The S-curve and reality

Preliminary and incomplete

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July 15, 2015

Abstract

We challenge the common wisdom that the income elasticity of insurance be higher, ceteris paribus, in developing countries (so-called ”S-curve hypothesis”). We show how the available evidence is contradictory and heavily dependent on methodology. Based on a new approach to consistent inference on the income elasticity of insurance, we show counterexamples to the theory. Although falsifying it in general, we discuss how it could be relevant in some particular settings.

1 Introduction

Enz (2000), based on earlier work by Carter and Dickinson (1992), put forth the hypothesis that insurance penetration may be approximated, country by country, by a logistic function of economic development, so that the scatterplot of current insurance penetration versus GDP per capita in the countries of the world may be effectively interpolated by means of a logistic (or sigmoid) curve. From this relationship one can also calculate the income elasticity of insurance at a given level of per-capita income. An implication is that the development of insurance is slower in the first stages of economic development, then grows more than proportionally and ultimately slows down again.

The idea that the evolution of insurance may be stylized this way is a powerful and elegant hypothesis which has received much attention among practitioners. It bears resemblances to a number of typical applications of the logistic function in various sciences – from models of population growth (Verhulst, 1845, 1847) to the diffusion of innovations in the economy (Ayres, 1990a,b) – which add to its theoretical appeal. Moreover, such a relationship, if confirmed by the empirical evidence, would provide a natural characterization of the evolutive pattern of insurance penetration in time and a solid link with that of income, allowing consistent forecasting of the market conditional (solely) on economic development at large.

Despite a number of weaknesses, this approach has become so ingrained in the common sense of both academics and practitioners as to be often taken for granted. In time, while this theory was gaining widespread acceptance, any evidence of non-linearity has been considered by-and-large consistent with it: see e.g., for the case of Life insurance, Chang and Lee (2012, comments to Figure 1 and Table 2), where most of the evidence presented (only one threshold, income elasticity three to five times higher in the richer half) actually points towards a strongly hyperbolic shape. [1]

As is underlined by Enz (2000), it may be unlikely for the often-used linear approximation to the income-insurance relationship to hold too far out of any given sample, as greater-than-one elasticities would eventually lead to indefinitely high values of the penetration rate. For all this, the argument goes, the use of non-linear functional forms capping the elasticity over a certain value of income is warranted, or will at least be at some point. Although suggestive, the logistic curve is one among many functional forms downweighing the elasticity at extreme values of income; it carries over a number of further features which might be inappropriate, first of all its symmetry, meaning that markets will be as slow in picking up from low penetration at the earliest stages of development as they will be fast in saturating after having reached maturity. For the sake of example, the evolution of markets might be better described by an asymmetric function, as long as its slope eventually becomes decreasing at the right end. At a first glance, the behaviour in the leftmost range seems to be the easiest part to verify empirically, as there is plenty of developing countries in the potential sample; the hardest part being, instead, to infer on the possible shape of the curve outside the right boundary of the sample on the basis of observations on a few big industrialized countries: has the turning point been reached already, or will penetration grow further as the economy does?

Moreover, the S-curve of Enz (2000) is estimated on pooled cross-section and time series data; yet the author recognizes the importance of allowing for country-level heterogeneity and therefore considers the residuals from the curve's fit regressing them against individual, time-invariant effects and time trends. Moreover, although as a statistical interpolation of the existing penetration rates of a pool of countries in different periods, the interpretation of it in marginal terms is not straightforward, nevertheless, as Enz (2000) shows, once fitted to the data it can predict the elasticity of one country at one given level of development. For this reason, we will attempt at estimating the income elasticity of insurance efficiently and consistently using recent estimators, and then come back to test the predictions of the S-curve hypothesis on the results.

So, what is the S-curve meant to be? A descriptive graph depicting a regular pattern in the (GDP, insurance penetration) space, or a theory of insurance elasticity as $dp/dy = f(y)$?

This distinction between statistical fitting of positive data and econometric modelling of a partial elasticity as a conditional expectation has, in our opinion, been neglected by the literature, where the two things often confuse. If one assumes that p/y=f(y) is a sufficient model, then fitting makes more sense, but still the descriptive curve as a snapshot of a moment in time has cross-sectional nature, while fitting it as a panel requires a model of its evolution in time. "Pooling" S-curve plots where snapshots across space, or equivalently trajectories in time, are superposed and fitted all together, are common but in our view problematic.

Obviously, while the first is to be taken per se as an interesting stylized fact, the second interpretation gives rise to testable hypotheses. In particular, as Enz

[1]See also Chang and Lee (2012, Footnote 67): "results [of robustness checks] show that there are three thresholds [but] this does not mean that the S-curve pattern does not hold, because [methodology is not established]" for another proof of how strong the *a priori* beliefs in favour of the S-curve model may be.

(2000) himself shows, the characterization of penetration ratios as a logistic function of income implies a hump-shaped distribution of elasticities along the income scale. Attempts at falsification of such hypothesis, in a Popperian sense, can therefore proceed along the lines detailed in the following, in more or less strict versions.

Individual estimates of elasticities from time-series models will be the observable feature on which to test the predictions of the theory. By the nature of the hypothesis considered, "falsification" will have to proceed by looking for evidence of either a particular non-linear shape, or generic nonlinearity, against the null of linearity. Statistical uncertainty will therefore be on the side of the simpler hypothesis, in a sense leaving the burden of proof to the defendant: which is somewhat unfair. Hence, of all the possible ones, we will focus on the simplest and loosest version of the hypothesis.

1.1 The S-curve: predictions and evidence

The S-curve hypothesis states that insurance penetration may be approximated, country by country, by a logistic function of economic development:

$$\frac{P}{Y} = \frac{1}{c_1 + c_2 c_3^Y} \tag{1}$$

where P are insurance premiums per capita, Y is real GDP per capita, so that the scatterplot of current insurance penetration versus GDP per capita in the countries of the world may be effectively interpolated by means of a logistic (or sigmoid) curve. From this relationship one can also calculate the income elasticity of insurance at a given level of per-capita income as:

$$\eta_{P,Y} = 1 - \frac{c_2(c_3^Y)Y\dot{l}n(c_3)}{c_1 + (c_2 c_3)^Y} \tag{2}$$

where P are insurance premiums and Y is real GDP per capita. Hence, if $c_3 \leq 1$ (which is considered the normal case), penetration starts from a minimum of $1/(c_1+c_2)$ and grows towards the asymptotic value of $1/c_1$, first with steepness growing up to the inflection point, then decreasing. Translating in terms of elasticity, this latter grows with income up to reaching a maximum at Y^* : $1 + Y^* ln(c_3) + \frac{c_2 c_3^{Y*}}{c_1} = 0$, then decreases reaching the same value it started from, meaning that the development of insurance is slower in the first stages of economic development, then grows more han proportionally and ultimately slows down towards the same elasticity it begun with.

At first consideration, the empirical support for a logistic-shaped relationship looks less robust than the theoretical a-priori grounds suggesting it. From a purely descriptive viewpoint, plotting insurance penetration versus per capita GDP at market prices rather suggests, if any, a logarithmic shape (see Figure 3, left); doing the same with PPP-weighted per capita GDP (idem, right) suggests a broken linear interpolant with two kinks, one after the cluster of poorer countries, one before developed ones, with a gentler sloping part in the middle. Spline smoothers (see, again, Figure 3) point at the symmetric of a logistic curve, with slopes actually higher at both ends of the data range.[2]

[2]The striking dissimilarity with Figure 3 in Enz (2000) is due to his using a logarithmic scale for the horizontal axis only, while we have preferred to preserve the original proportions.

