Journal of
Risk and Financial Management

MDPI

Article

The Declining Effect of Insurance on Life Expectancy

Jonathan Leightner

Hull College of Business, AllGood Hall, Summerville Campus, Augusta University, 1120 15th Street, Augusta, GA 30912, USA; jleightn@augusta.edu; Tel.: +1-706-667-4545

Abstract: This paper used Reiterative Truncated Projected Least Squares (RTPLS) to estimate the effects on life expectancy of an additional dollar of insurance premiums for 43 countries. The data shows a clear positive relationship between insurance and life expectancy with insurance premiums increasing much faster than the inflation rate. The relationship d(life expectancy)/d(insurance) fell by a statistically significant amount (at a 95 percent confidence level) for 35 of the countries (and the eight exceptions to this pattern had relatively short data series). By 2020, the last dollar of per capita insurance increased a US citizen's life expectancy at birth by only 6 days, a citizen in the United Kingdom by only 9 days, a citizen in Switzerland by only 7 days, and a citizen in Luxembourg by only 1 day. With such small returns to insurance, an important question is, "Could a society gain more life expectancy by shifting money from insurance into alternative uses"?

Keywords: life expectancy; insurance premiums; omitted variables bias; total derivatives; OECD; reiterative truncated projected least squares

check for updates

Citation: Leightner, Jonathan. 2023. The Declining Effect of Insurance on Life Expectancy. *Journal of Risk and Financial Management* 16: 6. https://doi.org/10.3390/jrfm16010006

Academic Editor: Thanasis Stengos

Received: 7 October 2022
Revised: 30 November 2022
Accepted: 20 December 2022
Published: 23 December 2022

1. Introduction

In contrast to post-modernism (which recognizes change, but never sees that change as "progress"), one of the greatest accomplishments of modern civilization is increased life expectancy. Many researchers have tried to find the determinants of humanity's rising life expectancy. A sampling of their results includes the following. Bergh and Nilsson (2010) find that globalization positively affects life expectancy. Barlow and Vissandjee (1999) found that literacy, per capita income, and access to safe water positively affected life expectancy, while fertility and tropical location negatively affected life expectancy. Per capita consumption of animal products had an inverted—U relationship with life expectancy. Urbanization and per capita health expenditure had a weak positive effect. Chetty et al. (2016) find that life expectancy is affected by gender, income, location, health behaviors (specifically smoking), and the percent of the population who are immigrants. Lemaire (2005) finds that firearm deaths in the USA decease life expectancy and increase life insurance costs. Meara et al. (2008) found that the education gap's effect on life expectancy rose among non-Hispanic blacks and whites in the 1980s and 1990s. Olshansky et al. (2005) find that obesity reduces life expectancy and hypothesize that the US is close to its maximum life expectancy due to rising obesity. On the other hand, Mathers et al. (2015) find that falling tobacco use and cardiovascular disease mortality are correlated with rising life expectancy at age 60, and they do not see evidence for a maximum longevity limit.

The literature on life expectancy can be criticized in several ways. First, no researcher has included all the possible forces that could affect life expectancy. This is a serious criticism because omitting an important variable from a statistical analysis ruins the estimates and statistics. Second many of the forces that affect life expectancy interact with each other in complicated and hard to model ways—consider literacy, education, income, and health behaviors. This paper avoids these problems by employing Reiterative Truncated Projected Least Squares (RTPLS) to estimate the effects of an additional dollar of insurance on life expectancy in 43 countries. RTPLS was designed to solve the omitted variables problem with regression analysis. RTPLS produces reduced form total derivative estimates that capture all the ways that the independent and dependent variables are related without having to acquire data on all possible omitted variables and without having to model all the possible interactions of omitted variables with the included variables. RTPLS produces a separate slope estimate for every observation where differences in these slope estimates are due to omitted variables. An open access article that explains RTPLS is Leightner et al. (2021). The appendix to Leightner (2015) contains the most extensive explanation of RTPLS published to date. The key intuition that underlies RTPLS is that the combined influence of all omitted variables determines the relative vertical position of observations (this intuition was first published in Branson and Lovell 2000). Thus, that relative vertical position can be used to capture the influence of omitted variables.

This paper finds that per capita insurance has been rising noticeably over time, the effect of an additional dollar of per capita insurance on life expectancy has significantly declined over time, and that the return to an additional dollar per capita of insurance is much higher in relatively poorer countries. The remainder of this paper is organized as follows. Section 2 explains the methods used. Section 3 presents the empirical results, and Section 4 concludes.

2. Materials and Methods

If a researcher studying the relationship between life expectancy and education in Germany during World War II did not include race (German versus Jew or gypsy) in his or her analysis, then his or her results would not be reliable because race did affect the relationship between life expectancy and education. In this case, the researcher has an omitted variables problem that ruins all his or her statistics and estimates. However, if that same researcher did not include each person's birth weight when estimating the relationship between education and life expectancy, then his or her estimates are probably not ruined. Birth weight may affect life expectancy, but probably does not affect the relationship between education and life expectancy. In this case, birth weight would just add "random" variation (which would decrease statistical significance) to the dependent variable (life expectancy) without affecting the numerical value of the estimates on how the included independent variable (education) affects the dependent variable (life expectancy).

In other words, omitting variables from an estimation is a "problem" (biases the numerical value of the estimates) only if the omitted variables interact with the included independent variables. Thus, if a researcher estimates Equation (1) while ignoring Equation (2), the resulting estimate of β_1 (how education affects life expectancy) is a constant when in truth β_1 varies with q_i (race), and this ignoring of Equation (2) creates an omitted variables problem. The αs and βs are coefficients to be estimated, Y is the dependent variable, X is the explanatory variable, u is random error, and "q_t" represents the combined influence of all omitted variables plus any random variation in β_1 itself.

$$Y_t = \alpha_0 + \beta_1 X_t + u \quad (1)$$

$$\beta_1 = \alpha_1 + \alpha_2 q_t \quad (2)$$

One convenient way to model the omitted variable problem is to combine Equations (1) and (2) to produce Equation (3).

$$Y_t = \alpha_0 + \alpha_1 X_t + \alpha_2 X_t q_t + u_t. \quad (3)$$

Consider the following derivation.

