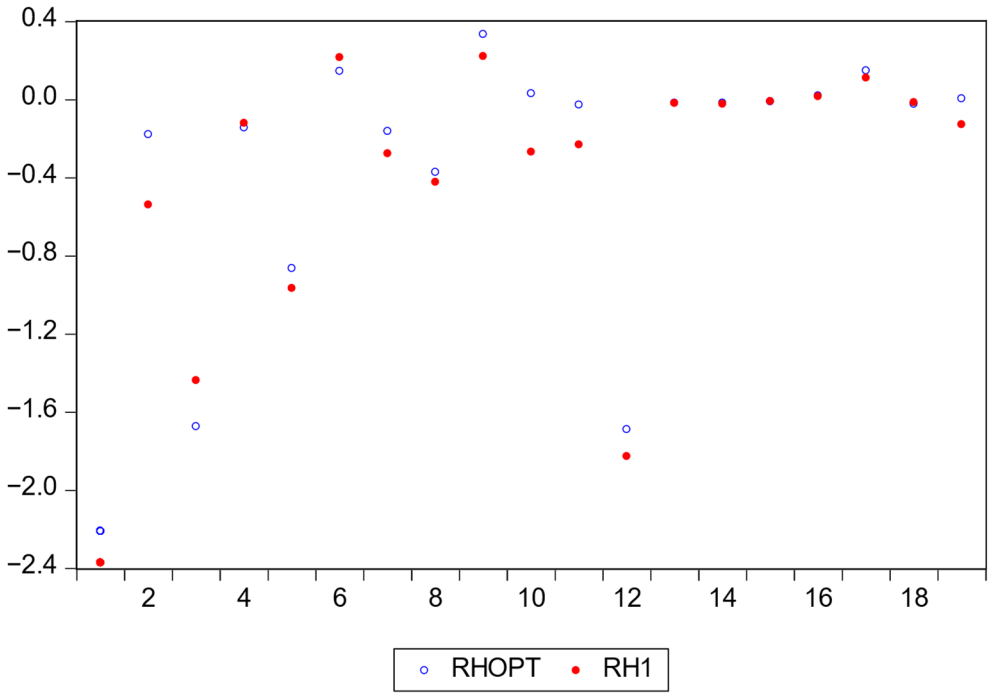

Figure 5. Risk aversion in 2022 with h^* (RHOPT) and h^1 (RH1).

This finding also indicates that education is not a good proxy for risk aversion, as both factors have different effects on life insurance demand. Outreville (2015) further explains that education itself may encourage risk-taking behavior because it can leave scholars with uncertain future outcomes. Brown et al. (2006) also demonstrate that more risk-averse individuals are inclined to pursue university education.

However, this study produced results that were different than those of Szpiro's (1986) paper. For example, this study finds that the majority of the countries examined have risk lover behavior, with an average risk aversion level of −0.35. This number differs from previous research conducted by Szpiro and Outreville (1988), which found a range between 0.81 and 4.99, with an average of 2.89, and all countries show risk-averse behavior. Szpiro's studies in 1988 also reported a range of 2.14 to 4.25, with an average of 2.97.

Foncel and Treich (2007) argue that it is difficult to rationalize insurance as a normal good by using standard rational theories like expected utility. Kunreuther et al. (2013) also argue there are some anomalies in the way consumers and insurers behave that cannot be explained with a rational theory; however, these can be explained by using behavioral economics. Rational theory has limitations that are well documented by Machina (1987), who argues that inconsistent individual behavior and individual reactions based on perception do not maximize utility.

Foncel and Treich conducted further research with Armantier (Armantier et al., 2023), which shows that both risky assets and insurance demand increase with income and can be explained using regret theory. Regret theory has also been employed in other research studies, such as Fujii et al. (2021) and Diecidue and Somasundaram (2017), which argue that this theory can be an alternative to expected utility in explaining financial decisions. Hwang (2016) employed prospect theory (Kahneman & Tversky, 1979), which posits that changes in income serve as a reference point, rather than the final level, that forms the basis for decisions under the expected utility model. The study shows that loss-averse consumers express low demand for insurance.