All in all, the issue of functional form may therefore look unresolved given this preliminary evidence.

The S-curve of Enz (2000) is estimated on pooled cross-section and time series data; yet the author recognizes the importance of allowing for country-level heterogeneity and therefore considers the residuals from the curve's fit regressing them against individual, time-invariant effects and time trends. Moreover, although as a statistical interpolation of the existing penetration rates of a pool of countries in different periods, the interpretation of it in marginal terms is not straightforward, nevertheless, as Enz (2000) shows, once fitted to the data it can give exact predictions for the elasticity of one country at one given level of development.

The biggest challenge to the s-curve hypothesis, nevertheless, is its incompleteness: if it is meant to be a "model", i.e. it is to be interpreted as a conditional expectation of premiums given income, then all statistically relevant information must have been included. In other words, given income, insurance premiums must be conditionally independent from every other characteristic of a country (and, if considering panel data, time period). Empirically, if this condition is violated then estimates are inconsistent.

For this reason, we will attempt at estimating the income elasticity of insurance efficiently and consistently using recent estimators, and then come back to test the predictions of the S-curve hypothesis on the results.

1.1.1 The empirical S-curve as a stylized fact

The S-curve hypothesis was born as a stylized fact and from a theoretical consideration. The stylized fact is based on the observation of the scatterplot of insurance penetrations versus per capita GDP in the cross-section of the World's countries. Moreover, Enz (2000) observes that insurance penetration cannot grow forever, as it is naturally capped by reasonable limits to the importance of insurance in the economy.

The logical argument on the share of GDP The logical argument in Enz (2000) that the share of insurance on GDP must admit an upper limit scarcely allows discussion, but its relevance at the current time is far less evident, especially when considering that premium income is not an appropriate measure of the sector's contribution to GDP. In fact, only the share of premiums related to intermediation and risk-bearing services enters the value added of (non-life) insurance, which can be measured as the sum of employee compensation and industry profits, or as total premium income minus claims[3]. In any case, the expense ratio (usually between 10-40% of premiums) can be considered as a proxy for the magnitude. Therefore, the actual share of value added for even the most developed non-life insurance markets stands much lower than the corresponding penetration ratio. Consider the case of the European Union. In fact, in 2011 the share of value added of the *financial and* insurance sector as a whole (5.7%, source: Eurostat) was much lower than the ratio of insurance premiums alone over GDP (7.9%, source: Insurance Europe). A penetration ratio of 3.2% therefore probably puts the share of non-life premiums in value added in the

In this last form, the scatterplot assumes an hyperbolic shape.

[3]There is a consistent literature on the subject, see e.g Hornstein and Prescott (1991a,b) and Sherwood (1999).

region of one percent. Doubling or even tripling it would hardly displace the rest of the economy in any significant manner.

Moreover, Enz (2000, Introduction) starts from the assumption that "income elasticity [is] generally greater than one" to conclude that under a linear model "there are no limits to insurance penetration"; this concern loses relevance if elasticity is actually not different from one.

The descriptive graph For all the strength of the argument, the evidence that the rightmost bend has been reached and passed by developed countries is far from compelling. A look at Enz's scatterplot (see the original from Enz (2000) in Figure 1.1.1) already reveals that most points follow a hyperbolic shape rather than a logistic one, the penetration in high-income countries showing scant evidence of moderation[4]; see also the comments to Figure 2 in Outreville (2013) (although these are referred to total insurance). Moreover, the apparent curvature is due to taking the log of GDP against the linear scale for penetration[5]. Hence one may want to avoid imposing a logistic shape from the

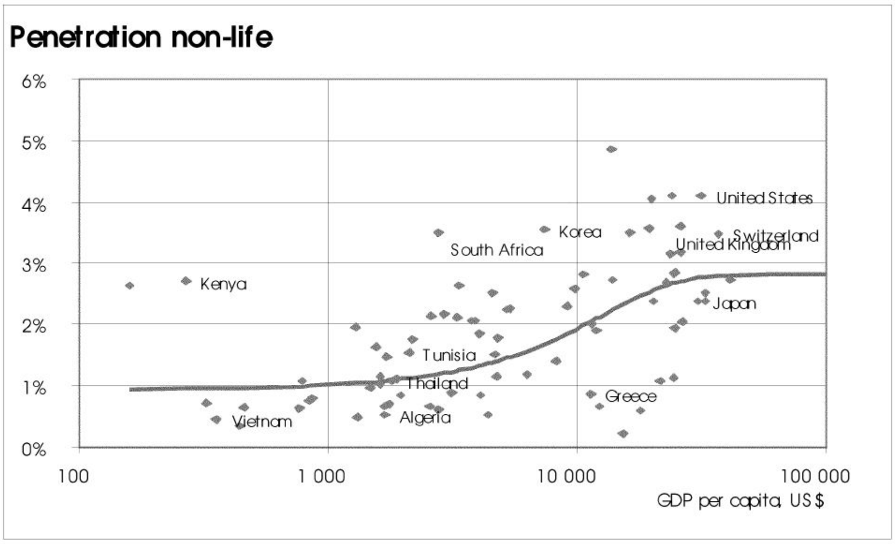

Figure 3: S-curve non-life business,1998 data points only

Figure 1: The original S-curve plot from Enz (2000).

beginning (see also Lee and Chiu, 2012). Fitting a non-parametric spline on the very same cloud (Sigma database, 1998) yields an almost-linear shape in a standard graph of penetration versus GDP per capita, an hyperbolic one when taking GDP on a log scale (Figure 1.1.1, respectively left and right panel). The

[4]The few high-income, low-penetration points on the right end of the graph are from "particular" countries: either Islamic oil-exporters, where income is high but insurance penetration is lower for religious reasons (see Grace and Skipper, 1991) or small city-states and financial centers like LUX, SGP, HKG.

[5]Notice that in the model, unlike in the plots, GDP is not logged.

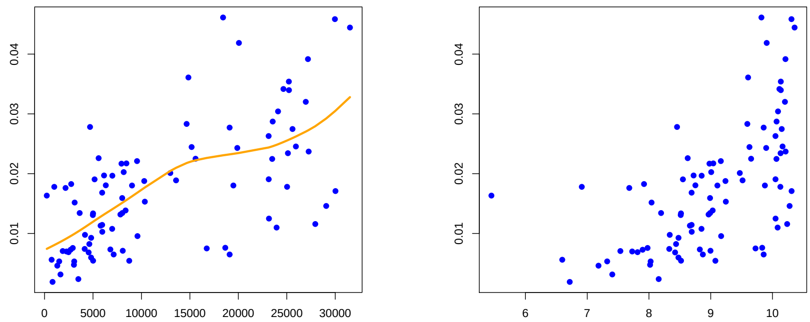

Figure 2: S-curve plots on same data as Enz (2000), linear scale (left) and log-linear scale (right), interpolated by Spline smoothers.

idea that ”elasticity” moderates in mature markets, although logically sound, is unsupported by descriptive evidence.

In this section we have investigated the shape of the penetration - GDP per capita relationship at a static level, simply plotting the available data. In subsequent ones, we will argue that the correct perspective from which to look at the elasticity is a time series one, and consequently bring the focus of the analysis from pooled premiums to GDP ratios towards the coefficient of income in a by-country regression model of insurance expenditure. We will also highlight the importance of considering determinants other than income for obtaining an unbiased estimate of income elasticity. But first we will argue that graphical assessments too have to be based on the marginal effect of income on insurance development rather than on snapshots of the existing levels, which last might have been arrived at in different, although observationally equivalent, ways than through an S-curve like evolutionary pattern.

