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Underwriting Apophenia and Cryptids: Are Cycles Statistical Figments of our Imagination?*

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Abstract

The Lloyd's 2007 Survey of Underwriters states that "for the third year running, managing the cycle emerged as the most important challenge for the industry, by some margin". The premise is, of course, that underwriting cycles exist in property and casualty insurance, and are economically significant. Using a meta-analysis of published papers in the area of insurance economics, we show that the evidence supporting the existence of underwriting cycles is misleading. There is, in fact, little evidence in favour of insurance cycles with a linear autoregressive character. This means that any cyclicality in firm profitability in the property and casualty insurance industry is not predictable in a classical econometric framework. It follows that pricing in the property and casualty insurance industry is not incompatible with that of a competitive market.

JEL Classification: G22.
Keywords: Property and Liability Insurance, Underwriting Profits, Insurance Pricing.

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Introduction

Ever since Brockett and Witt (1982) showed that insurer profitability may be modelled by a second-order autoregressive process, insurance economists have presumed the existence of profitability cycles usually based on linear time series analysis. Winter (1991), for instance, states that "the existence of cycles in insurance markets is a central topic of insurance literature" (p. 117). These cycles are believed to be present in the property and casualty insurance industry, but not in the life insurance industry. Insurance practitioners also generally assume that cycles exist, although the cycles are not necessarily specified to be of the AR(2) variety. For example, one can read in Lloyd's 2007 Survey of Underwriters that "for the third year running, underwriters in the Lloyd's market have identified managing the cycle as the most important challenge for the industry" (Lloyd's, 2007).

These *underwriting cycles* appear to happen at regular intervals in many OECD countries according to the literature: see Venezian (1985), Cummins and Outreville (1987), Lamm-Tennant and Weiss (1997), Chen *et al.* (1999), Harrington and Niehaus (2000), Meier (2006a, b), Venezian and Leng (2006), Wang *et al.* (2010), Lazar and Denuit (2012), among others. The cycles are characterized by periods of high profitability followed by periods of low profitability. The existence of a predictable underwriting cycle has been seen by some authors as a sufficient condition for concluding that insurance markets are inefficient (Gron, 2010; Outreville, 1990), so that regulatory intervention might be warranted (Derien, 2008). On the other hand, Winter (1991) argues that intervention would exacerbate cycles. Trufin *et al.* (2009) associate underwriting cycles, again modelled by an AR(2) process, with higher probability of insurer ruin. This furnishes another reason why cycles can become the catalyst for government intervention in the insurance markets.

The purpose of this paper is to caution against the presumption that underwriting cycles are perfectly described by a linear autoregressive process, particularly for the purposes of insurance enterprise risk management. The AR(2) process is a statistical model which provides a simplified representation of insurance market behaviour; it is not the only possible description for cycles and certainly does not provide a perfect representation of insurance markets. The word "apophenia" is apposite in the title of this paper because it refers to the behavioural bias whereby one sees patterns where there is none in random data. The tests that have been used in previous research on underwriting cycles were biased in favour of finding such cycles, so that any inference and/or conclusion drawn from these tests may be misleading. Once these biases are corrected, significant underwriting cycles become the exception rather than the norm. The word "cryptids", which also appears in the title and means mythical creatures, refers to autoregressive cycles which are not really there.

This paper complements the study of Boyer *et al.* (2012) who show that there is neither in-sample nor out-of-sample evidence which supports the view that there is any type of predictability in annual insurance underwriting performance in the United States. We extend the results of Boyer *et al.* (2012) in a number of ways. First, we pool the results, as published in the relevant literature, of the time series analysis of nearly 200 data sets, diversified by country and by product line. Second, we analyse the significance of AR(2) parameter estimates in these time series regressions. Third, we show that estimation errors are large enough—because the annual data in these studies is short relative to the presumed 6–7 year-long cycle periods—that neither the presence nor the absence of AR(2) cycles can be established statistically.

It is important to note that the conclusion in this paper is not that insurance prices and insurer profitability are unaffected by external or internal shocks; rather, it is that there is no evidence that such shocks are anything other than random unpredictable occurrences. There may therefore be merit in the pragmatic view of insurance professionals, who do not ascribe the attribute of predictability, in the econometric sense, to the concept of underwriting cycles. Theorists should stress that their autoregressive modelling of insurance profitability provides a simplified description of the insurance market, designed to estimate cyclicality approximately and thereby provide some assistance to professionals when they manage risk. They provide definitive evidence neither in favour nor against linear autoregressive cycles, and must be open to the possibility that the true underlying processes which generate cycles are nonlinear, and indeed to the possibility that there is no predictable cyclicality. (The departure from linearity taken by Jawadi *et al.* (2009) and Wang *et al.* (2010) is a case in point.) There is a high probability of uncovering an autoregressive cycle if one takes a short enough sample of any Brownian motion time series. Successive periods of higher profitability and lower profitability in the property-casualty insurance market may simply be the occurrences of random draws. Therefore, scientific rigour demands that we do not dismiss a random walk in insurer profitability and that we do not reject speculative efficiency on the insurance markets. At the same time, this does not contradict the industry viewpoint concerning the presence of cycles, as long as 'cycles' are not defined within the econometric strictures of linear time series.

This article is organised as follows. Section 2 summarizes the classical theories on property and casualty insurance underwriting cycles, and describes the papers that are used in our meta-analysis. Section 3 presents the methodology used to analyse the likelihood that cycles occur in any time series. The key statistical tests and results of this paper are also presented in Section 3. Concluding remarks are offered in Section 4.