In addition to the theoretical approach, other explanations for the difference include the subject of observation and the period of research. While Szpiro focuses on non-life

insurance data, this study focuses on life insurance. Then, this study is conducted in a post-COVID-19 situation that may significantly affect consumers (Qian, 2021).

Furthermore, the average income in our study is USD 38,519, which is almost three times higher than the limit for high-income countries based on the World Bank's threshold of USD 14,005. Therefore, the findings of this research represent conditions in high-income countries. Further research is needed which includes more countries in the middle-income classification, which ranges from USD 1146 to USD 14,005 (World Bank, 2024).

This study also has the limitation of only analyzing income and education as control variables. Other research links demographics to risk aversion (Halek & Eisenhauer, 2001), allowing for the identification of individuals who have the potential to buy insurance. Other variables, such as gender and age, arguably can play a significant role in determining risk aversion and life insurance demand. Ampaw et al. (2018) show that women who are married and have dependents have a higher propensity to buy life insurance, while men with higher education are more likely to buy life insurance policies. Similarly, Albert and Duffy (2012) show that older people are more risk-averse than younger people; then Sauter (2014) shows that age has a positive effect on life insurance demand.

Despite the different results, this study has contributed to measuring risk aversion at the country level with Szpiro's approach using life insurance data. It then uses cross-sectional data to provide evidence of the relationship between risk aversion and life insurance demand. This study also supports the IRRA hypothesis; thus, insurance is a normal good. This study also contributes to demonstrating that education is not a good proxy for risk aversion.

Szpiro's approach can also be used to help insurers with further analysis, such as calculating the sum insured, optimum loading, and the maximum underwriting profit. Moreover, Szpiro's approach also enables a proxy of life insurance demand from the claim side. However, this study only analyzes this based on the premium.

The method for measuring risk aversion can also be refined with individual observation units, as seen in Halek and Eisenhauer (2001), so that the value of individual risk aversion is clarified. Other methods using survey data can also be used to measure risk preferences. Lyu and Barré (2017) and Nagy et al. (2020) utilized a survey, demonstrating that it can be used to explain the demand for insurance. The systematic evaluation of the measures of risk preference has been provided by Galizzi et al. (2016) and Charness et al. (2020).

Furthermore, as the insurance industry faces serious risk selection problems, it is important for life insurance companies to understand the risk preferences of their consumers (Einav et al., 2023). This knowledge assists in risk selection, choosing potential consumers for risk pooling, and determining premium subsidies. Therefore, understanding risk aversion significantly helps life insurance companies address the risk selection problem.

6. Conclusions

This study shows that risk aversion has a positive and significant effect on life insurance penetration, while showing that income has a positive effect, and education has a negative effect. This study also demonstrates the positive effects of income and education on life insurance demand.

These results contribute to the theory by providing evidence of the increasing relative risk aversion (IRRA) hypothesis and indicating that education is not a good proxy for risk aversion. This study also has significant implications for demand prediction, suggesting that insurers should focus on risk-averse consumers, as well as for pricing analysis, which helps insurers better manage risk and improve the penetration of the life insurance market.

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Data Availability Statement: Data of world life insurance penetration were manually extracted and can be found in Sigma Explorer (https://www.sigma-explorer.com/, data extracted on 19 May 2024). Data of life insurance penetration and life insurance density on various countries were manually extracted and can be found in OECD.Stat (https://www.oecd-ilibrary.org/finance-and-investment/oecd-insurance-statistics_2307843x, data extracted on 19 May 2024). Data of GDP per capita (current USD) were manually extracted and can be found in World Bank Open Data (https://data.worldbank.org/indicator/NY.GDP.PCAP.CD, data extracted on 19 May 2024).