Derivative of Equation (3):

$$(dY/dX)^{True} = \alpha_1 + \alpha_2 q_t \quad (4)$$

Dividing Equation (3) by X_t:

$$Y_t/X_t = \alpha_0/X_t + \alpha_1 + \alpha_2 q_t + u_t/X_t \quad (5)$$

Rearranging Equation (5):

$$\alpha_1 + \alpha_2\, q_t = Y_t/X_t - \alpha_0/X_t - u_t/X_t \tag{6}$$

From Equations (4) and (6):

$$(dY/dX)^{True} = Y_t/X_t - \alpha_0/X_t - u_t/X_t \tag{7}$$

Recall that u_t is random error which should be relatively small, and u_t/X_t even smaller if $|X_t| > 1$. Leightner et al. (2021) show that eliminating u_t/X_t from Equation (7) does not bias the results, and that elimination produces Equation (8).

$$dY/dX = Y_t/X_t - \alpha_0/X_t \tag{8}$$

Reiterative Truncated Projected Least Squares (RTPLS) peels the data down layer by layer (like an onion) to produce slope estimates for every layer; each Y_t/X_t is then subtracted from the corresponding layer's slope to produce a new dependent variable; and then a final regression is run between that new dependent variable and $1/X_t$ to find an α_0 which is then plugged into Equation (8) along with Y_t and X_t. The mathematical equations underlying RTPLS are explained in Leightner (2015). In this paper's application, Y is life expectancy and X is insurance premiums per capita.

The best way to explain RTPLS is with a diagram like Figure 1. To construct Figure 1, one hundred values for a known independent variable (X) and one hundred values for an "omitted variable" (q) were randomly generated. Then, a dependent variable (Y) was generated as equal to 300 + 10X + 0.7Xq. In this example, the omitted variable (q) makes an 800 percent difference to the true slope—the true slope (dY/dX) is 10 + 0.7q, thus when q = 0, the true slope is 10 and when q = 100, the true slope is 80. Figure 1 plots the values for Y versus the values for X and identifies each point with the value of the omitted variable (q).

For this example, the values for q are known; however, imagine that a researcher does not know the values for q because q is immeasurable, q is the combined effect of hundreds of other variables for which the researcher cannot model with any certainty the interactions of, or because the researcher does not know what omitted variables affect the dependent variable. Even when q is unknown, unmeasurable, or its effects cannot be modelled, Figure 1 shows that the relative vertical position of each observation contains information about q. Specifically, the observations in the upper left part of Figure 1 correspond to the largest qs (31, 90, 92, 98, 97, and 97) and the observations in the lower right correspond to the lowest values for q (1 and 1). Note, that if 0.7Xq had been subtracted from 300 + 10X instead of added when calculating Y, then the smallest values for q would have been at the top of Figure 1 and the highest values for q at the bottom of Figure 1; either way, the relative vertical position of the observations contains information about the omitted variable, q. Another way to think about this vertical position of observations is to examine the values for q as one moves from the top of Figure 1 to the bottom for a given value of X. For example, when X is approximately 25, the corresponding values for q, reading from the top to the bottom, are 90, 62, 36, and 3—the fact that these values are declining show that the relative vertical position of observations contains information about the impact of important variables omitted from the analysis.

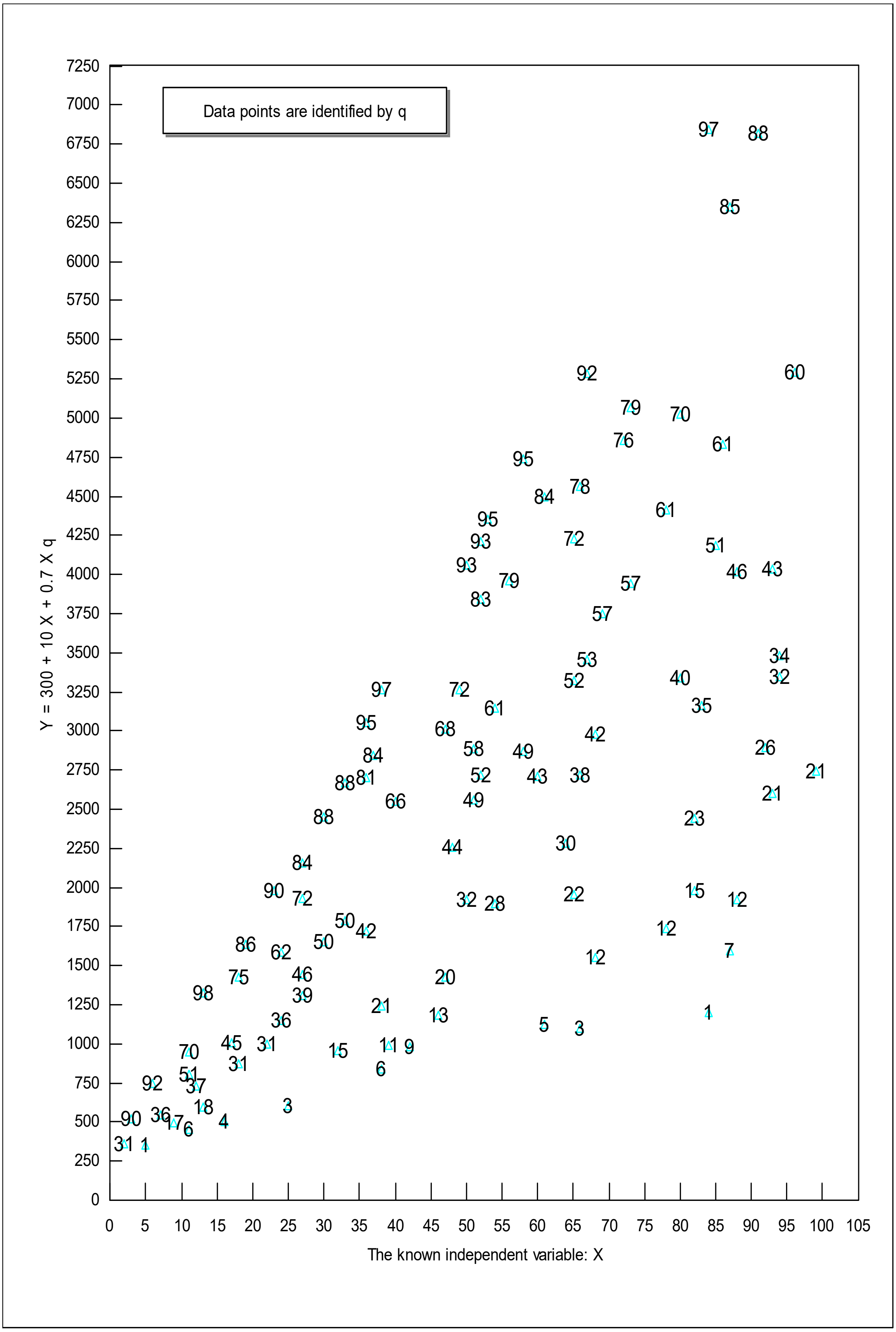

Figure 1. The Intuition behind RTPLS.