Insurance cycles

Many theories have been proposed to explain the existence of underwriting cycles as defined by Brockett and Witt (1982). We do not present all these theories here, and instead invite the interested reader to consult the surveys of Harrington (2004), Meier and Outreville (2006) and Wang *et al.* (2010). Some of these theories are nevertheless seminal and deserving of further comment in this section.

Insurance cycles are concerned with prices, so financial pricing theories are relevant to explanations of cycles. There are various insurance pricing models based on financial theory (Cummins and Phillips, 2000). They assume perfect markets, risk-neutral insurers with rational expectations, and possibly equilibrium risk-return relationships or absence of arbitrage. At its simplest, financial pricing theory predicts that the price of insurance is the expected present value of future claims and expenses. Interest rate variations can therefore explain some of the volatility in underwriting cycles (Doherty and Kang, 1988; Fields and Venezian, 1989).

Underwriting cycle theories come into their own because several studies show that the variation in prices or profits cannot be fully explained by the perfect markets theory. For example, Harrington and Niehaus (2000) find that insurance prices follow a second-order autoregressive process. They suggest that premium variations are only partially due to variations in fundamentals. They focus on capital shock models to explain both hard and soft market periods in the insurance industry. This relies on the assumption that markets are imperfect and the supply of capital to insurers adjusts slowly in the short run, particularly after an industry-wide loss shock. The capacity-constraint theory argument is that underwriting cycles are the result of frictions caused by a temporary incapacity of the industry to insure all risks (Gron, 1994a, b; Winter, 1994), or the impact of a major catastrophe (Cummins, 2006; Born and Viscusi, 2006) which depletes part of the capital in the reinsurance market (Berger *et al.*, 1992; Meier and Outreville, 2006). As insured risks are not independent, premium nonlinearity results from the dependence between losses.

Cummins and Outreville (1987) propose that autoregressive AR(2) cycles are the result of external factors, such as institutional and regulatory lags, as well as accounting practices. They contend that, even though premiums and profit margins are rationally set to reflect all available information, cycles may arise because of external factors which vary across countries owing to different regulations and regulatory lags. In the same vein, Venezian (1985) suggests that fluctuations in underwriting profit margins are caused by adaptive rate-making methods. The methods used by insurers to forecast future rates violate rational expectations and induce AR(2) cycles. Consequently, insurer profitability should be a combination of a predicable cyclical component and of random components (see also Lamm-Tennant *et al.*, 1992, Harrington and Yu, 2003, and Boyer *et al.*, 2012).

Various other studies purport to show autoregressive cycles in insurer profitability. Lamm-Tennant and Weiss (1997) extend the approach of Cummins and Outreville (1987) to different countries and their specific institutional features, as well as to different product lines. Chen *et al.* (1999), Meier (2006a, b) and Meier and Outreville (2006) find similar and more recent evidence in countries other than the United States.

A few studies do not rely on autoregressive linear time series. Wang *et al.* (2010) detect a well-known asymmetry between hard and soft markets: prices and profitability rise faster in the hard phase than they fall in the soft phase. (In extreme cases, hard markets lead to 'insurance crises'. Wang *et al.* (2010) do not discuss any asymmetry in the availability of coverage when markets harden or soften.) They find that a nonlinear Markov model provides a better fit to insurance data than does an AR(2) model.

Other authors supplement or replace an analysis based on the AR(2) model with a spectral analysis on univariate insurance profits and loss ratios: see Doherty and Kang (1988), Grace and Hotchkiss (1995), Venezian (2006) and Venezian and Leng (2006). Their results are suggestive of cycles, but the sparseness of data, choice of bandwidth, and periodogram smoothing methods do not afford conclusive results. A more powerful and modern test for peaks in spectra is carried out by Lazar and Denuit (2012) and appears to detect a cycle in premium data. However, this is also not clear-cut because it points to a longer cycle period than is estimated in time-domain analysis, possibly conflicting with autoregressive cycles.

Another line of work examines the relationships, in the short and long runs, between insurance profits and variables such as interest rates, stock market indices and GDP through cointegration. Haley (1993), Grace and Hotchkiss (1995) and Choi, Hardigree and Thistle (2002) find various cointegrated relationships, which supports the existence of underwriting cycles by linking them to the macroeconomic business cycle. However, Harrington and Yu (2003) find that underwriting profits are not non-stationary, therefore undermining the hypothesis of cointegration. Jawadi *et al.* (2009) apply a novel nonlinear cointegration methodology, and report two distinct regimes in the data, with strong cointegrated relationships within each regime. This may indicate that linear time series-based underwriting cycles are an oversimplification.

Many underwriting cycle theories do not predict any autoregressive time series but do suggest other testable statistical relationships. Harrington and Danzon (1994) propose that cycles are partly caused by the moral hazard of weaker insurers betting on resuscitation: a less established insurer with low intangible capital and with depleted assets—because of large losses, say—is tempted to sell its products at a low price in an attempt to improve its market share. This underpricing of insurance can also stem from heterogeneous information and poor loss forecast quality (see also Fitzpatrick, 2004, and Boyer *et al.*, 2011). Both cases induce insurers to cut their prices to protect their market share. Harrington and Danzon (1994) find support for their hypothesis as forecast revisions and prices are inversely related.