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

ADF	Augmented Dickey–Fuller
CRRA	Constant Relative Risk Aversion
GDP	Gross Domestic Product
IRRA	Increasing Relative Risk Aversion
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares
VIF	Variance Inflation Factors
WB	World Bank

Appendix A. Stationarity Test

Table A1. ADF test for all variables of the 29 countries in model 1.

i	Country	P		D(P)		W		D(W)		L x W		D(L x W)	
		t-Stat	Prob	t-Stat	Prob	t-Stat	Prob	t-Stat	Prob	t-Stat	Prob	t-Stat	Prob
1	Peru	2.781	0.992	−3.078	0.013	0.615	0.823	−2.187	0.040	−4.540	0.062	−0.830	0.882
2	Austria	−4.398	0.003	−2.907	0.065	−2.140	0.232	−4.369	0.003	−4.347	0.004	−5.403	0.000
3	Mexico	−0.497	0.874	−4.935	0.001	−1.992	0.288	−4.722	0.001	−0.731	0.821	−3.488	0.018
4	Slovak Rep.	−0.535	0.472	−1.677	0.088	1.615	0.970	−3.369	0.002	0.239	0.746	−3.946	0.001
5	France	−1.232	0.640	−4.802	0.001	−1.513	0.511	−4.415	0.002	1.082	0.922	−2.267	0.025
6	Turkiye	−0.846	0.788	−4.014	0.007	−1.576	0.479	−4.242	0.003	−0.738	0.958	−6.318	0.000
7	Italy	−3.637	0.014	−0.079	0.939	−1.597	0.469	−4.384	0.002	0.693	0.989	−5.685	0.000
8	Chile	−0.975	0.266	−2.777	0.013	−0.249	0.568	−3.829	0.003	−0.742	0.367	−2.618	0.017
9	Finland	0.325	0.770	−2.358	0.021	1.025	0.914	−3.948	0.000	−1.301	0.173	−4.458	0.000
10	Switzerland	−0.134	0.624	−2.054	0.041	−1.410	0.829	−4.925	0.004	−3.822	0.038	−2.795	0.216
11	Sweden	1.814	0.979	−3.299	0.003	0.739	0.867	−1.936	0.053	3.631	1.000	−8.056	0.000
12	The Netherlands	−3.610	0.055	−3.184	0.119	−1.555	0.779	−4.378	0.011	−1.616	0.755	−3.981	0.025
13	Australia	−0.421	0.520	−1.651	0.092	−1.271	0.624	−3.574	0.016	−1.180	0.664	−4.705	0.001
14	Ireland	−0.350	0.548	−2.000	0.046	−2.807	0.209	−3.669	0.045	−1.140	0.901	−4.776	0.004
15	Denmark	0.055	0.954	−3.413	0.025	−1.921	0.317	−4.333	0.003	−2.791	0.078	−3.857	0.011
16	Germany	−0.953	0.930	−4.340	0.013	−2.008	0.569	−4.525	0.008	−3.097	0.129	−6.058	0.000
17	Japan	−3.354	0.028	−1.086	0.696	−1.527	0.497	−2.793	0.080	−17.477	0.000	−6.708	0.000
18	Singapore	6.265	1.000	−1.943	0.059	1.487	0.948	−1.958	0.056	−0.689	0.377	−1.883	0.063
19	U.K.	−2.897	0.063	−2.542	0.121	−4.260	0.004	−3.861	0.009	−2.739	0.009	−2.309	0.024