1.2 Graphical tools: descriptive vs. marginal S-plots

To this end, we will distinguish between two possible graphical tools, which we will both call *S-plots*: a “descriptive S-plot” plotting insurance penetration (premiums over GDP, on the vertical axis) against the level of development, measured as GDP per capita; and a “marginal” S-plot where the (partial) elasticity of insurance premiums to income is, again, plotted versus the level of development.

As already observed, under the S-curve hypothesis the points in the former graph should follow a sigmoid shape, those in the latter a humped one. Of course, while given the data the descriptive S-plot is uniquely determined (up to transformations, at most) the shape of the marginal S-plot will be dependent on the underlying model employed to estimate the individual coefficients.

Moreover, in the next Section we will introduce another graph: a timeline linking all subsequent points in the (penetration, development) space. If the descriptive S-plot is a snapshot of the position of different countries in this space

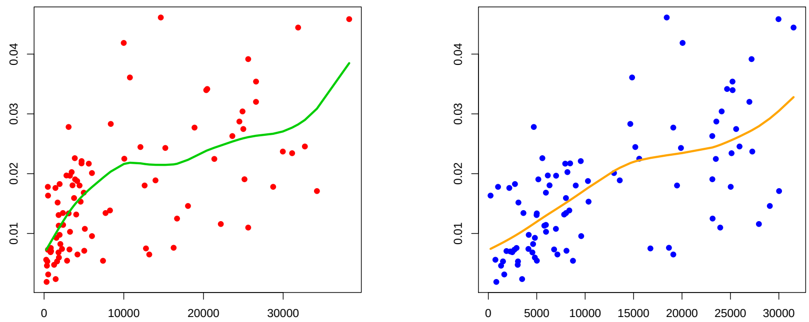

Figure 3: Enz's (2000) S-curve plot: insurance penetration versus 1998 per-capita GDP at market prices (left) and at PPP (right), linear scale on both axes and interpolated by spline smoothers. On the far right, Luxembourg is excluded as an outlier and to preserve the ideal banking ratio.

at a given moment in time[6], the timeline depicts the evolution of one single market. Without the need to assume a steady evolution towards development, for any growth pattern of per-capita income through time, if the S-curve hypothesis holds then the timelines should mimick the sigmoid shape of the original S-curve *limited to the domain spanned by the evolution of the country over the observed sample*. In other words, a developed country can only be expected to cover the rightmost, convex-to-flat part of an ideal S-curve, and so on.

2 Descriptive evidence

At world level, insurance penetration over GDP has remained approximately constant in the 2.4-2.8 range throughout the last three decades. This is largely the result of the overwhelming weight of developed markets, of which only European ones have shown a recognizable upward trend, compensated for by a slight contraction in the US and especially in Japan during its two "lost decades" (see Table 2).

So while there is little doubt that the share of insurance over GDP has been on an increasing pattern throughout the developing world for the last 40 years, in developed countries it seems to have been stabilizing for a long time, the exception of Europe being probably attributable to the need to surrogate in the ongoing retreat of the welfare state. Therefore, at a first descriptive glance, the intuition of rich, saturated markets as opposed to younger ones where there is plenty of opportunity left for growth seems to be confirmed. Nevertheless, it remains to be ascertained whether this is the effect of rising income or of other factors, perhaps institutional.

Returning to our main research question, however, it is clear that the sit-

[6]It has become customary to employ the S-plot with panel data. As observed elsewhere in this paper, such usage is highly problematic.

	1970	1980	1990	2000	2010
North America	4.02	4.46	5.03	4.26	4.46
Latin America and Caribbean	-	0.90	1.10	1.29	1.53
Western Europe	2.12	2.36	2.60	2.86	3.18
Eastern Europe	-	-	-	1.49	2.05
Middle East and Central Asia	-	-	0.42	0.78	1.11
Japan	-	1.73	2.52	2.26	2.11
South-East Asia	-	0.34	0.58	0.71	1.07
Africa	-	0.59	1.09	1.12	1.13
Oceania	2.27	2.75	3.05	3.25	2.99

Table 1: Insurance penetration by macroarea, 1970-2010. Source: Swiss Re, Sigma database.

uation is unlikely to be uniform across the world. It has been argued (Enz, 2000) that the income elasticity of insurance follows a nonlinear pattern across countries with different levels of development, being comparatively low in the less developed markets, then growing together with the economy and finally, beyond a certain stage of development, falling again.

Descriptive evidence is mixed, as each case study is heavily influenced by idiosyncratic factors. Looking at the patterns of insurance penetration versus real per capita GDP (PPP weighted) in Figure 4, we can see examples of a mature market undergoing various economic cycles (USA), another one still with a clear upward trend (Germany) and one with the sector first rising in importance, then shrinking as the economy as a whole fails to grow (Japan); lastly, one pertaining to a country which can be said to have passed most of the stages of economic development in the last 40 years (South Korea), showing an ever-rising tendency interrupted only by the setback of the 1997 Asian crisis.

3 Model-based evidence

We will now set the S-curve theory in the form of testable hypotheses. We will distinguish a stricter version of the theory from weaker ones, ranging from imposing a logistic form to simply checking for non-linearity.

We will then review the existing literature, commenting on the consistency of the results with the above hypotheses and on the empirical issues of the estimatiors employed, before setting out our preferred specification and choice of estimator, on which the main part of the paper will be based. Consistent estimation of the elasticity of premiums to income will be done country by country and at a panel level, as done in Millo (2014) using a common-factor augmented pool of individual time series. A reassessment of the relationship between the income elasticity of insurance and the level of economic development of a country will follow on this new basis, against which the predictions of the S-curve model will be tested.

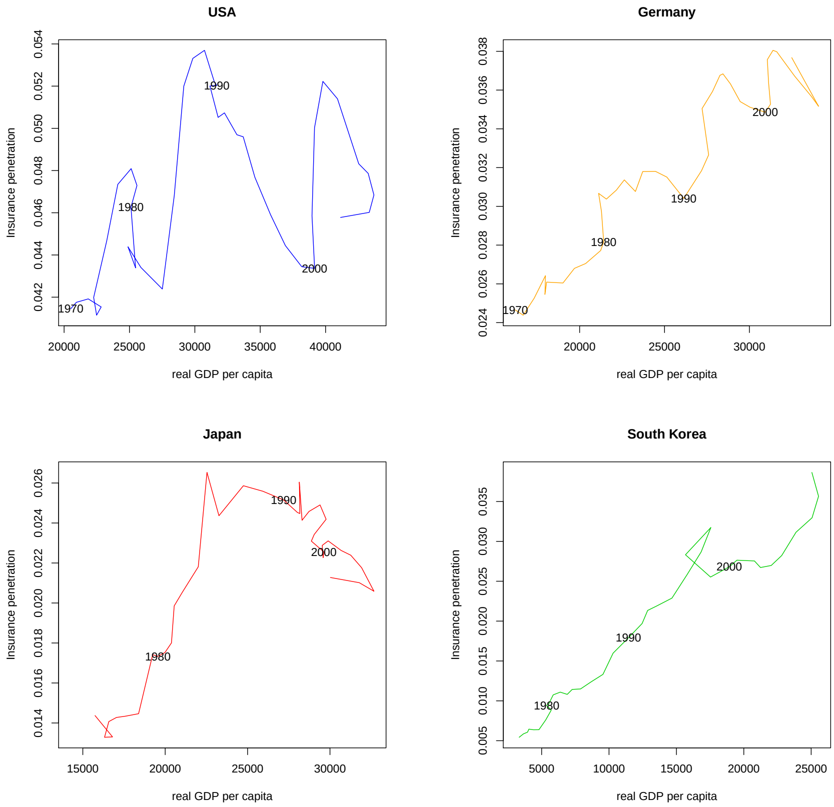

Figure 4: Relative patterns of insurance penetration and economic development (measured as real GDP per capita at PPP in international dollar) in four developed countries, ca.1970-2009.