Another asymmetric information approach is that of Cummins and Danzon (1997), whereby the price of insurance is inversely related to insurer's default risk. As insurers raise capital in response to adverse shocks, their loss ratio should be inversely related to their default risk, which means that insurance premiums should be positively correlated to financial quality. (See also Doherty and Kang (1988) and Doherty and Garven (1992).) Niehaus and Terry (1993) observe cases of premiums being explained by past losses, along with strong evidence that they are determined by past surplus in the industry. Their findings support the hypothesis that underwriting cycles are partly the result of costly external capital. The consensus in the economic literature is summarised by Cummins (2006) when he cites Winter (1994), Cummins and Danzon

(1997) and Cummins and Doherty (2002) and writes that "hard and soft markets are driven by capital market and insurance market imperfections such that capital does not flow freely into and out of the industry in response to unusual loss events" (p. 345).

Background and data

Background

The insurance industry goes through periods of high and low premiums relative to losses, or periods of high and low profitability. The typical approach used to examine cycles in the property and casualty insurance industry is based on standard econometric models (Stock and Watson, 1988; Nelson and Plosser, 1982) which can be represented as:

$$\Phi(B)\, q_t \;=\; \mu + \epsilon_t, \qquad \epsilon_t \sim \text{i.i.d.}\, \mathrm{N}(0, \sigma^2), \tag{1}$$

where $\mu \in \mathbb{R}$, q_t is a profitability measure (such as the underwriting ratio, loss ratio, combined ratio, or any other measure of insurer profitability), and $\Phi(B)$ is a polynomial of degree $p \in \mathbb{N}$ in the backshift operator B. (See Boyer *et al.* (2012) for more details.) When $p > 1$, the characteristic equation, $\Phi(z) = 0$, $z \in \mathbb{C}$, may have conjugate pairs of complex roots with non-zero imaginary parts, if the corresponding discriminant is negative. Then, for any such pair λ and λ^*, with norm $||\lambda||$ and real part $\mathcal{R}(\lambda)$, there is a cycle in the autocorrelation of q_t with period:

$$\tau \;=\; \frac{2\pi}{\arccos\left(\frac{\mathcal{R}(\lambda)}{||\lambda||}\right)}. \tag{2}$$

This suggests a maximum likelihood estimator of τ based upon the maximum likelihood estimator of the complex roots, which itself follows from the maximum likelihood estimator of Φ, expressed as a vector of autoregressive parameters in equation (1).

In particular, when we examine autoregressive models of the second order (i.e. AR(2) models), then $\Phi(z) = 1 - \phi_1 z - \phi_2 z^2$, with $\phi_1, \phi_2 \in \mathbb{R}$. It is well-known (Sargent, 1986; Hamilton, 1994) that complex roots occur provided that $\phi_1^2 + 4\phi_2 < 0$, giving a cycle period of

$$\tau \;=\; \frac{2\pi}{\arccos\left(\frac{\phi_1}{2\sqrt{-\phi_2}}\right)}. \tag{3}$$

Data collection and summary statistics

We collected the AR(2) coefficients from a set of well-known studies in the literature: Venezian (1985), Cummins and Outreville (1987), Chen *et al.* (1999), Harrington and Niehaus (2000), Meier (2006a, b) and Meier and Outreville (2006). These papers were chosen because they are authoritative and peer-reviewed, and cover diverse countries, lines of property-casualty business, and periods of time. They are also influential papers and are regularly cited in the literature on insurance cycles. Our own AR(2) parameter estimates were also used and are based on data provided by A.M. Best's *Aggregates & Averages* for the United States and by the Insurance Bureau of Canada for Canada, as used by Trufin *et al.* (2009). As can be seen from Table 1 in the Appendix, this exercise yields a total of 98 regressions which cover different periods, different countries and different econometric specifications.

The summary statistics associated with these time series are presented in Table 2 in the column under the heading '*ALL*'. Of the 98 series, 69 series exhibit AR(2) cycles, i.e. a proportion of 70% contains cycles. Conditional on cycles being present, the mean period or length of these cycles is 8.11 years, and the standard deviation of the cycle periods is 3.51 years. (Table 2 in the Appendix contains a wealth of other information, and we return to it repeatedly at the appropriate points in the paper.)

There is another set of 96 time series of insurer profitability which is studied by Lamm-Tennant and Weiss (1997). None of the AR(2) coefficients is supplied, so these time series are not included in the final analysis. The summary statistics for these time series are presented in Table 2 in the column under the heading '*LTW*'. Of the 96 time series in the *LTW* sample, 61% contained AR(2) cycles, with a mean cycle period of 7.05 years. The column headed '*Combined*' aggregates the 98 observations in *ALL* and the 96 observations in *LTW*, yielding 66% cyclicality in the 194 combined time series.[1]

It is important to note that there is no statistical difference (according to a two-tailed Student test at the 5% level) between the mean cycle periods in the *LTW* and *ALL* samples, especially if we remove the longest cycle (28 years) that is obtained after performing a regression without a trend component using U.S. data from 1969–2004. However, a non-parametric Kolmogorov-Smirnov test on the two samples shows that the distributions of cycle lengths in *LTW* and in *ALL* are not equal, that neither is normally distributed, and that neither is lognormally distributed. This biases the Student equality test used on the means of the two samples. The 96 regression results in *LTW* are not included in the final analysis because Lamm-Tennant and Weiss (1997) did not report the standard errors and t-statistics of their AR(2) parameter estimates.

Figure 1 presents the point estimates of the ϕ_1 and ϕ_2 parameters of the 98 regression results which are displayed in Table 1 in the Appendix. This corresponds to the *ALL* sample for which the standard errors of the AR(2) regression parameters are known.