Table A1. *Cont.*

i	Country	P		D(P)		W		D(W)		L x W		D(L x W)	
		t-Stat	Prob	t-Stat	Prob	t-Stat	Prob	t-Stat	Prob	t-Stat	Prob	t-Stat	Prob
	Norway	−2.361	0.164	−1.906	0.323	−1.684	0.724	−3.339	0.087	−2.739	0.009	−2.309	0.024
	Belgium	−2.333	0.402	−1.595	0.765	−1.185	0.664	−4.563	0.002	−1.087	0.705	−5.421	0.000
	Spain	−0.721	0.960	−2.948	0.166	0.841	0.886	−3.896	0.000	0.070	0.995	−3.814	0.039
	Hungary	−2.421	0.148	−1.612	0.459	1.578	0.968	−1.644	0.093	−0.682	0.961	−6.073	0.000
	Colombia	−0.625	0.935	−1.544	0.726	−0.890	0.304	−4.047	0.002	−1.914	0.057	−5.375	0.000
	Poland	−2.004	0.283	−1.666	0.435	2.166	0.991	−4.082	0.000	−8.542	0.000	−9.143	0.000
	Portugal	−2.036	0.271	−1.603	0.466	1.264	0.943	−4.005	0.000	−3.375	0.002	−4.311	0.000
	United States	0.924	0.993	−1.458	0.527	3.414	1.000	−0.968	0.731	2.047	1.000	−6.763	0.000
	Korea Rep.	−1.194	0.884	−3.114	0.130	−1.801	0.369	−4.710	0.002	−2.454	0.140	−6.317	0.000
	Slovenia	0.439	0.996	−2.284	0.402	−0.922	0.740	−3.783	0.021	−0.718	0.382	−3.882	0.001

Table A2. ADF test for all variables of the 19 selected countries in model 2, 3, and 4.

Variable	t-Stat	Prob
Y	−3.5937	0.0170
D(Y)	−5.7421	0.0003
R, h^*	−5.5330	0.0003
D(R, h^*)	−10.7358	0.0000
R, h^1	−5.2477	0.0006
D(R, h^1)	−9.7450	0.0000
W	1.5781	0.9988
D(W)	−3.1930	0.0384
E	−2.2759	0.1898
D(E)	−13.2554	0.0000

Note: R, h^* means risk aversion with h optimum, while R, h^1 means risk aversion with $h = 1$.

Appendix B. Multicollinearity Test

Table A3. Multicollinearity test of the 19 selected countries in model 1.

No.	Country	R Squared (Main Regression)	R Squared (Auxiliary Regression)	VIF
1	Australia	0.530	0.328	1.487
2	Austria	0.624	0.010	1.010
3	Chile	0.588	0.250	1.332
4	Denmark	0.768	0.017	1.017
5	Finland	0.438	0.006	1.006
6	France	0.854	0.035	1.036
7	Germany	0.894	0.744	3.906
8	Ireland	0.477	0.596	2.475
9	Italy	0.753	0.192	1.238
10	Japan	0.450	0.873	7.858
11	Mexico	0.909	0.308	1.446
12	The Netherlands	0.787	0.275	1.378
13	Peru	0.852	0.000	1.000
14	Singapore	0.894	0.012	1.012
15	Slovak Republic	0.879	0.487	1.950
16	Sweden	0.968	0.112	1.126
17	Switzerland	0.553	0.412	1.701
18	Turkiye	0.872	0.313	1.456
19	United Kingdom	0.519	0.719	3.559

Table A4. Multicollinearity test of the 19 selected countries in model 2, 3, and 4.

Model	R Squared (Original Regression)	R Squared (Auxiliary Regression)	VIF
2 (d.v = Y)	0.192	-	-
3 (d.v = R)	0.484	0.445	1.803
3 (d.v = W)	0.484	0.378	1.608
3 (d.v = E)	0.484	0.149	1.174
4 (d.v = W)	0.445	0.044	1.046
4 (d.v = E)	0.445	0.044	1.046

Note: d.v = dependent variable.