3.1 The S-curve hypothesis in broad and strict sense

Stricto sensu, the (logistic) S-curve hypothesis implies that the elasticities be a precise function of income levels: that the function be bell-shaped and symmetric, so that at the beginning and at the end of the income spectrum the elasticity be lowest, while highest in the middle. This, which we can label "S-curve hypothesis in strict sense", can be specified as follows:

- *H1: the relation between the (per capita) income level and the income elasticity of insurance is well described as* $dp/dy = f(y) + \varepsilon$, *where* f *is the derivative of the logistic function and* ε *a well-behaved stochastic disturbance*

Yet this is in all likelihood too strict a requirement, even allowing for a good deal of (non-sistematic) statistical uncertainty. A more reasonable, and natural, benchmark requirement for consistency with the S-curve theory is that the elasticity be *some* non-linear function of income levels that be at least qualitatively consistent with the strict S-curve hypothesis. Let us specify an "S-curve hypothesis in broad sense" as follows:

- *H2: The income elasticity of insurance is systematically higher in developing countries both with respect to developed and to underdeveloped ones*

Lastly, a minimal necessary (but not sufficient) condition for compliance with any version of the S-curve theory is the following

- *H3: There is some systematic relation between the income level and the income elasticity of insurance*

Of course, some nonlinear behaviour may also be inconsistent with $H1-2$.

These benchmarks have been presented from stricter to looser, i.e. ordered by logical implication, so that if the evidence is not consistent with the latter, it is against the former as well. In the following we will review the previous evidence for consistence with $H1-3$, then present our own attempt at measuring the income elasticity conditional on income levels and evaluate $H1-3$ on this new basis.

3.2 The S-curve as an econometric model: a survey

In the following we review the previous literature for consistency with $H1-3$.

There have been two main approaches at econometric estimation of S-curve-like relationships: either parametric estimation of a logistic function or of threshold models allowing for regime changes.

Enz (2000)'s original contribution fits a logistic model to pooled data on 88 countries over the years 1970-98. The logistic specification predicts that elasticity starts at one in less developed countries, then rises in developing ones, then reduces again to one in developed countries, so that the elasticity as a function of income levels has a distinct humped shape. His estimates yield a maximum elasticity of 1.7 for non-life at 8900 PPP weighted 1997 US dollar (2.3 for life insurance). While the functional form is postulated to be a logistic on theoretical grounds and not compared against viable alternatives, he acknowledges the possible misspecification from not controlling for country fixed effects (see Enz, 2000, Footnote 4).

Zheng et al (2008) apply Enz's model to more recent data (95 countries, 1980-2006) in order to draw long-term predictions on the development of the Chinese market. They do not test the functional form neither do they control for any heterogeneity, serial or cross-sectional correlation, nor do they discuss stationarity. Maximum elasticity is 1.425 at 7531 constant 1990 US dollar.

Lee and Chiu (2012, Introduction) criticize Enz (2000) and Zheng et al (2008) for imposing a logistic instead of testing for the optimal functional form. They employ a smooth transition model discriminating between linear, hyperbolic and logistic functional forms on the basis of data. The model for non-life premiums turns out to be nonlinear with two regime changes, but the difference with respect to a linear form is very small in magnitude. Moreover, regimes are inverted with respect to the logistic of Enz (2000): see their Figures 1 and 2. Importantly, unlike the previous work, they allow for country heterogeneity through fixed effects; elasticities fall, which is unsurprising considering that fixed effects are probably going to account for a number of development indicators which are otherwise omitted from the model and are positively related to income.

Non-life premiums elasticity is, respectively, 1.039 and 1.08 in the two regimes, hence they claim that NL is a luxury good and that this is consistent with Enz (2000) (at 1.5) and Zheng et al (2008) (1.425). While formally correct, such claims neglect the different magnitude of the former estimates and the latter, and relies heavily on the precision of the estimates. As will be discussed below, there are reasons to advocate the use of more tolerant standard errors, leading in all likelihood to wider confidence bands which would not allow to exclude one (i.e., the hypothesis of insurance as a normal good) from the confidence interval of the estimated elasticity.

Moreover, the pattern of elasticity vs. GDP levels follows an inverted "U" shape (see p.252 and Fig.2), which – apart from the minimal range spanned (1.055 to 1.08) – is the opposite with respect to the predictions of the S-curve model. Hence, despite having the expected double threshold, the functional form is ultimately *not* consistent with the S-curve hypothesis (it is, though, with the specular shape in Figure 1.1.1, left panel).

As a robustness check, Lee and Chiu (2012, p.254) also do a separate estimation by (linear) 2SLS on subsamples of developing and developed countries, finding that the elasticity of NL premiums in developed countries, at 1.073, is higher than those for emerging countries, at 1.016: again, a 0.057 difference.

Although considering individual heterogeneity and testing for the functional form can be considered big steps forward with respect to the earlier literature, there are problematic aspects in Lee and Chiu (2012)'s work too, testified by their own diagnostics which in the end support our specification choice rather than theirs. Cross-sectional dependence is found in the descriptive statistics (see Table A2) and considered when using robust unit root tests (Table A3), but not when estimating the model. Hence, the latter is misspecified to some extent: at a minimum, if there is neglected cross-sectional dependence in errors but no (endogenous) time effects or common factors, such misspecification is probably leading to overoptimistic standard errors and hence to exceedingly narrow confidence bands for the parameters.

Secondly, their claim that real GDP and premia are stationary is problematic at best. The critical values for the CIPS test given in Lee and Chiu (2012, Table

A3) are those excluding both trend and intercept (see Pesaran, 2007, Table 3a); allowing for an intercept, let alone for trends, already reverses Lee and Chiu (2012)'s results, supporting nonstationarity (compare their Table A3 to Pesaran, 2007, Tables 3b, 3c).

Although we do find evidence of unit roots even when allowing for trends (see Table 1), it is common wisdom that at most GDP can be considered *trend-stationary*[7]: but then, one should allow for (individual) time trends in the model too. Actually, the CCEMG and CCEP models are applied in Lee and Chiu (2012, Table A4) as well, and give considerably different results (0.688 vs. 0.787, both significantly less than one) which are not discussed in the text, apart from conceding that elasticities are "relatively small" versus the other, maintained estimates (Lee and Chiu, 2012, p.253).

Summing up – and skipping the unit root issue altogether – the evidence of nonlinearity, although statistically significant, is very small in absolute value. The statistical significance comes in all likelihood from the narrow confidence interval estimates associated with the assumptions of homogeneous coefficients (pooling) and independent and homoskedastic errors, not allowing either for cross-sectional correlation in the error terms – yet testified by the CD tests in their Table A2 – nor for the serial correlation induced by the time-demeaning of variables they employ to eliminate fixed effects[8] (as mentioned in 3.3 on page 250). The statistical significance of the small difference between the two regimes is unlikely to survive if taking these features of the data into account.