[1] We also analyzed the 1874-1901 U.S. fire insurance experience reported in Baranoff (2003), the 1874-1906 fire insurance industry loss ratio reported in Zanjani (2004), the recent data from 1992 until 2011 reported in Hartwig (2011) for P&C commercial lines, homeowner and workers' compensation, and South African marine insurance data from Tarr (2008). Because these papers are not regularly cited in the established literature, they are not included in the overall analysis. Their incorporation would not change the conclusion of this paper. For the sake of completeness, we note that the data in Baranoff (2003) and Zanjani (2004) do not yield cycles, as defined by Brockett and Witt (1982), since both ϕ_1 and ϕ_2 parameters are positive, and only one of the three time series data in Hartwig (2011) yields such a cycle. Finally, there was only one cyclical time series out of the the two time series of Tarr (2008).

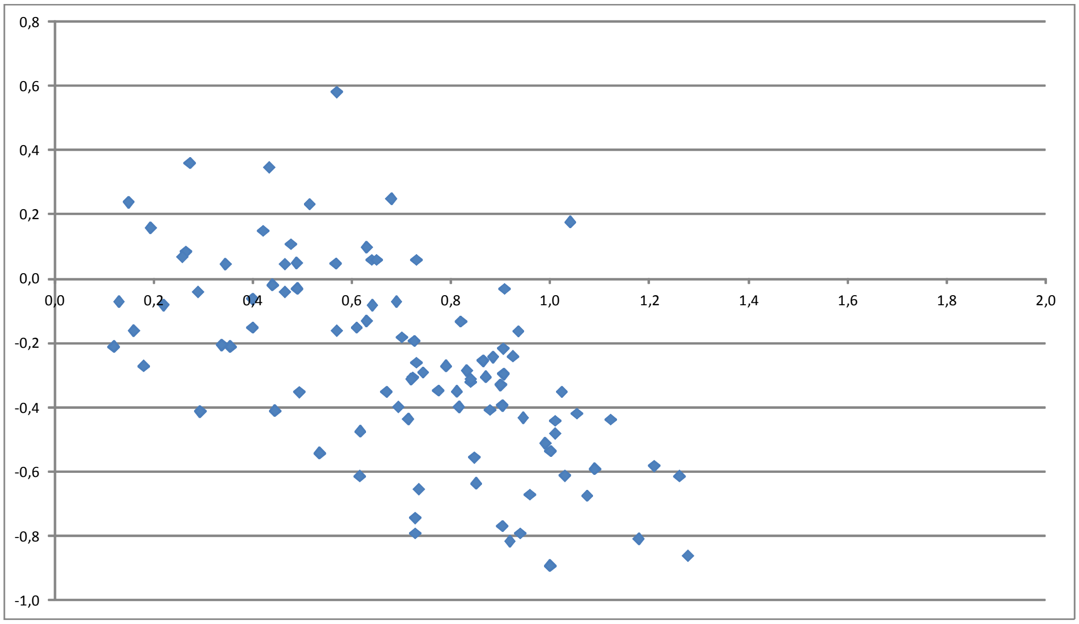

Figure 1: Plot of ϕ_2 (vertical axis) versus ϕ_1 (horizontal axis) showing AR(2) coefficients for each time series in the *ALL* sample.

Data analysis and results

A key issue raised by Boyer *et al.* (2012) is that there may be a wide confidence interval around estimates of any AR(2) cycle period. This is because of the nonlinear relationship seen in equation (3) between τ and the autoregressive parameters ϕ_1 and ϕ_2. The commonly quoted estimates of cycle period are therefore very likely to be obtained by chance. This compromises the very statistical evidence for the presence of cycles. In this section, we apply their insights to the data described in the preceding section.

Proportion of cycles in time series data

Of the 98 regression results in the *ALL* sample listed in Table 1, only 69 are such that we can actually compute a cycle period. Figure 2 illustrates the 98 regression results with square markers representing regression results for which a cycle is absent. The observations represented by diamond-shaped markers are such that the values of ϕ_1 and ϕ_2 allow the calculation of an underwriting cycle period.

Further, if we add the 59 instances of cycles presented by Lamm-Tennant and Weiss (1997), out of the 96 regressions they conducted (12 countries, 8 lines of business), the proportion of instances where a cycle is reported is $128/194 = 66\%$, as can be seen under the column labelled *Combined* in Table 2. Now, some of these series may be partially correlated, either because of overlaps and coincident time periods, or because of the dependence of insurance product lines. Nevertheless, the conventional view, stemming from the studies