RTPLS uses the relative vertical position of observations to capture the effect of omitted variables on estimated slopes. The RTPLS procedure starts by drawing a frontier around the upper left observations (the ones with the largest values for q in Figure 1). RTPLS then projects all other observations to that frontier and then runs an ordinary least squares (OLS) regression through the frontier observations and the observations projected to that frontier. The slope estimates generated by this OLS regression (called TPLS estimates) are then appended to the data for the frontier observations. The frontier observations are then deleted, and the procedure repeated, producing a slope estimate for the observations with the second highest values for q (for Figure 1, those qs would be 36, 70, 86, 90, 95, 95, 95, 95, 92, and 88). This process is reiterated peeling the data down layer by layer until there are 10 or fewer observations remaining. Next RTPLS starts over with the original data and peels from the bottom to the top until there are only 10 observations remaining at the top.

RTPLS then runs a final OLS regression where the dependent variable is the TPLS estimates from the peeling down and up process minus Y/X and the independent variable is 1/X as per Equation (8) above slightly rearranged. The resulting α_0 obtained from this final regression along with values for Y and X are plugged into Equation (8) to produce an estimated slope value for each observation where differences in these slope estimates are due to omitted variables, q. The purpose of this final regression is to create more accurate estimates. If every observation on every frontier in the peeling down and up process corresponded to exactly the same value for q (for example, 95, 95, 95, and 95 for the first iteration and 93, 93, 93, and 93 for the second iteration, etc.), then the TPLS estimates would be 100 percent accurate. This final regression eliminates most of the inaccuracy added to the TPLS estimates by the q values along a given frontier not being identical.

If instead of using RTPLS, OLS is used to estimate the relationship between Y and X for the data underlying Figure 1 and q was omitted, OLS produces the following estimate: Y = 562 + 38.9X with the standard error of X being 4.16 and the R^2 being 0.47. Since the estimated coefficient for X is highly significant and 47 percent of the variation in Y is explained, this regression looks successful, but it is not. Remember the correct equation is 300 + 10X + 0.7Xq. The OLS regression did the best it could given its assumption of a constant dY/dX; indeed OLS produced an estimated dY/dX in the ballpark of 10 + 0.7E[q] where E[q] is the expected (or mean) value for q. For Figure 1, E[q] is 49.7 and 10 + 0.7E[q] is 44.8 which is in the ballpark of the estimated 38.9.

Leightner et al. (2021) ran 5000 simulations each for the 27 combinations of the omitted variable making a 10 percent, 100 percent, and 1000 percent difference to the true slope, with random error being 0 percent, 1 percent, and 10 percent of the standard deviation of X, and with sample sizes of n = 100, 250, and 500. Leightner, Inoue, and Lafaye de Micheaux found that RTPLS noticeably outperformed assuming that there are no omitted variables and using OLS except when random error effected the equation as much as the omitted variables affect it. This exception makes sense since RTPLS uses the relative vertical position of observations to capture the effects of omitted variables and relatively large amounts of random error would make it impossible to distinguish between the influence of omitted variables and randomness.

Specifically, Leightner, Inoue, and Lafaye de Micheaux found that when the effect of the omitted variables was ten times bigger than random error, using OLS while assuming there are no omitted variables produced approximately 3.8 times the error produced RTPLS. Furthermore, when the effect of the omitted variables was one hundred times the size of random error, using OLS while ignoring omitted variables produced more than 27 times the error from using RTPLS. In the most extreme case examined (omitted variables made 1000 percent difference to the true slope, zero random error, and n = 100) using OLS while ignoring the omitted variables problem produced 2138 times the error produced by RTPLS.

RTPLS finds total derivatives that show all the ways that the dependent and independent variables are related. Confidence intervals for RTPLS estimates can be calculated using the central limit theorem.

$$\text{Confidence interval} = \text{mean} \pm (s/\sqrt{n})t_{n-1,\alpha/2} \quad (9)$$

In Equation (9), "s" is the standard deviation, "n" is the number of observations, and $t_{n-1,\alpha/2}$ is taken off the standard t table for the desired level of confidence. Leightner et al. (2021) used an estimate along with the 4 estimates before it and a 95% confidence level to create a moving confidence interval (much like a moving average) for a given set of RTPLS estimates. This 95% confidence interval can be interpreted as meaning that there is only a five percent chance that the next RTPLS estimate will lie outside of this range if omitted variables maintain the same amount of variability that they recently have.

3. Results

Data were downloaded from OECD.statistics for the 43 countries shown in Table 1. The data downloaded were for life expectancy at birth as measured in years, total expenditures on insurance premiums as measured in millions of US dollars, and the population. Insurance premiums were divided by the population and multiplied by one million to get "insurance per capita in US dollars." Life expectation in years were multiplied by 365 to get life expectation in days. With only a couple of exceptions, the data that constrained the analysis were insurance premiums. The earliest that the insurance data started was 1983, and (as of the writing of this paper) insurance premium data were not available for 2021. The gaps in Table 1 show the years that the insurance data were not available.

The original plan was to do this analysis with specifically health insurance data, not total insurance data; however, data on just health insurance were not available. However, to the extent that any type of insurance reduces worry and the risk of financial ruin, all types of insurance should positively affect life expectancy. When people face financial ruin, they often forgo medical attention and healthy foods first. Figure 2 shows a clear positive relationship between insurance premiums and life expectancy.

Figure 3 shows that per capita insurance premiums have risen substantially over time for the 17 countries for which there were continuous data between 1985 and 2020. Only part of this increase is due to inflation—according to the Bureau of Labor Statistics Consumer Price Inflation Calculator, USD 379.11 in 1983 is equivalent to USD 1000 in 2020. Thus between 1983 and 2020, consumer prices in the USA rose 2.6378-fold (USD 1000/379.11). In contrast, Figure 3 shows that per capita insurance premiums in the USA rose 9.02-fold between 1983 and 2020 (8853/981) which is more than three times faster than the inflation rate. All 15 of the countries for which there were data for 1983 and 2020 had insurance premiums increase more than the US inflation rate (2.64 fold): Australia 7.76-fold, Belgium 6.69-fold, Denmark 17.68-fold, Finland 7.65-fold, France 9.34-fold, Germany 7.68-fold, Greece 48.67-fold, Iceland 3.65-fold, Italy 21.83-fold, Japan 5.31-fold, Norway 5.57-fold, Portugal 35.77-fold, Spain 24.35-fold, Switzerland 4.41-fold, and USA 9.02-fold.