All that said, we tend to attribute the sharp findings of earlier nonlinear models to neglected heterogeneity, common factors and individual trends: the features we aim to control for in our specification. It is telling that when controlling for fixed country effects the difference between country groups (regimes) becomes so small even in Lee and Chiu's model.

Moreover, despite the sharpness of results (narrow confidence bands, well defined functional forms), typically associated to pooled homogeneous panel models, we consider these models at a far greater risk of misspecification than can be our relatively innocuous linear approximation in the context of a heterogeneous and factor-augmented model a la Pesaran (2006).

In the following, we will adopt a consistent approach to the estimation of the elasticity of premiums to income, country by country and at a panel level, based on a heterogeneous linear panel model augmented with common correlated effects (Pesaran, 2006) as done in Millo (2014). Such model produces a population of estimated elasticities β_i for each individual unit (here: country) in the sample (see the details in Millo, 2014, Section 3), so that the distribution of the elasticities can be assessed, *a la* Enz (2000), versus per capita income.

The short section summarizing the methodology which follows is based on Millo (2014, Section 3).

[7]The question whether there is a unit root in real GDP has been debated since Nelson and Plosser (1982); see the review in Papell and Prodan (2004). Ever since, the debate has been between unit roots or *trend*-stationarity.

[8]See Wooldridge (2002) on how subtracting the time means induces serial correlation with a coefficient of $-\frac{1}{T-1}$ if the original errors were serially independent.

3.3 The income elasticity of insurance in a pooled time series perspective

Enz (2000) himself acknowledges:

- the influence of *all other factors*
- the role of individual heterogeneity
- the possibility of (individual) trends

For all these reasons, a multiple regression framework is in order if we want to infer about the relationship between income and insurance net of other potentially confounding factors. Based on a regression of (per capita) insurance consumption on GDP *and other control variates* one can directly estimate the *partial* income elasticity of insurance as the regression coefficient of GDP.

Given that our subject of interest will be a regression coefficient, we are left with the choice of the relevant empirical setting. To infer about income elasticity across different stages of economic development, we must first choose a sample that spans them all, either across countries or in time. Being able to observe the behaviour of the insurance market during the transition a country from underdeveloped to developing, and then developed, is far less likely to be feasible, given that we can only rely on data from the last forty years and precious little countries can be thought of as having gone the whole path (South Korea might be a candidate).

A coefficient is always estimated ("averaged", in a sense) across one (or more) dimension(s). In order to distinguish between countries at different stages of economic development, we must either: estimate a nonlinear relationship in income; or estimate a separate coefficient for countries or country groups, ordered by income. We will choose the second possibility.

The traditional way of assessing the elasticity is to start from a cross-sectional perspective and then either use one cross-section only, pool some cross-sections with or without adding panel features (individual effects). We change perspective,

- taking the time series as our primary perspective
- augmenting it with common factors

so as to obtain one elasticity for each country, and then assign that country (and its elasticity) to one development class. This method also has issues, as for example it depends on the year chosen. Therefore as a robustness check we will compare the distribution of individual elasticities with different choices of base year.

We consider the following linear heterogeneous panel model:

$$p_{it} = \alpha_i + d_t + \beta_i' \mathbf{x}_{it} + u_{it} \tag{3}$$

where p_{it} indicates nominal per-capita insurance consumption in current dollars in cuntry i at time t, $\mathbf{x}_{it}$ is a $kx1$ set of regressors including GDP and controls, α_i is a country-specific intercept, and u_{it} ia an error term. Premiums and GDP are expressed in natural logs, so that the coefficient can be directly read as an elasticity.

The error term is in turn specified according to a multifactor structure as the sum of m unobserved common effects and an idiosyncratic remainder error term:

$$u_{it} = \gamma_i' \mathbf{f}_t + \epsilon_{it} \tag{4}$$

Such structure is capable of generating cross-sectional correlation because of the similar, albeit not identical, response across countries to modifications in the common factors, measured by the factor loadings γ_i. The common factors are allowed to be correlated with the regressors, as is most likely to be the case, so their effect comes both through factor loadings and through the indirect effect on the observed regressors. The common factors are also allowed to be nonstationary.

Pesaran's Common Correlated Effects (CCE) estimators can be used to consistently estimate (3) with errors as in (4). The CCE estimators work by augmenting the basic model with cross-sectional averages of both the response and regressors, which pick up the effect of the common factors. Being robust to strong forms of cross-sectional dependence, they are also to weak ones like spatial correlation.

CCE estimation can be performed either imposing parameter homogeneity (but maintaining heterogeneity in intercepts, factor loadings and possibly time trends) which leads to the CCEP (pooled) estimator, and is to be preferred on efficiency grounds when the underlying assumption that $\beta_i = \beta$ is reasonable; or parameters β_i can be left free to vary, and the average elasticity $E(\beta)$ is estimated by the Mean Groups (MG) method, this last estimator being known as CCEMG.

Controlling for omitted variables Like many others, we regress premiums on GDP too. How is this a complete model? In the following, we explain how the peculiar features of the chosen estimator can account for the other potentially relevant omitted regressors in terms of common factors, individual intercepts and trends.

Country-specific (real) interest rates were added to this very specification in Millo (2014) and deemed insignificant. More generally, the comovement of safe bonds and listed equity across the world's markets is substantial. Considerable cross-sectional correlation can be observed in equities' markets (Longin and Solnik, 1995; Forbes and Rigobon, 2002; Bekaert et al, 2009) and *a fortiori*, via the real interest rate parity condition (Dooley and Isard, 1980), in fixed income markets (Gagnon and Unferth, 1995).This is not a feature of the increased level of financial market integration in recent years but it has been present throughout our sample period. Real interest rates, in particular, show a common component, the *world*, or *global, interest rate*, "arguably the most important price in financial markets" (Helbling and Wescott, 1995), determined mainly by stockmarket booms and oil shocks, and to a lesser extent by (world aggregate) monetary growth and public debt, around which national rates fluctuate as the result of "substantial and often persistent [...] individual-country components" (**?**). Equity markets across countries and industrial sectors, too, turn out to be well approximated by global factors related to market momentum, (average) cash flow to price ratios and global risk factors (Hou et al, 2011). The world real interest rate is represented in this specification by a common factor, varying in time but not over the cross-section, to which each country's insurance market is allowed to react in its idiosyncratic way, according to the factor loading γ_i.

We should account for risk conditions too, which in cross-sectional studies is done with population density. In this setting, the time-persistent differences in population density are absorbed by fixed country effects in the homogeneous fixed effects model; by the intercept and by the deterministic trend in each time series regression both in the augmented homogeneous CCEP and in the heterogeneous CCEMG models. The changes in risk conditions along the time dimension can instead be considered as common unobserved factors, as they are usually of global nature: the rise of product liability, the boom in world commerce, the emergence of terrorism after 2001 etc.. Standard panel models take them into account through time fixed effects, which constrain the factor loadings to be equal; a CCE model (irrespective of whether CCEP or CCEMG) allows instead for the reaction of each domestic market to be different.