Appendix C. Graph of the Relationship Between h and SSR

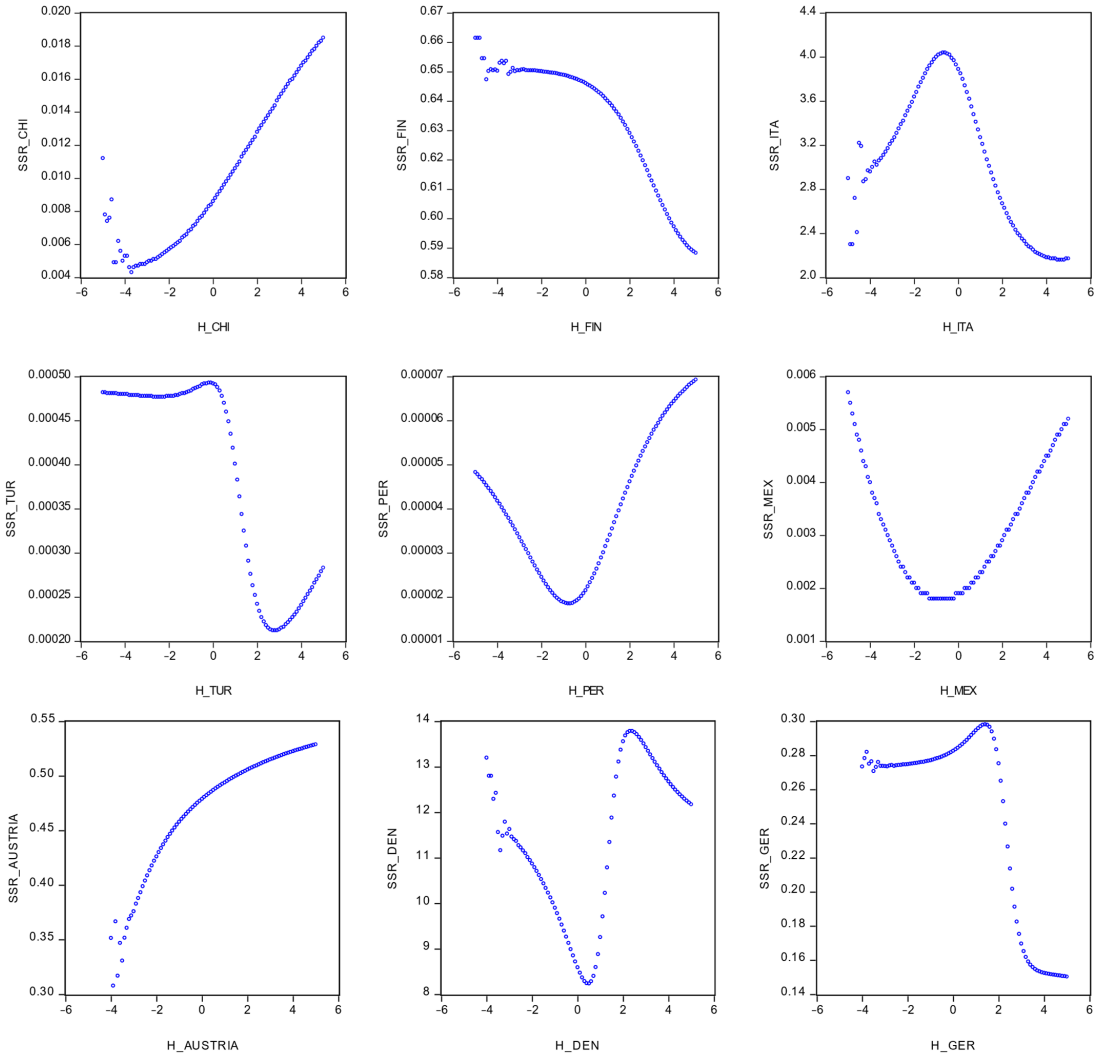

Figure A1. *Cont.*

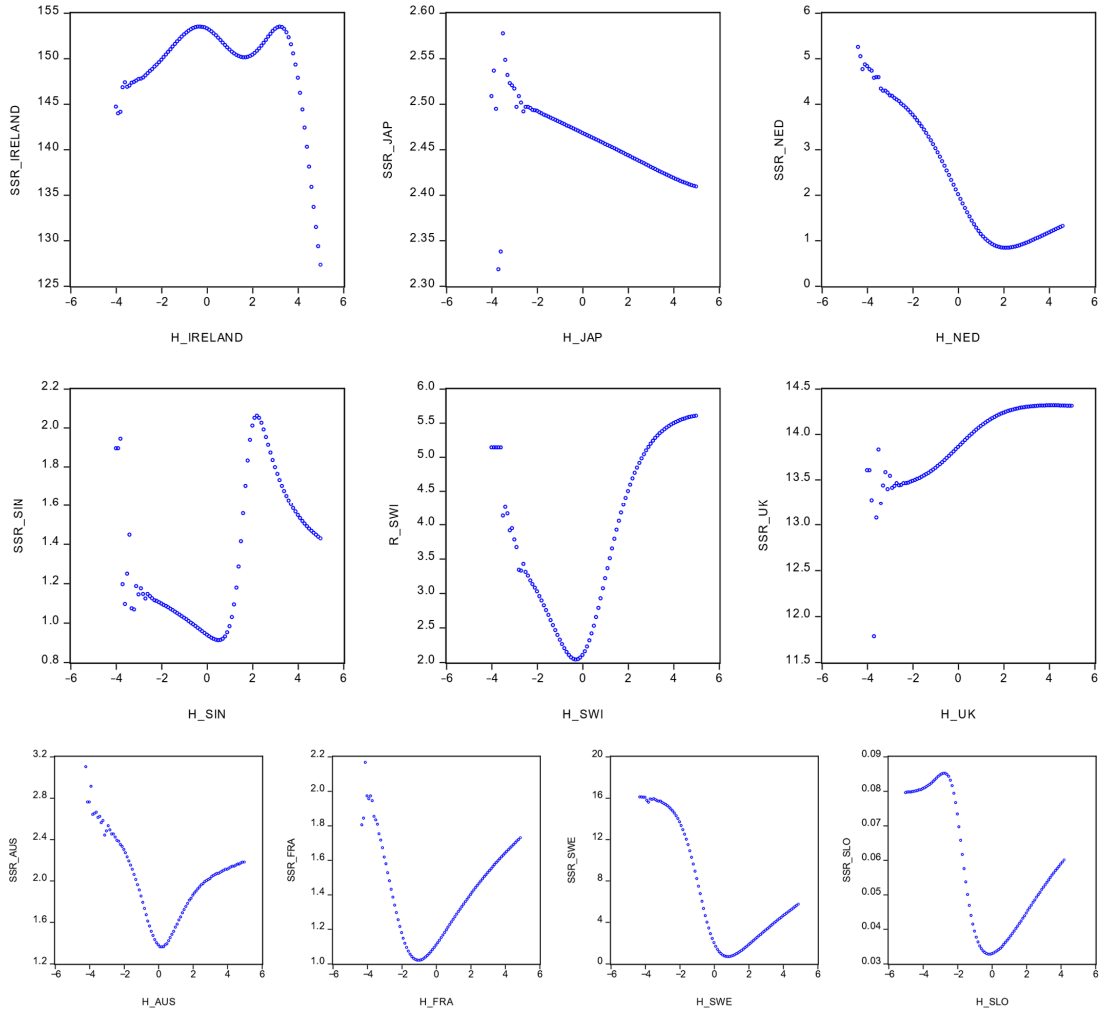

Figure A1. The first line represents Chile, Finland, and Italy. The second line represents Turkiye, Peru, and Mexico. The third line represents Austria, Denmark, and Germany. The fourth line represents Ireland, Japan, and The Netherlands. The fifth line represents Singapore, Switzerland, and United Kingdom. The sixth line represents Australia, France, Sweden, and Slovak Republic.