Changes in the value of the US dollar would also affect the values shown in Figure 3. For example, between 2015 and 2016 the US dollar rose in value relative to many currencies. Even if other countries kept the same level of insurance per capita (or increased it) as measured in their own currencies in 2015–2016, the values shown in Figure 3 fell for most of them because the values in Figure 3 are shown in US dollars (the 4 exceptions are the USA, Chile, Argentina, and Indonesia).

This paper used all the numbers provided on the OECD.Stat website including the one observation with a probable decimal place error. That one observation was for Iceland in 2005. Iceland's per capita insurance premiums for 2003 to 2007 are, respectively 1249, 1337, 148, 1529, and 1876—the 148 in 2005 does not fit the pattern, but 1480 would (this inconsistency is clearly seen in Figure 3. This one decimal place error in 1161 observations which did not produce an outlier (see Figure 2: near the y-axis where y = 29,747.5 days) would only affect Iceland's estimate for 2005 and not substantially affect any other estimate.

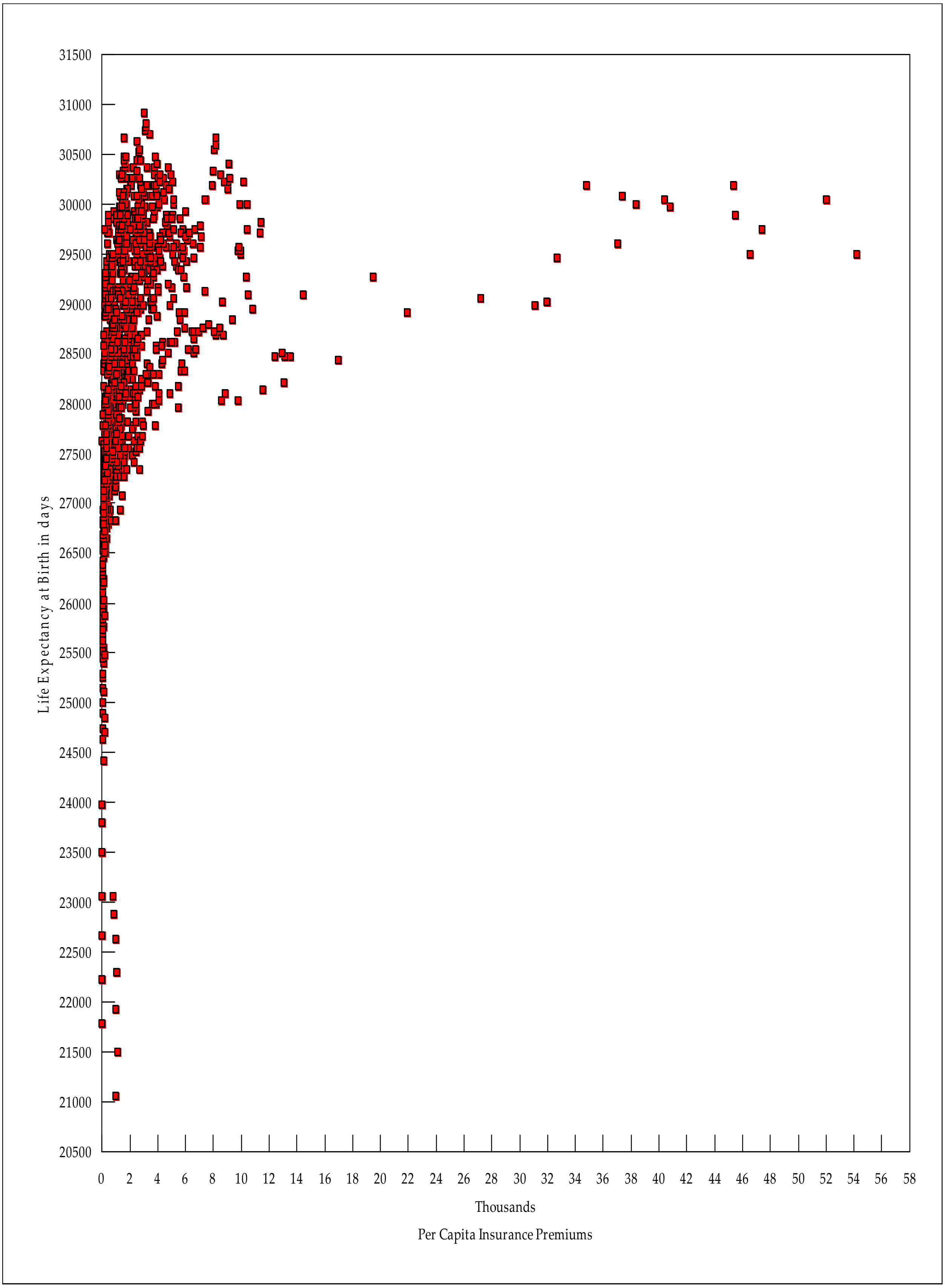

Figure 2. Life Expectancy in Days versus Per Capita Insurance Premiums in US Dollars.

Figure 2 depicts the life expectancy in days versus the per capita insurance data as measured in US dollars. In Figure 2, with only two exceptions, all the observations that exceeded USD 12,000 in per capita insurance premiums correspond to Luxembourg. The two exceptions were Ireland in 2007 (with USD 14,457) and 2008 (with USD 19,471). According to OECD.Stat, Luxembourg's per capita insurance exceeded $50,000 in 2010 (USD 54,176) and 2014 (with USD 52,030). These numbers look suspicious (but less suspicious when one considers Luxembourg's extremely high GDP per capita). Thus, the analysis was conducted twice—first with Luxembourg included and second with Luxembourg deleted. The RTPLS estimates for *d*(life expectancy)/*d*(insurance) when Luxembourg was included are presented in Table 1. When Luxembourg was deleted all of the *d*(life expectancy)/*d*(insurance) estimates fell between 0.011 percent and 0.014 percent {0.00014 > [*d*(life expectancy)/*d*(insurance) with Luxembourg minus *d*(life expectancy)/*d*(insurance) without Luxembourg]/[*d*(life expectancy)/*d*(insurance) with Luxembourg] > 0.00011}.