The international price of reinsurance is another very important common factor in insurance, as determining the conditions at which direct insurers can transfer excess risk to reinsurers. As such, increases in the reinsurance price will readily, although partially, be reflected in insurance prices. The unavailability of reinsurance price indices over sufficiently long timespans is another problem to be tackled when analyzing our subject. Time fixed effects are in fact too restrictive, as forcing the factor loading on each country to be equal, which is not realistic: bigger or more developed countries will often have bigger insurers with more capacity, less need to reinsure and hence a lower sensitivity to changes in international reinsurance tariffs. Fortunately, again, the CCE estimator allows for an unobserved factor affecting countries to different degrees.

The inclusion of an individual time trend in each separate time series regression (CCEMG) or in the model augmentation (CCEP) accounts for those characteristics that are indeed time-variant but usually follow a regular, linear pattern, as is the case for urbanization, the share of agriculture, the literacy rate or income inequality.

The final reality check for the completeness of the model is given by its cointegration properties, testified by the stationarity of the residuals, in the light of the property of invariance of cointegration spaces: Millo (see, again 2014).

Asymptotics It must be borne in mind, nevertheless, that the good statistical properties of heterogeneous estimators of this kind depend on pooling a reasonably big number of individual coefficient estimates; which last are indeed consistent, but being based on the time series only they are often unstable and overdispersed. For this reason, we will limit to assessing the behaviour of the average $\hat{\beta}_{i \in S}$ over relatively big subsets of countries.

A reassessment of the relationship between the income elasticity of insurance and the level of economic development of a country will follow on this new basis, against which the predictions of the S-curve model in the weakest form of hypothesis $H3$ will be tested. Before formal testing, now that we have estimated individual coefficients for each State, in the next paragraph we employ marginal S-plots to get a first intuition of the behaviour of partial elasticities of insurance to income across the economic development spectrum.

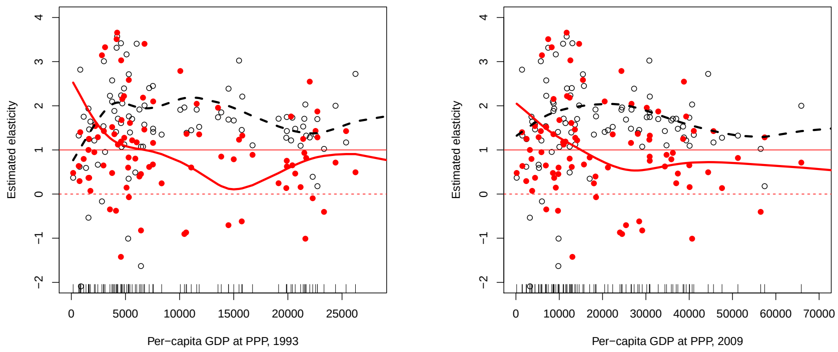

Figure 5: Individual estimated income elasticities of insurance from OLS (hollow points) and Common Correlated Effects Mean Groups with individual intercept and trend (full points).

3.4 Graphical assessment

Regardless of the above concerns, the specification we employ, allowing for individual heterogeneity in coefficients, intercepts and trends, can in principle be compatible with any ex-post distribution of countries in the S-graph. Even a pooled specification with fixed or common correlated effects, although imposing homogeneity in the elasticity, would be consistent with it, explaining the different positions by (historical accumulation of) shift factors like individual effects and trends. Only in absence of these would it in fact predict a flat, horizontal S-curve. Therefore, if we allow for different starting points and deterministics, a descriptive S-plot tells us little about the behaviour of insurance at different levels of development. To graphically check $H1-3$ against linearity we must resort to the partial elasitcities, i.e. the marginal, plot.

In this paragraph we report marginal S-plots for all countries in the sample, with economic development measured in purchasing power parity (PPP) terms in two diffrerent years: 1993, the "gravity centre" of the distribution of available data, and 2009, the last reasonably complete year in the sample. We concentrate on the importance of estimating out individual intercepts, trends and common cross-sectional factors, contrasting the results from a mean groups (MG) estimator (hollow black points) with those of our preferred common correlated effects mean groups (CCEMG) estimator (full red points). Spline smoothers are added to the two points clouds to try and identify an overall tendency; the latter are of course dependent on the chosen bandwidth, and only as reliable as the number of available observations in each "region" on the horizontal axis. To help the reader assess the sample size at each level of development, a "rug" graph highlighting the position of each data point is added to the horizontal axis.

As can be seen, individual elasticities scatter widely, often assuming implausibly high or low (even negative) values. This is typical of MG estimators, which are not meant to be consistent pointwise, for each individual/State i, but rely instead on averaging the individual coefficients β_i over the cross-sectional dimension to get a consistent estimate of the average β. By extension of this line of reasoning, the smoothing spline can be seen as depicting a moving average of the individual coefficients in the "vicinity" of each income level.

While the point cloud from the MG estimator is generally higher and, by and large, consistent with the humped shape predicted by the S-curve theory, accounting for individual heterogeneity and common factors gives rise to a cloud of partial elasticities that are, on average, lower in value and do not follow the predicted shape any more. Rather, CCEMG elasticities tend to be higher in the lower regions of per-capita income, the majority of them staying below one with a tendency to rise in the rightmost part of the income spectrum: i.e., for rich countries.

The main message we get from this marginal version of the S-plots regards the general importance of controlling for idiosyncratic country-specific elements and common factors. As for the S-curve theory, the shape of the smoothing spline actually departs from the predicted one after controlling for common correlated effects; yet this graphical evidence can, at most, be looked at as a very rough indication. Apart from the slight rightmost hump, one could even argue that this distribution could still be interpreted as depicting only the right part of an hypothetical S-curve, where the leftmost countries represent developing ones and the truly underdeveloped world is not even represented.

In the following, we elaborate on statistical tests from Millo (2014) in order to formally assess the linearity hypothesis $H3$ first over the cross-section, and then – for the average coefficients – over time.

3.5 The S-curve hypothesis vs. linearity: formal testing

In this paragraph we address the robustness of a linear model to the implications of the S-curve hypothesis, i.e. to potential nonlinearity of the income elasticity of insurance and in particular to the hypothesis that $\beta_i = f(y)$. This has two possible meanings: elasticity changing with levels of development *across the sample of countries* at a given point in time, or *within a single country*, as it transitions through different levels of development itself.

3.5.1 Cross-section "homogeneity"

Our reference model does not assume a constant elasticity for each country, but makes the milder assumption that individual elasticities be drawn randomly from a distribution of mean β, to be estimated as the average of individual coefficients. Hence if the pattern of elasticity in the cross section were sistematically related to income groups, it would invalidate the hypothesis of random drawing from the same population. As a consequence, the individual estimates would still be consistent but the average estimate would be meaningless.

In Table 2 we report t-tests for difference in means over subsamples of individual coefficients from CCEMG estimates as in Millo (2014), separating country groups either according to their income level or to their OECD membership. As a robustness check, we consider coefficients from progressively reduced samples according to the length of the available time series.

Only in one case (High-income versus Low- plus Mid-income, sample of all countries with at least 15 observations in time) is the difference between coef-

	Low-income	Mid-income	High-income	OECD members
T>14	0.80	1.64	-2.04*	-0.70
	(0.43)	(0.11)	(0.05)	(0.49)
T>19	-0.33	1.26	-0.40	-0.23
	(0.74)	(0.22)	(0.69)	(0.82)
T>24	1.29	0.45	-1.52	-1.02
	(0.22)	(0.66)	(0.14)	(0.32)
T>29	0.57	0.50	-0.90	-0.45
	(0.58)	(0.63)	(0.38)	(0.66)

Table 2: Pairwise t-tests for difference of each subset of individual coefficients from rest of population: low-, mid- or high-income countries according to quantiles in the 2000 distribution of per-capita GDP at PPP, and OECD vs. non-OECD. p-values in brackets.

ficients populations marginally significant. According to the “OECD members” criterion, which is the preferred one in most of the literature, it is never.