Appendix D. Further Analysis on h^1 Condition

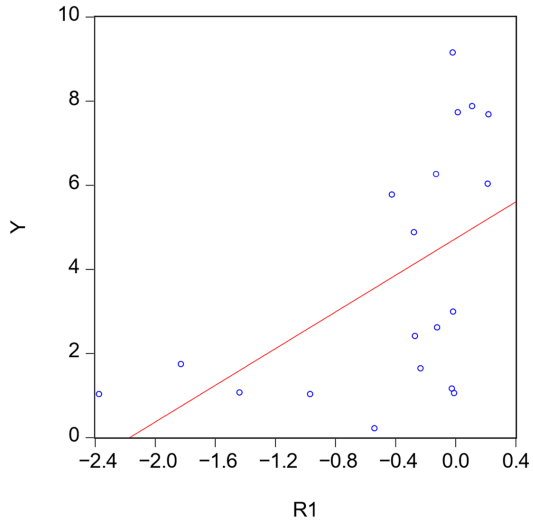

Figure A2. Linear regression line between risk aversion with h^1 (R1) and life insurance penetration (Y) of the 19 selected countries.

Table A5. The results of models 2 and 3 using risk aversion with h^1.

VARIABLE	2	3
α	1.25 ***	
β		0.83
Risk aversion	0.69 **	0.41
log(Income)		0.64 *
log(Education)		−1.47 *
R-squared	0.2462	0.4942
Adjusted R-squared	0.2019	0.3931
F-statistic	5.5546	4.8859
Prob(F-statistic)	0.0307	0.0145

Note: *** $p < 0.01$, ** $p < 0.05$, amd * $p < 0.1$.

Table A6. The results of model 4.

Coefficient			R-Sqrd	Adj R-Sqrd	F-Stat	Prob (F-Stat)
C	log(I)	log(E)				
−8.41 ***	0.55 ***	0.49	0.4167	0.3438	5.7149	0.0134

Note: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

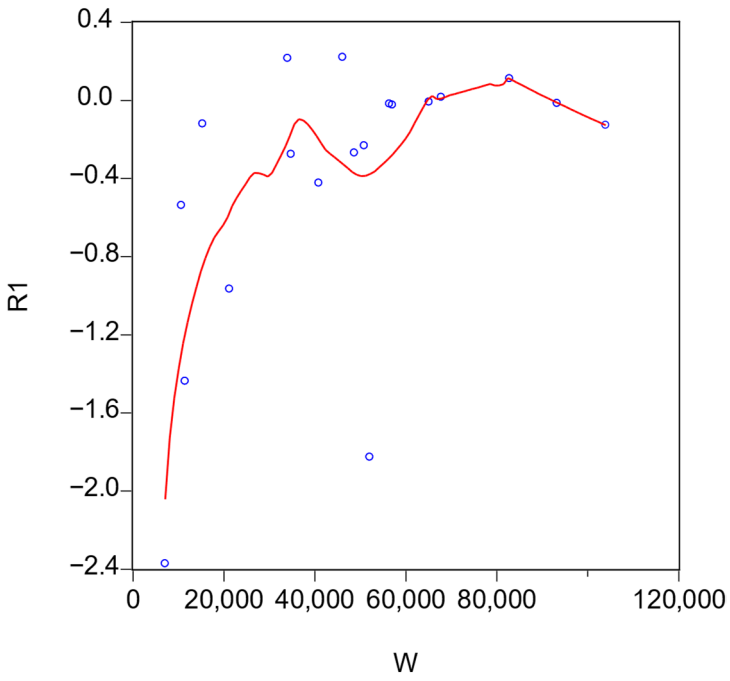

Figure A3. Kernel regression fit between Income (W) and risk aversion with h^1 (R1) of the 19 selected countries.

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