The RTPLS estimate given in Table 1 for *d*(life expectancy)/*d*(insurance) of 177 for Australia in 1983 means that if Australia had spent one more dollar per person on insurance in 1983, then life expectancy at birth would have increased by 177 days. Turkiye in 1983 had the highest RTPLS estimate for *d*(life expectancy)/*d*(insurance) of 8754 days. This implies that if Turkiye had spent an additional dollar per person on insurance in 1983 then life expectancy at birth would have increased by almost 24 years (8754/365). However, by 2019 Turkliye's RTPLS estimate for *d*(life expectancy)/*d*(insurance) had declined to 356 days, slightly less than one year. The country with the lowest RTPLS estimates for *d*(life expectancy)/*d*(insurance) was Luxembourg, which also had the highest per capita expenditures on insurance. Luxembourg's *d*(life expectancy)/*d*(insurance) fell to less than 3 days after 2003.

Table 1. RTPLS Estimates for *d*(Life expectancy in days)/*d*(per capita insurance premiums in US $).

	1983	**1984**	**1985**	**1986**	**1987**	**1988**	**1989**	**1990**	**1991**	**1992**	**1993**	**1994**	**1995**
Australia	177	92	109	208	67	52	46	41	43	47	34	67	66
Austria				82	61	53	54	44	43	38	37	34	30
Belgium	113	120	119	86	68	62	62	50	48	43	46	43	35
Canada		69	64	57	50	51	48	44	42	46	53	53	51
Chile													
Columbia													
Costa Rica													
Czech Rep.											659	505	409
Denmark	128	115	93	70	53	45	48	38	37	32	33	27	24
Estonia													
Finland	109	114	105	72	56	48	45	33	33	36	87	81	61
France	106	106	100	70	53	45	43	36	34	29	28	26	22
Germany	88	95	94	69	56	50	51	43	38	28	28	25	22
Greece	5976									522	453	392	321
Hungary										678	623	567	537
Iceland	127	134	134	109	79	61	66	59	52	50	60	61	59
Ireland			112	81	55	56	51	45	43	40	38	37	31
Israel													
Italy	426	409	372	248	181	156	149	113	99	83	84	77	63
Japan	90	81	71	43	33	23	23	25	23	21	18	16	15
Korea (S)												51	39
Latvia													
Lithuania													
Luxembourg		151	138									13	5
Mexico										850	736	717	1183
Netherlands	77	85	83	60	48	43	42	33	33	28	30	27	23
NewZealand			336			184	94	97	114	113	124	111	102
Norway	72	74	66	50	43	40	42	37	36	33	37	83	76

Table 1. *Cont.*

	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995
Poland											1113	1045	830
Portugal	1682	1596	1392	871	625	479	411	270	228	180	163	143	108
Slovak													
Slovania													
Spain	830	773	686	311	209	115	154	142	120	104	106	84	76
Sweden									58	59	79	65	59
Switzerland	28	32	30	21	16	15	15	13	12	11	11	10	8
Turkiye	8754	8293	8229	7924	6314	5717	4787	2974	2684	2273	1801	2650	2097
UK			68	49	73	65	64	54	48	41	21	22	21
USA	52	48	40	33	29	19	23	21	21	20	19	18	18
Argentina													
Brazil													
Indonesia													
Russia													
South Africa													
mean	1108	688	593	526	408	351	301	201	177	216	241	243	220

	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
Australia	29	26	28	25	29	32	28	26	22	22	21	17	17
Austria	26	32	32	32	34	35	31	25	22	22	21	18	17
Belgium	34	36	31	29	29	29	28	19	15	13	15	13	13
Canada	51	52	56	34	30	29	27	22	19	17	16	13	16
Chile											179		
Columbia													
Costa Rica													
Czech Rep.	345	345	304	289	287	246	188	139	120	108	98	82	66
Denmark	22	23	21	23	26	24	19	18	16	13	12	10	9
Estonia											537		
Finland	51	58	51	45	43	50	47	42	38	35	36	34	31
France	21	22	25	25	25	26	25	19	16	14	12	11	12
Germany	22	24	24	24	26	26	22	18	15	15	16	16	14
Greece	281	286	254	217	239	240	208	155	127	119	97	81	75
Hungary	505	479	441	418	381	347	263	203	171	147	131	100	99
Iceland	60	65	64	60	59	65	57	43	40	360	35	28	36
Ireland	27	24	18	13	9	14		8	6	6	5	4	3
Israel											48	43	36
Italy	61	58	48	42	44	41	34	26	23	21	21	21	22
Japan	18	19	22	20	20	22	23	22	21	20	21	19	17
Korea (S)	36	38	49	45	39	46	43	40	36	29	24	21	24
Latvia													
Lithuania													
Luxembourg	6	4	4	4	4	4	4	3	2	2	2	2	2
Mexico	1110	917	749	587	446	437	389	472	428	418	360	314	299
Netherlands	22	23	21	21	22	21	20	16	14	14	15	13	12
New Zealand	76	75	97	120	137	160		116	80	70	76	67	72
Norway	33	32	32	32	31	29	23	19	16	14	15	13	10
Poland	630	511	432	413	404	355	348	303	257	203	161	123	79
Portugal	94	103	87	76		75	67	51	43	33	34	30	25
Slovak		533	447	473	456	408	336	234	184	389	152	118	92
Slovania												47	37
Spain	71	74	71	60	55	56	47	45	38	36	33	31	27
Sweden	52	32	31	40	24	23		19	16	15	16	16	16
Switzerland	10	11	10	11	11	10	9	9	9	9	10	9	7
Turkiye	1872	1610	1438	1190	1008	1417	1334	987	712	655	591	423	397
UK	20	18	16	14	12	13	12	10	9	9	6	5	7
USA	17	16	14	14	13	13	11	9	9	9	9	8	8
Argentina													