3.5.2 Timewise linearity

By contrast, in our model the elasticity is indeed assumed to be constant over time, within a single country. The CCEMG assumes invariance of individual coefficients in time. Hence – under the S-curve hypothesis – the fact that a country transitions through different levels of development inside the sample's time horizon would invalidate the estimate for that single country because of incorrect functional form. Intuitively, not many countries will have transitioned across broad stages of economic development within the timespan of our sample: according to the OECD membership criterion, after Australia and New Zealand (1971, 1973) only the Czech Republic (1995), Hungary (1996), South Korea (1996), Mexico (1994), Poland (1996) and Slovakia (2000) did, while Chile, Estonia, Israel and Slovenia all joined the Organization in 2010. Nevertheless, some formal diagnostic testing is in order.

Our time dimension is way too short to endeavour by-country linearity testing. Moreover, the standard tool – the RESET test of Ramsey (1969) – is neither robust to nonstationarity (Hong and Phillips, 2010) nor to autocorrelation (Leung and Yu, 2001) of regressors. While nonstationarity has been detected in the preliminary analysis, as discussed above autocorrelation can be taken for granted in a static model of insurance consumption. Hence, a RESET test on single regressions is not feasible, nor are panel versions.

We resort to the linearity test proposed in Lee and Chiu (2012), which amounts to adding squares and cubes of log income testing their joint significance, and is analogous to a pooled RESET test. The $\chi^2(2)$ test statistic for the maintained CCEMG model takes a value of 0.0824 (p-value: 0.96) hereby accepting the linearity hypothesis; for comparison we run the same test on the FE2 model, which strongly rejects ($\chi^2(2) = 142.49$). We attribute this result to the overly restrictive nature of the fixed effects specification, and especially to its inability to account for individual trends. A visual inspection of by-country residuals (not shown) supports this view.

We conclude not rejecting both hypotheses: that of heterogeneous coefficients drawn from the same population, and that of linearity in time.

4 Saving the S-curve?

We have shown many counterexamples to the S-curve theory, even if taken in a rather broad sense, based on the observation in time of large international samples of national markets. Our statistical evidence does therefore clearly not support it in general.

As observed, nevertheless, assessing the S-curve theory against linearity leaves the burden of proof to the defendant: the power of statistical tests in detecting departures from linearity as $H3$ will depend on the signal to noise ratio in the given sample. "Noisy" data, full of idiosyncratic variation – and so insurance data use to be – might overshadow a nonlinear data generating process.

If this were the case, advocates of the theory might find an easy explanation for the paths observed in the marginal S-plots. While the Sigma dataset is probably the most comprehensive insurance database at hand, it still comprises almost exclusively countries already endowed with a functional financial market and a reasonable level of economic development. India, Indonesia, Ecuador and Vietnam, for example, all fall into the lowest development quintile. Therefore, we can think of our working sample as starting out at income levels already higher than those at which, according to the S-curve hypothesis, an insurance market would slowly come into existence. Putting it another way, we might already be looking exclusively at the right half of an hypothetical, rather asymmetric S-curve of world insurance. Still, for how far this line of argument has been taken by others,[9] it seems awkward to speak of a symmetric empirical regularity with two opposite sides of which we can only observe one.

Moreover, if we concede that nonlinearity be present, but too much drowned in random variation to be detectable by formal testing; and take the shape of the smoother splines to represent the average behaviour of income elasticities as per-capita income varies; and also concede that we are observing only the rightmost part of the marginal S-curve; still, Enz's device is incapable of explaining the second hump in the distribution of elasticities at the right end of the income distribution.

We attribute this to the implicit hypothesis of product homogeneity underlying it.

4.1 The two waves of insurance growth

It is common wisdom that premiums for traditional insurance lines (like motor, fire, theft) have lower elasticities in developed countries, so that if we were able to observe income for these lines alone we might perhaps confirm the S-curve's

[9]Researchers have often picked the part of the curve which best fitted the S-curve hypothesis: e.g., Chang and Lee (2012, p.242) dismiss the inconsistency between their results (elasticity is at least three times higher for developed countries) and those of Ward and Zurbruegg (2002, p.405) (elasticity is three times *lower* for the OECD with respect to developing Asia): "it could be interpreted that our findings here portray the former half segment of the S-curve, while Ward and Zurbruegg characterise the latter-half one." when Ward and Zurbruegg (2002)'s sample is actually a proper subset of theirs.

predictions. Yet typically the mature markets of rich countries develop new business mostly in the insurance lines associated with modern service economies: professional and product liability, legal protection, travel assistance, business interruption, long term care and so on. A changing product mix might therefore be the explanation for the "second youth" in the life cycle of insurance markets pointed at by the results of our estimates, in the spirit of the "two waves of service-sector growth" of Eichengreen and Gupta (2013). In turn, the general failure of the S-curve theory in describing the available evidence – and, more in general, the tendency of nonlife insurance market to grow in line with GDP at any level of development documented by Millo (2014) – might stem from compensations between mature, commoditized business lines (Motor TPL, Fire) whose market saturates, and "young", innovative lines taking their place.

We now ask ourselves whether the S-curve theory can be useful in explaining the evolution of smaller, yet important, branches of Non-life.

Data limitations will be more binding than above, because of the unavailability of databases of geographical breadth and time depth comparable to that of the Sigma dataset. Given the smaller and shorter sample available, we will limit ourselves to a graphical analysis as a first assessment of compliance with the theory. If encouraging, this will provide directions for future work.

To address the issue of composition within the non-life sector, we must resort to a different dataset than Sigma. Insurance Europe (formerly known as CEA) has been publishing data over European insurance premiums since 1992, divided into (life and) some standard subsets of non-life: motor, property, liability, accident and health, marine aviation and transit (MAT) and legal expenses.

Despite the "European" focus of the dataset, the development spectrum covered is comparable with that of the Sigma World dataset. Comparing marginal S-plots for both in the year 2000 (see Figure), the behaviour of the European subset is largely consistent with the rest, but for the fact that idiosyncratic and common factors seem to play a lesser role.

Moving towards a by-line analysis, we start with descriptive S-plots of non-life vs. each subsector

Despite dispersion, the tendency of motor to have the highest penetration in the middle section is rather evident; even clearer the tendency of countries to gather in two distinct groups for property insurance, the richer ones having, on average, about double the insurance penetration of the poorer ones. although not so clear-cut, the tendency is similar for the other non-motor branches, perhaps with the exception of MAT which is very much dependent on the peculiar characteristics of the country, and therefore has a few outliers (the UK, Norway) in an otherwise flat points cloud.

Turning to the marginal S-plots, we can clearly see how the rightmost hump in the distribution of non-life elasticities is due to the contribution of non-motor, motor showing a set of very high elasticities at the lowest end of the development range and then a very flat distribution, mostly concentrated in the zero-one range. The high elasticities in the leftmost part of the figure are likely to be relative to Eastern European countries, where the time period of our sample witnessed the contemporaneous development of private insurance and the surge in private car transport after the fall of the Berlin Wall. Once more, an individual idiosincracy.