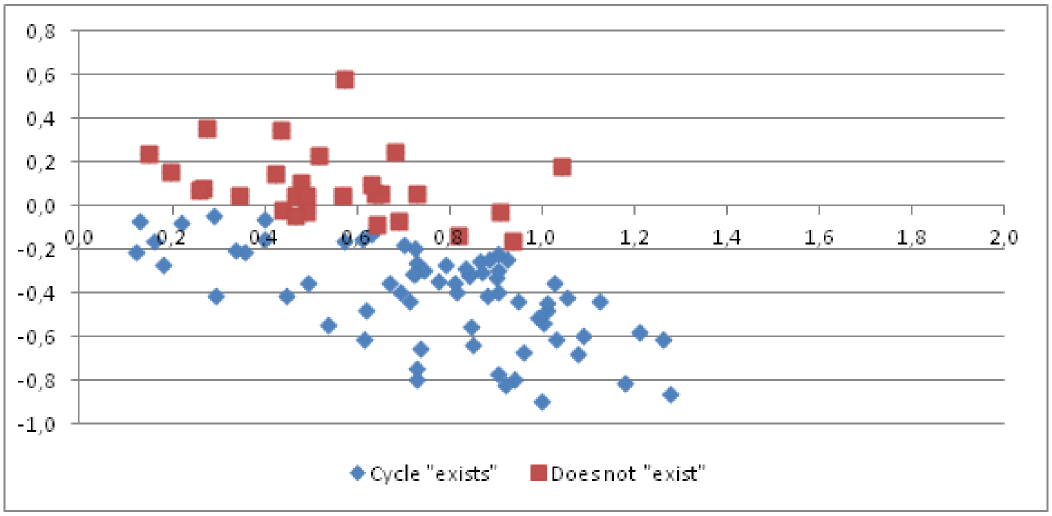

Figure 2: Plot of ϕ_2 (vertical axis) versus ϕ_1 (horizontal axis) showing AR(2) coefficients for each time series in the *ALL* sample. A cycle period cannot be computed for the observations displayed using square markers.

summarised in Table 2, seems to be that insurance cycles are very likely to exist. Is there a 66% likelihood of observing a cycle and, if so, how significant is the 66% likelihood?

A Monte Carlo thought experiment

Consider an AR(2) process in the mould of equation (1). If and only if it is covariance-stationary, then the roots of the characteristic equation $\Phi(z) = 0$ lie outside the centered unit circle on the complex plane. This in turn means that ϕ_1 and ϕ_2 lie on a "stationarity triangle" with vertices at $(-2, -1)$, $(2, -1)$ and $(0, 1)$ on the ϕ_1–ϕ_2 plane (Stralkowski, 1968; Zellner, 1971; Sargent, 1986; Hamilton, 1994).[2] Formally, define the stationarity triangle as the domain

$$\mathcal{D}_0 \;=\; \{(\phi_1, \phi_2) \in \mathbb{R}^2 \,|\, \phi_2 > -1,\, \phi_1 + \phi_2 < 1,\, \phi_2 - \phi_1 < 1\}. \tag{4}$$

As stated in the vicinity of equation (3), cycles occur provided that $\phi_1^2 + 4\phi_2 < 0$, so another domain in the parameter space which is of interest is

$$\mathcal{D}_1 \;=\; \{(\phi_1, \phi_2) \in \mathbb{R}^2 \,|\, \phi_1^2 + 4\phi_2 < 0\}. \tag{5}$$

Suppose that we draw values for (ϕ_1, ϕ_2) randomly and independently from a bivariate uniform distribution on the stationarity triangle $\mathcal{D}_1$. The probability of observing a cycle in an AR(2) process, given that the process is stationary, is equal to the area of $\mathcal{D}_0 \cap \mathcal{D}_1$ normalized by the area of $\mathcal{D}_1$. In other words, it is equal to the area under the parabola $\phi_1^2 + 4\phi_2 = 0$ and above the base of the stationarity triangle, divided by the area of the stationarity triangle. That is, the probability is $\frac{1}{4}\left(4 - \int_{-2}^{2} \frac{1}{4} u^2 du\right) \;=\; 2/3$.

[2] Note that there is a typographical error in the stationarity conditions in Boyer *et al.* (2012).

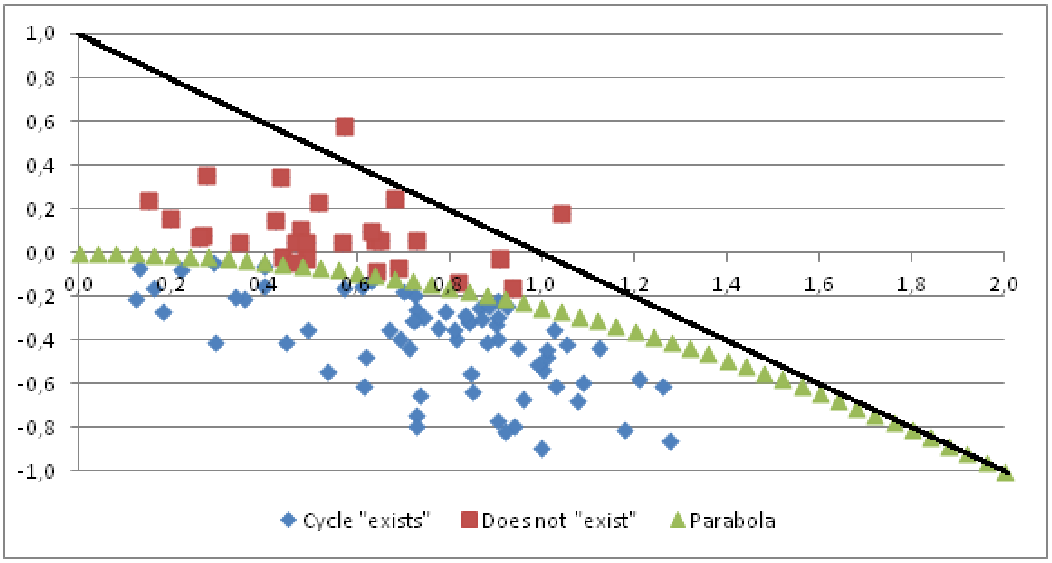

Figure 3: Plot of ϕ_2 (vertical axis) versus ϕ_1 (horizontal axis) showing AR(2) coefficients for each time series in the *ALL* sample. A cycle period cannot be computed for the observations displayed using square markers because they lie above the parabola. The straight line represents the upper right limit of the stationarity triangle.