Table 1. *Cont.*

	1996	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**
Brazil													
Indonesia													
Russia											433	320	231
South Africa													
mean	193	185	164	146	136	143	135	104	84	95	96	63	55
	2009	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**Mean**
Australia	20	17	14	14	14	13	16	18	18	19	22	24	42
Austria					18	18	22	23	23	22	23		32
Belgium	14	15	14	14	16	16	19	20	20	18	17	18	37
Canada	24	21	20	19	19	20	23	24	22	23			35
Chile	141	108	93	81	79	85	83	77	76	71	79	103	97
Columbia	428	356	308	259	235	251	308	310	282	273	277	312	300
Costa Rica		331	304	264	240	218	243	213	198	199	189	188	235
Czech Rep.	72	67	62	70	69	73	89	92	87	79	78	77	182
Denmark			9	9		8	9	9	8	8	8	8	30
Estonia	198	121	122	111	88	81	90	84	74	63	63	65	131
Finland	30	24	28	31	22	21	25	29	29	57	44	64	49
France	11	12	12	14	13	12	14	11	11	11	11	12	29
Germany	18	18	17	14	13	13	15	15	14	13	13	12	30
Greece	81	85	86	101	108	115	145	147	136	128	126	122	381
Hungary	125	126	125	150	142	141	169	160	144	134	127	128	268
Iceland	61	45	41	43	41	40	42	37	30	29	32	36	66
Ireland	5	5	5	5	5	5	5	5	5	5	5	6	23
Israel	39	36	33	34	31	31	32	30	27	26	25	25	33
Italy	19	19	21	23	20	17	20	21	21	20	20	20	83
Japan	14	13	12	15	20	20	22	16	18	17	17	18	25
Korea (S)	26	22	19	16	16	15	15	15	15	14		14	29
Latvia	209	243	188	180	163	147	171	169	136	110	102	107	160
Lithuania		262	223	228	199	187	206	186	162	139	136	131	187
Luxembourg	1	1	1	1	1	1	1	2	1	1	1	1	13
Mexico	326	296	259	253	222	224	248	259	238	226	206	231	462
Netherlands	13	17	15	17	18	19	24	12	11	11			28
New Zealand	77	69		51	46	45	53	53	50		37		97
Norway	28	13	11	10	11	10	14	14	14	13	13	14	30
Poland	119	110	103	104	109	115	137	141	121	116	120	122	308
Portugal	28	27	36	41	33	30	40	46	43	37	41	50	252
Slovak	96	99	93	100	94	94	117		56		101	101	217
Slovania	35	37	36	39	39	39	46	46	42	39	38	36	40
Spain	29	33	29	34	33	33	38	34	34	32	35	36	125
Sweden	19	20	18	21	19	10	13	14	12	11	11		28
Switzerland	7	7	6	6	6	6	6	7	7	7	7	7	11
Turkiye	432	372	368	335	300	327	346	301	320	375	356		2215
UK	10	10	10	9	10	9	10	9	9	8	9	9	22
USA	8	8	8	7	7	7	6	6	6	7	6	6	16
Argentina				153	130	118	114	114	123	114	185	189	138
Brazil						147	187	178	159	174	171	224	177
Indonesia				751	786	879	864	741	666	693	673	743	755
Russia	393		296			267	420	401	327	303	312		337
South Africa		46	42	47	45	49	55	62				64	51
mean	90	84	81	92	87	92	105	99	90	91	96	92	173

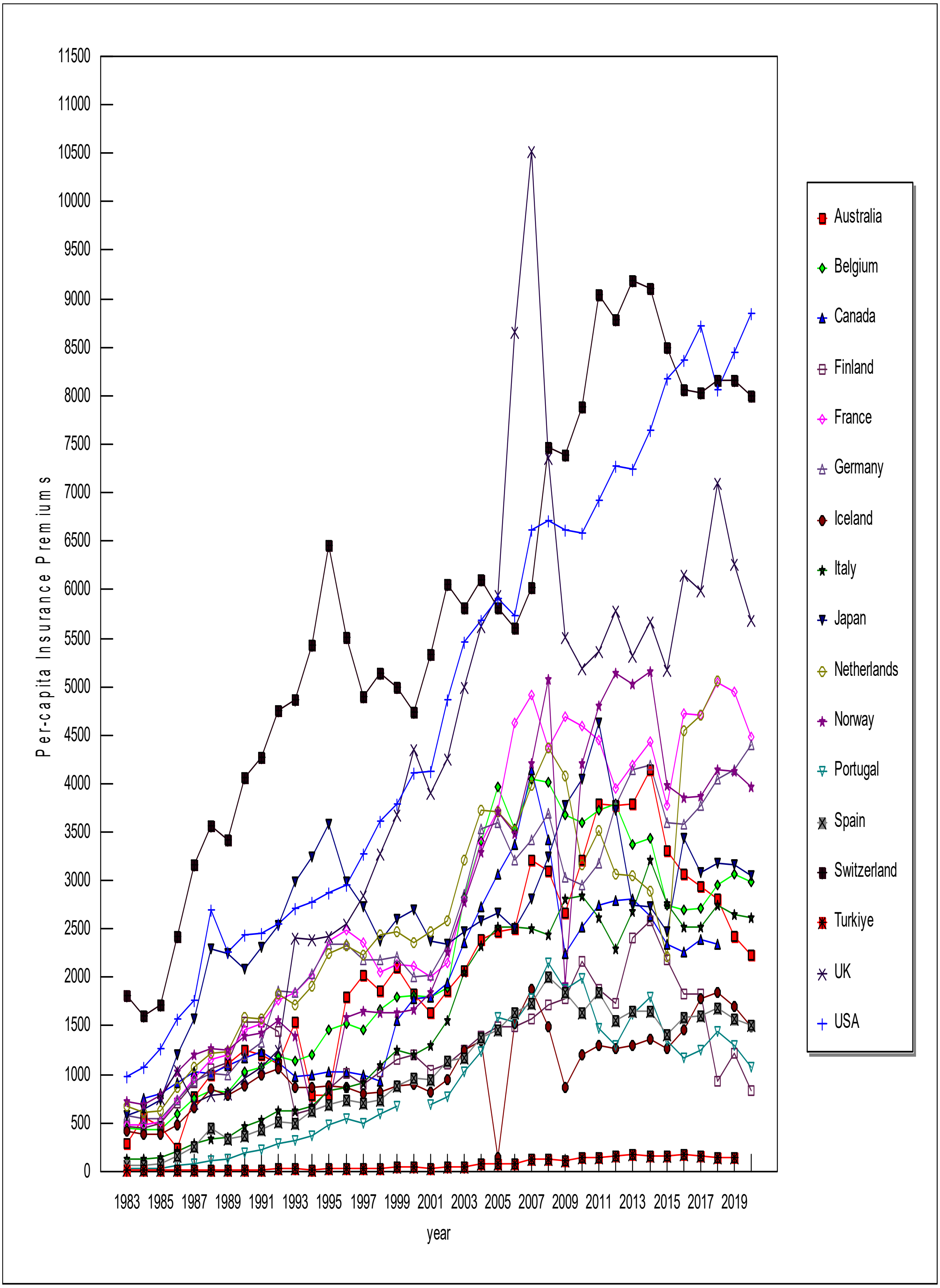

Figure 3. Per-capita Insurance Premiums for the countries with continuous data from 1985 to 2020.