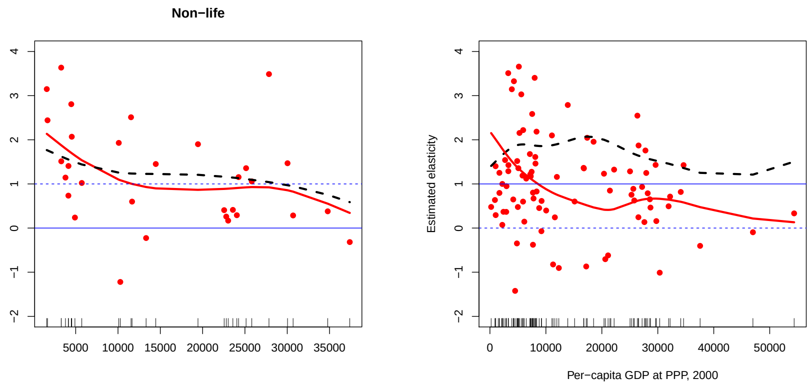

Figure 6: Individual estimated income elasticities of insurance from Common Correlated Effects Mean Groups with individual intercept and trend (full points), plotted against per-capita GDP at PPP in 2000 for European sample (left) and World (right). Spline smoothers for CCEMG (red) and for MG (dashed black line, points not shown) are superposed to the graph.

5 Conclusions

The S-curve hypothesis has been taken for granted by much of the recent literature on insurance growth. Various kinds of inconsistent evidence have been accommodated by basically choosing some part of the curve which best fitted the available data, or more generally by considering any nonlinearity as evidence in its favour. This does a bad service to the theory itself. To paraphrase the incipit of a famous paper in economic growth theory, this paper ”takes Rudolf Enz seriously”, first by trying a precise understanding of what the S-curve is meant to be, then by checking whether its predictions are confirmed by the data.

As we have shown drawing on a) a critical review of previous empirical studies, and on b) the specific results of a recent paper providing a consistent method to estimate the average elasticity to income of a set (or a “big enough” subset) of countries, the S-curve hypothesis does not generally hold, even in very mild form, for the sample of the Sigma dataset (most relevant insurance markets in the world) when considering the non-life market as a whole.

The S-curve hypothesis remains nevertheless an appealing and intuitively plausible description of the evolution of insurance markets, and it would be a very useful forecasting model. All hope of reconciling it with empirical evidence is not lost. It may well be that composition effects, i.e. an excessive aggregation of data into the big categories of life and non-life, have prevented us from finding any evidence in its favour. An assessment of its relevance in more disaggregated settings is left for future work, the preliminary results of which are encouraging.

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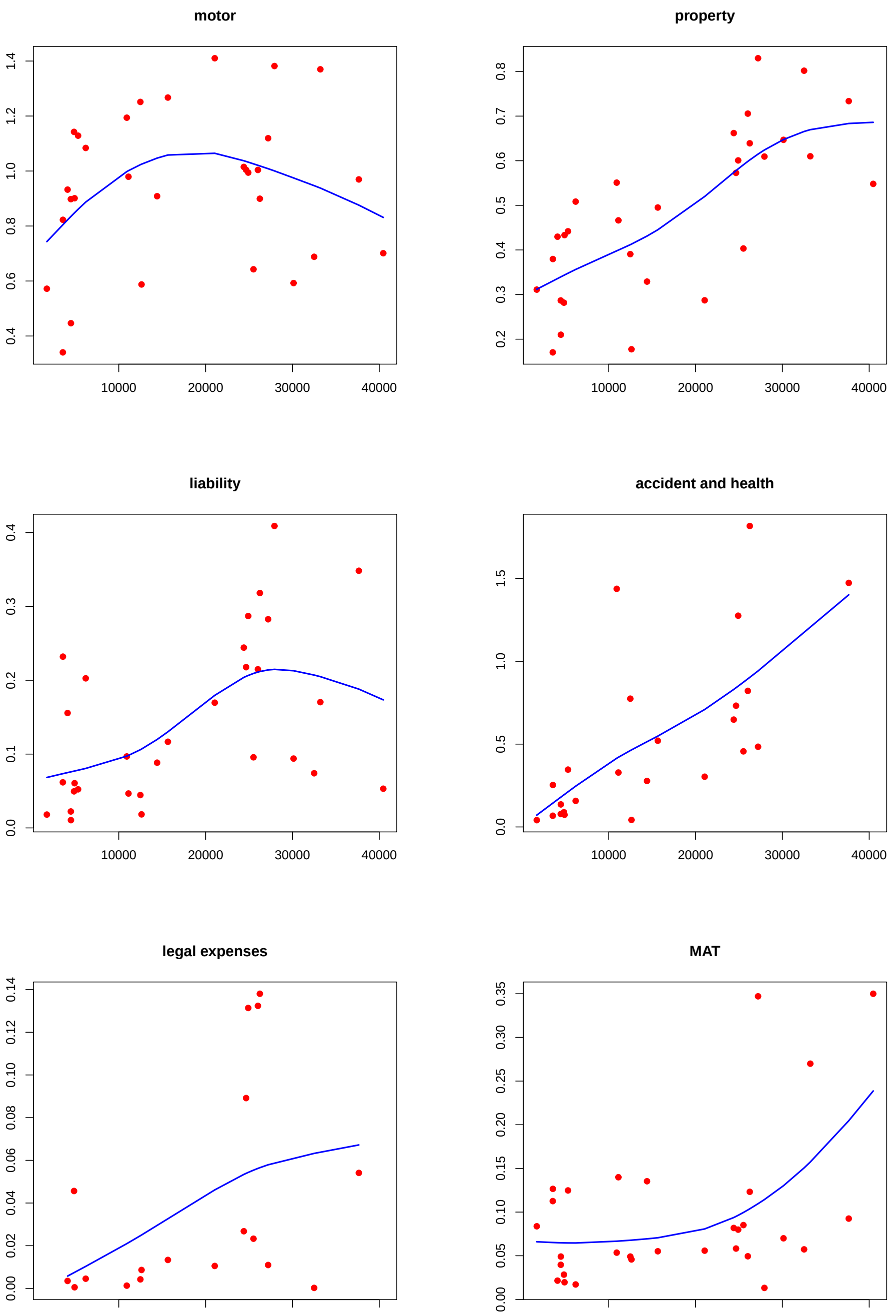

Figure 7: By-line descriptive S-plots: insurance penetration vs. GDP per capita at PPP. Spline smoothers added.

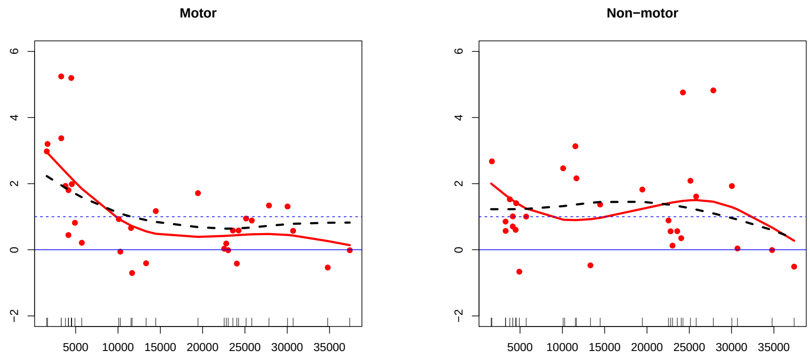

Figure 8: Individual estimated income elasticities of Motor (left) and Non-motor insurance (right) from Common Correlated Effects Mean Groups with individual intercept and trend plotted against per-capita GDP at PPP in 2000.

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