It is striking that the proportion (66%) of observations where cycles are observed in the *Combined* set in Table 2 is almost equal to the probability (2/3) of cycles occurring from randomly constructed stationary AR(2) processes. Admittedly, the 194 insurance time series in the *Combined* set do not constitute an independent and identically distributed sample, despite diversification across countries, periods and lines of business. At the very least, this shows that caution is required before inferring from the existing insurance cycle studies that cycles are very likely to occur.

Before proceeding further, it is worth noting that, in all the regressions from which our data is pooled, the authors of these studies have estimated the ϕ_1 parameter to be positive (see Table 1).[3] This is equivalent to conditioning on persistence (i.e. a positive lag-one autocorrelation) in addition to stationarity, in our Monte-Carlo thought experiment above. This means that we may sample from the right-half of the stationarity triangle (rather than all of it), i.e. over the domain

$$\mathcal{D}_2 \;=\; \{(\phi_1, \phi_2) \in \mathbb{R}^2 \mid \phi_1 > 0,\, \phi_2 > -1,\, \phi_1 + \phi_2 < 1\}. \tag{6}$$

Symmetry means that the same probability of 2/3 for cycles ensues again.[4]

[3] Correlograms of insurance profitability measures tend to decay quickly, sometimes with oscillations, conforming to stationarity. Rapid 'switching behavior' in the autocorrelation function $\{\rho_k, k \in \mathbb{Z}_+\}$, whereby $\text{sgn}(\rho_k) = (-1)^k$, would signal a negative value of ϕ_1 (see also Hamilton, 1994), but this is not visible in sample correlograms. (Here, sgn denotes the sign function: $\text{sgn}(x) = +1$ for $x > 0$, and -1 for $x < 0$.)

[4] It follows from the stationarity of an AR(2) process that $|\phi_2| < 1$, i.e. $(\phi_1, \phi_2) \in \mathcal{D}_0 \Rightarrow |\phi_2| < 1$. The lag-one autocorrelation

Distribution of cycle periods

We now consider the distribution of cycle periods in our metadata. Boyer *et al.* (2012) show, by means of stochastic simulations, that randomly chosen values of ϕ_1 and ϕ_2 generate a right-skewed distribution for τ. As may be seen in Table 2, all three key samples, labelled *ALL*, *LTW* and *Combined*, are also positively skewed. Furthermore, both the Jarque-Bera test and the non-parametric Kolmogorov-Smirnov normality test reject the hypothesis of normality, at the 95% level of confidence, in the distribution of cycle periods in *ALL*, *LTW* and *Combined*. (There are three smaller subsamples in Table 2, to be defined and explained later, where normality cannot be rejected, at the 95% confidence level, even using the small-sample Shapiro-Wilk test.)

In order to investigate this further, we repeat and extend the stochastic simulations of Boyer *et al.* (2012). Values for (ϕ_1, ϕ_2) are simulated from a bivariate uniform distribution over the right-half of the stationarity triangle, i.e. over domain $\mathcal{D}_2$. More specifically, 700 series of 200 random draws of (ϕ_1, ϕ_2) are simulated. The *Random* column of Table 2 displays the cycle length statistics, conditional on cycles being present. Using the same 140,000 simulated values of ϕ_1 and ϕ_2, the last column (*Trunc.*) of Table 2 shows the statistics obtained when the longest cycle in the *Random* sample is limited to 30 years. Thirty years is the maximum cycle period that is observed in the first six columns of Table 2: see the fifth row from the bottom, labelled 'Longest cycle', in Table 2. *Trunc.* may therefore be regarded as a realistic, truncated subsample of *Random*, where 'impractical' values of ϕ_1 and ϕ_2 lying towards the edges of domain $\mathcal{D}_2$ are eliminated.

Boyer *et al.* (2012) paid no heed to actual data when describing the distribution of cycle periods. We can now compare the cycle period statistics in the actual data (*ALL*, *LTW*, *Combined*) with those in the simulated data (*Random*, *Trunc.*) in Table 2. We note, in particular, the closeness of the first two moments and of the median, when comparing across these five samples. For instance, the mean of the cycle period in the *Combined* sample (7.62 years) is not statistically different from the mean of the cycle period in the *Trunc.* sample (7.50 years). Notice also that the *Trunc.* sample retains positive skewness in the cycle period distribution (and indeed fails the Jarque-Bera test for normality) even though impractical and unrealistic values of ϕ_1 and ϕ_2 in the outskirts of domain $\mathcal{D}_2$ have been discarded.

This would all seem to support the case made by Boyer *et al.* (2012) that the evidence for cycles gathered in various studies may be spurious, and that the estimates of cycle lengths is subject to large chance variations.

Finally, we carry out a basic verification. All the data time series in samples *ALL*, *LTW* and *Combined* have an estimated value of ϕ_1 which is positive. The simulated samples *Random* and *Trunc.* also satisfy this positive condition on ϕ_1. (Recall that the simulations are carried out on domain $\mathcal{D}_2$, by design.) Now,

is $\rho_1 = \phi_1/(1-\phi_2) > 0$. Hence, for a stationary AR(2) process, $\rho_1 > 0 \Leftrightarrow \phi_1 > 0$. We may therefore constrain our sampling to the half-plane $\phi_1 > 0$ only. Both the stationarity triangle and the parabola $\phi_1^2 + 4\phi_2 = 0$ are symmetrical in $\phi_1 = 0$, yielding the same probability of 2/3 that was obtained above.

a positive ϕ_1 parameter means that cycles cannot occur with a period less than 4 years.[5] The fourth row from the bottom in Table 2 displays the shortest cycle period in various samples: none of these samples has a sample period shorter than 4 years.