Forty countries in the data set showed declining d(life expectancy)/d(insurance) over time. Only three countries (all of which are non-OECD countries and all of which had relatively short data series) had rising d(life expectancy)/d(insurance) over time: Argentina's d(life expectancy)/d(insurance) estimate of 153 days in 2012 rose to 189 days in 2020, Brazil's d(life expectancy)/d(insurance) estimate of 147 days in 2014 rose to 224 days in 2020, and South Africa's d(life expectancy)/d(insurance) of 46 days in 2010 rose to 64 days in 2020. Note that the rise in d(life expectancy)/d(insurance) that occurred for many countries between 2014 and 2015 could be due to a rise in the value of the US dollar as discussed above.

As described in Section 2 of this paper, a moving 95 percent confidence interval for the RTPLS estimates for d(life expectancy)/d(insurance) was calculated for every estimate that had four uninterrupted years of estimates before it. Only Iceland's confidence intervals for 2005 to 2009 contained zero. However, recall that Iceland's insurance data for 2005 looks like a decimal place error was made. If a decimal place error was made, then Iceland's d(life expectancy)/d(insurance) estimate for 2005 would have been approximately 36 instead of 360, and Iceland's 95 percent confidence intervals for 2005 to 2009 would not have contained zero. Thus correcting for that probable decimal place error would result in all the RTPLS estimates given in Table 1 being statistically significant at a 95 percent confidence level.

Furthermore, for 35 of the countries analyzed there was a statistically significant change in the d(life expectancy)/d(insurance) estimates as shown by their beginning 95 percent confidence intervals not overlapping with their ending confidence interval. The eight countries that had overlapping confidence intervals at the beginning and ending of their data also had relatively short data series: Chile, Columbia, Slovenia, Argentina, Brazil, Indonesia, Russia, and South Africa. The difference in the beginning and ending 95 percent confidence intervals was quite stark for many countries; for examples between 1987 and 2020 the 95 percent confidence interval went from 60–114 to 11–12 for France, from 61–100 to 12–15 for Germany, from 248–875 to 33–35 for Spain, and from 29–51 to 5.9–6.4 for the USA.

Figure 4 shows the d(life expectancy)/d(insurance) estimates for the seventeen countries for which there was continuous data for 1985 to 2020. The y axis of Figure 4 was capped at 220 in order to prevent there from being one line at the top of Figure 4 for Turkiye and all the other lines indistinguishable from each other due to being squinched together at the bottom of the graph. Capping the y axis at 220 led to Turkiye's results not appearing in Figure 4 and the early estimates for Italy, Portugal, and Spain also not appearing because they also exceeded the 220 cap. The one spike upward in 2005 (also exceeding the 220 cap) is for Iceland and it corresponds to the probable decimal place error discussed above.

It is important to remember that RTPLS estimates are total derivatives (not partial derivatives) that show all the ways that the dependent and independent variables are related. Thus if insurance premium increases are correlated with advances in health technology, then the RTPLS estimates presented here capture that correlation. Indeed it is likely that one of the major ways that insurance and life expectancy are correlated is by insurance making it possible for people to receive medical treatments that use advance health technology that without insurance would be prohibitively expensive. If a researcher were to estimate d(life expectancy)/d(insurance) holding medical technology constant, then that researcher might find no relationship between life expectance and insurance when (in truth) insurance is playing a key role by making modern medical technology affordable. Furthermore, holding per capita GDP constant while estimating the effects of insurance on life expectancy is also problematic because higher per capita GDP could be viewed as a substitute for insurance or higher per capita GDP increasing wealth (which can be used to sustain the lives of the elderly) could stimulate more insurance to protect that wealth. The total derivatives found in this paper for d(life expectancy)/d(insurance) capture all the ways that insurance and life expectancy are related. It is impossible to test the robustness of this paper's results by comparing them to the results of different multivariate analyses that use varying sets of independent variables because RTPLS produces total derivatives while multivariate analysis produces partial derivatives. Apples and oranges are both fruits (RTPLS and multivariate analyses are both statistical methods), but beyond that one similarity, apples and oranges are very different.

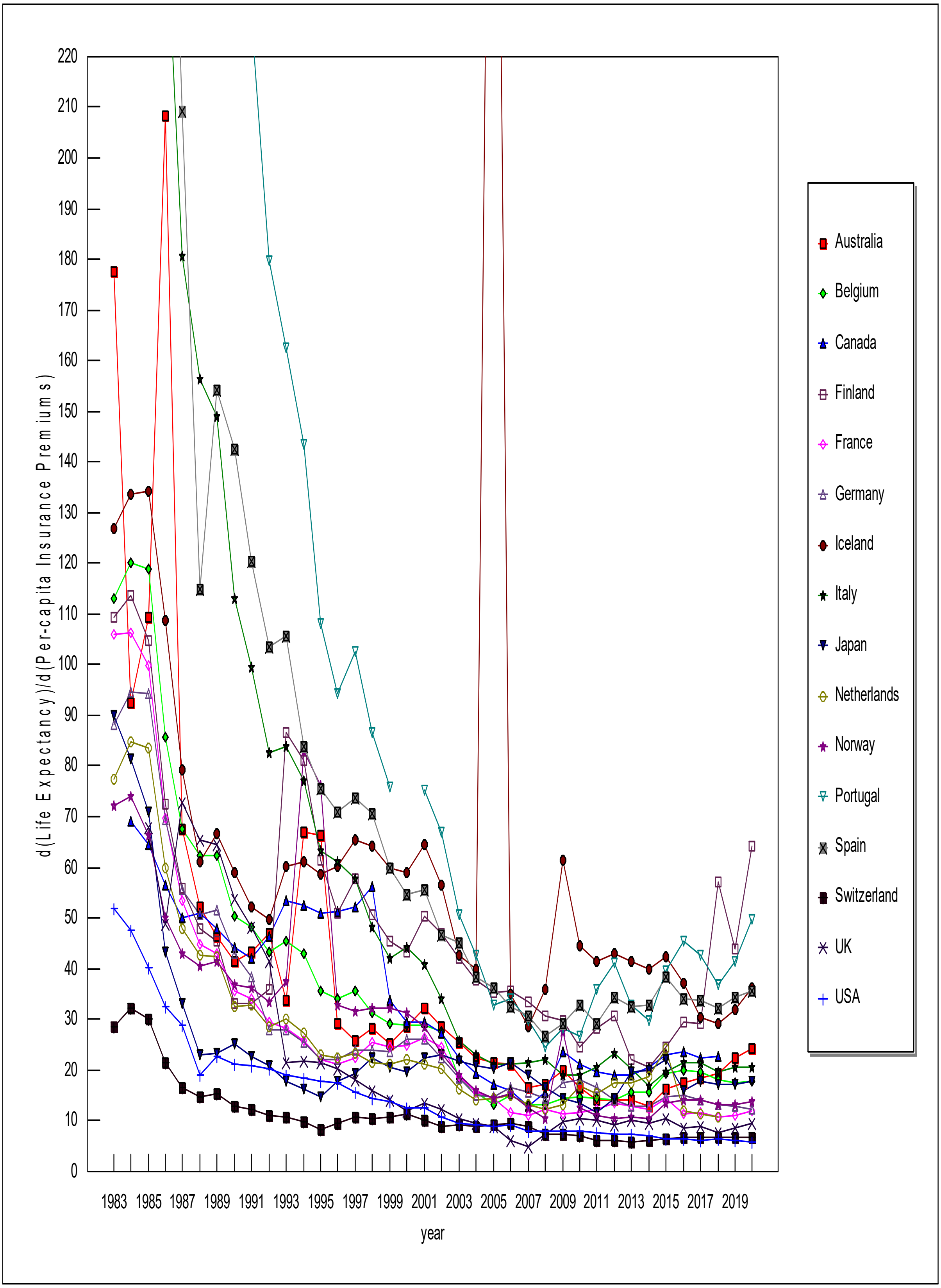

Figure 4. d(Life Expectancy in Days)/d(Insurance Premiums Per Capita in US Dollars).

4. Conclusions

This paper used the best data publicly available to analyze the effects of per capita insurance premiums on life expectancy in 43 countries. This paper's conclusions include the following. First, insurance premiums increased much faster than the inflation rate. Second, d(life expectancy)/d(insurance) noticeably declined for 40 of the countries (and the three exceptions to this pattern had relatively short data series of less than 10 years). Third, the falls in d(life expectancy)/d(insurance) was significantly significant at a 95 percent confidence level for 35 of the countries (again the 8 exceptions to this pattern had relatively short data series). In most countries the return (in terms of increased life expectancy) of an additional dollar of insurance per capita is falling. By 2020, the last dollar of per capita insurance increased a US citizen's life expectancy at birth by only 6 days, a citizen in the United Kingdom by only 9 days, a citizen in Switzerland by only 7 days, and a citizen in Luxembourg by only 1 day. With such small returns to the last dollar of insurance, an important question is, "Could a society gain more life expectancy by shifting money from insurance into alternative uses?" However, such a study is beyond the scope of this paper.

The analysis conducted here could be improved if better data was available. For example, if sufficient data was available, it would be best to conduct this analysis using each country's own currency corrected for inflation. Furthermore, if data on different types of insurance was available, it would be insightful to redo the analysis for each type of insurance—health insurance, property insurance, and life insurance treated separately.

Funding: This research received no external funding.

Data Availability Statement: All data is available to the public on OECD. Stat. RTPLS can be conducted by interfacing a DEA program (a free one is available on the Internet) with a spreadsheet that does regression analysis (such as Excel or Lotus).

Acknowledgments: Eric Jenkins downloaded the data, organized the data, and proofread the paper.

Conflicts of Interest: The author declares no conflict of interest.

References

Barlow, Robin, and Bilkis Vissandjee. 1999. Determinants of National Life Expectancy. *Canadian Journal of Development Studies/Revue Canadienne D'études Du Développement* 20: 9–29. [CrossRef]

Bergh, Andreas, and Therese Nilsson. 2010. Good for Living? On the Relationship between Globalization and Life Expectancy. *World Development* 38: 1191–203. [CrossRef]

Branson, Johannah, and Charles Albert (Knox) Lovell. 2000. Taxation and Economic Growth in New Zealand. In *Taxation and the Limits of Government*. Edited by Gerald W. Scully and Patrick James Caragata. Boston: Kluwer Academic, pp. 37–88.

Chetty, Raj, Michael Stepner, Sarah Abraham, Shelby Lin, Benjamin Scuderi, Nicholas Turner, Augustin Bergeron, and David Cutler. 2016. The Association Between Income and Life Expectancy in the United States, 2001–2014. *Journal of the American Medical Association* 315: 1750–66. [CrossRef] [PubMed]

Leightner, Jonathan E. 2015. *The Limits of Fiscal, Monetary, and Trade Policies: International Comparisons and Solutions*. Singapore: World Scientific.

Leightner, Jonathan E., Tomoo Inoue, and Pierre Lafaye de Micheaux. 2021. Variable Slope Forecasting Methods and COVID-19 Risk. *Journal of Risk and Financial Management* 14: 467. [CrossRef]

Lemaire, Jean. 2005. The Costs of Firearm Deaths in the United States: Reduced Life Expectancies and Increased Insurance Costs. *Journal of Risk and Insurance* 72: 359–74. [CrossRef]

Mathers, Colin D., Gretchen A. Stevens, Ties Boerma, Richard A. White, and Martin I. Tobias. 2015. Causes of international increases in older age life expectancy. *The Lancet* 385: 540–48. [CrossRef] [PubMed]

Meara, Ellen R., Seth Richards, and David M. Cutler. 2008. The Gap Gets Bigger: Changes In Mortality And Life Expectancy, By Education, 1981–2000. *Health Affairs* 27: 350–60. [CrossRef] [PubMed]

Olshansky, S. Jay, Douglas J. Passaro, Ronald C. Hershow, Jennifer Layden, Bruce A. Carnes, Jacob Brody, Leonard Hayflick, Robert N. Butler, David B. Allison, and David S. Ludwig. 2005. A Potential Decline in Life Expectancy in the United States in the 21st Century. *New England Journal of Medicine* 352: 1138–45. [CrossRef] [PubMed]