Interestingly, the histogram of cycle periods shown in Boyer *et al.* (2012, Fig. 1) is not bounded below by 4 years, because they do not condition on persistence, i.e. they do not assume that $\phi_1 > 0$. Had they done so, their distribution would have displayed a median much closer to actual data, as we have shown here.

Statistical tests

Next, we analyse the significance of the AR(2) parameter estimates in the regressions which are detailed in Table 1 (in the Appendix) and whose cycle statistics are summarised under column *ALL* in Table 2.

Not all the regression results presented in Table 1 have regression coefficients that are significant. In fact, of the 98 regression results under study, only 30 actually have ϕ_1 and ϕ_2 coefficients that are both significantly different from zero.[6] In other words, more than half of the regressions where a cycle has been presumed to exist are subject to important errors in variable problems. Another interesting observation is that the real test one should conduct is not for the ϕ_1 and ϕ_2 coefficients to be different from zero, but to be different from the parabola that delimits the existence or not of a cycle. Surprisingly, no one in the literature has conducted a joint significance test on the two parameters of interest. Therefore, our formal hypothesis test is:

$$\begin{aligned} \mathrm{H}\emptyset: &\quad (\phi_1, \phi_2) \notin \mathcal{D}_1 \qquad \text{(absence of AR(2) cycle)} \\ \mathrm{H1}: &\quad (\phi_1, \phi_2) \in \mathcal{D}_1 \qquad \text{(presence of AR(2) cycle)} \end{aligned}$$

Using a Bonferroni test (see Abdi, 2007) or a Student test reduces even more the likelihood that a cycle is observed. The Bonferroni test is a simple conservative joint estimation test whereby if there are two parameters of interest in a regression, then the Bonferroni p-value of the joint test is equal to twice the highest p-value. For example, if the two coefficients have individual p-values of 1% and 3%, the combined p-value is $2 \times \max[1\%, 3\%] = 6\%$. The Student statistic is computed as $(\phi_1 + 4\phi_2) / \sqrt{(se_1)^2 + (4se_2)^2}$, where se_1 and se_2 denote the standard errors in the estimates of ϕ_1 and ϕ_2 respectively, and where the covariance between these estimates is assumed to be zero[7]. It is important to note that neither test is precise: the Bonferroni test by design, and the Student test by absence of data, since the covariances of the parameter estimates are not provided by the authors of the studies whence our data is sourced.

[5] Assuming $\phi_1 > 0$ and that we take only the positive value of $\sqrt{-\phi_2}$ in equation (3), then τ is bounded below at 4, since $\arccos\left(\phi_1/2\sqrt{-\phi_2}\right) \to \pi/2$ and $\tau \to 4^+$, as $\phi_1 \to 0^+$.

[6] Of the 19 observations where ϕ_2 is positive, only 2 are statistically so. In neither case is the corresponding ϕ_1 coefficient statistically different from zero.

[7] The proper test is actually $(\phi_1 + 4\phi_2) / \sqrt{(se_1)^2 + (4se_2)^2 + Cov\,(se_1, 4se_2)}$, but since we do not have the covariance between the two regressor estimates, we need to suppose that $Cov\,(se_1, 4se_2) = 0$.

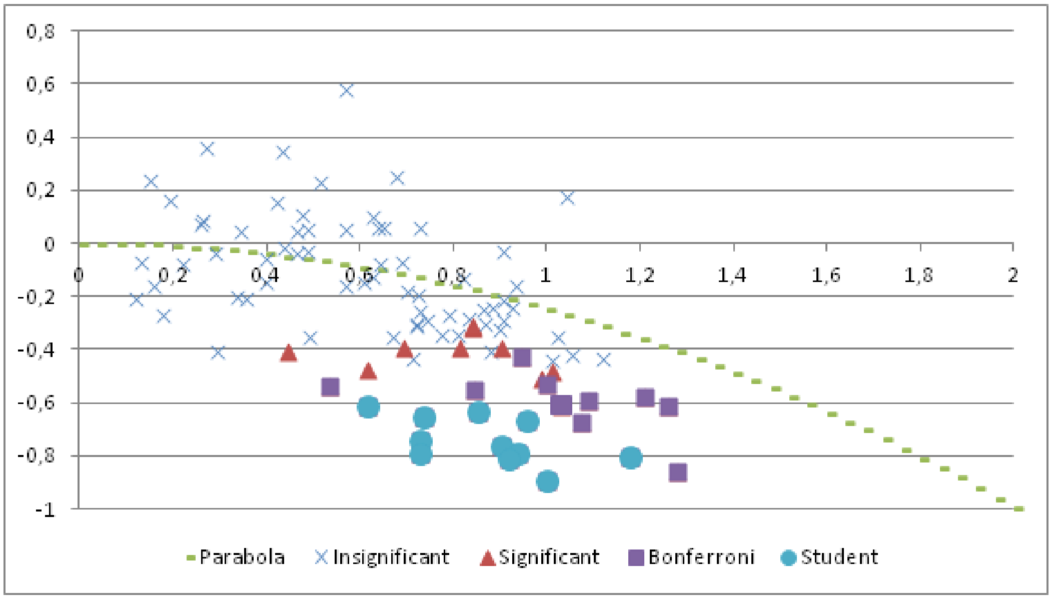

Figure 4: Plot of ϕ_2 (vertical axis) versus ϕ_1 (horizontal axis) showing AR(2) coefficients for each time series in the *ALL* sample. Different levels of test significance are reported using different markers. 'Insignificant' means that either ϕ_1 or ϕ_2 is not significantly different from zero. The other three measures are relative to the parameter values on the parabola which delineates whether a cycle period can be computed or not: 'Significant' means that ϕ_1 and ϕ_2 are significantly different from zero but not different from the parabola, whereas 'Bonferroni' and 'Student' mean that ϕ_1 and ϕ_2 pass the eponymous tests (the Student test being more stringent than the Bonferroni test).

Figure 4 highlights the correspondence of parameter values between observations where at least one parameter is statistically different from zero (*Insignificant*), the 30 observations (*Significant*) whereby both parameters are statistically different from zero but do not pass the Bonferroni test, the 21 observations (*Bonferroni*) whereby the parameters pass the Bonferroni test but not the Student test, and finally the 11 observations (*Student*) which pass all tests, including the most stringent Student test.[8]

If one focuses only on the observations which pass the Bonferroni test, there are merely 21 observations whereby it would be reasonable to believe that a cycle exists out of the 98 original observations. This represents a success ratio of 22%. From these 21 observations, one calculates an average cycle period of 6.9 years (median of 6.5 years) and a standard deviation of 1.3 years. See the column with the heading "*Bonf.*" in Table 2 for these and related statistics. Comparing columns "*Bonf.*" and "*Trunc.*" in Table 2, the average cycle period (6.9 years) in the subsample which passes the Bonferroni test is shorter than the mean (7.5 years) of the randomly obtained cycle periods calculated using an independent and uniform distribution of ϕ_1 and ϕ_2 when restricting to cycles of less than 30 years.

[8] Incidentally, only 6 out of the 20 observations in Cummins and Outreville (1987) pass the Bonferroni test, 8 out of 12 in Venezian (1985), 2 out of 25 in Chen *et al.* (1999) and 3 out of 6 in Harrington and Niehaus (2000). None of the observations in Meier (2006a, b) passes the Bonferroni test.

Using the Student test as the appropriate statistic, only 11% of the data points display coefficient values that are consistent with a cycle. Table 2, column *Stud.*, contains the relevant statistics. The mean and median cycle period then become approximately 6 years with a very small standard deviation of 0.6 years. Interestingly, 6 years is the median cycle period for both the *Random* and *Stud.* samples in Table 2.

Discussion of results

In the preceding section, we have sought to show that the evidence for insurance cycles, based on the authoritative established studies to date, is weak. In this section, we discuss various issues related to our analysis.

Admissible area

We showed that randomly constructed stationary AR(2) processes yield cycles almost as often as cycles appear in the studies on which we base our meta-analysis (with a probability of 2/3). This was based on sampling from the area under the parabola but within the stationarity triangle, when drawing randomly and uniformly over the whole of the stationarity triangle: see Figure 5, based on Stralkowski (1968) and replicated in Sargent (1987 , p. 189) and Hamilton (1994, p. 17). We also showed that, conditioning on persistence (or positive autocorrelation at lag one) as well as on stationarity, resulted in the same probability of 2/3.

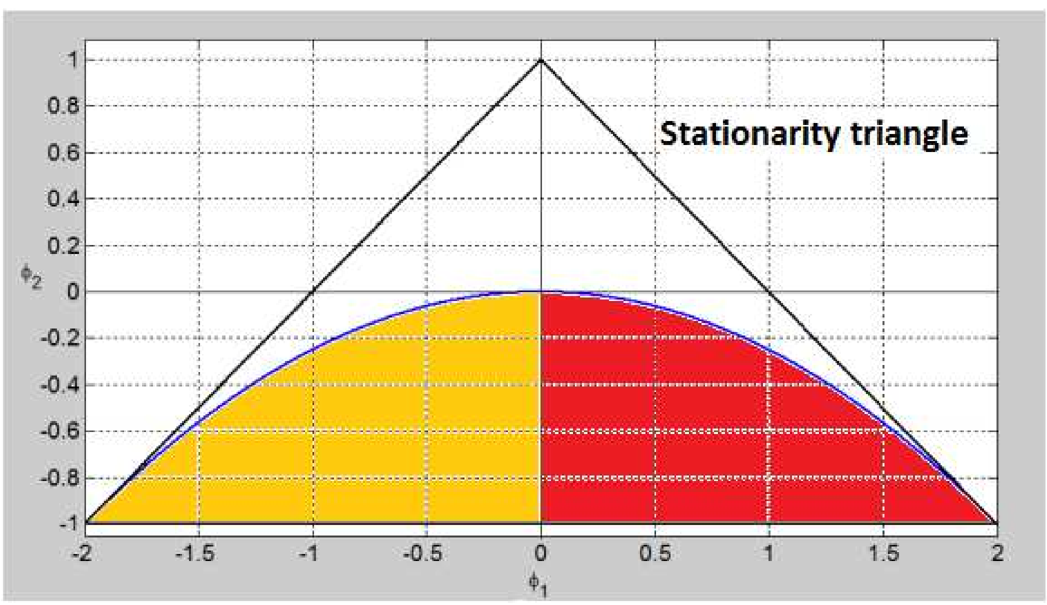

Figure 5: Stationarity triangle and cycle parabola in an AR(2) regression.

An argument may be made that it is the probability of finding both cycles and persistence, conditioned on stationarity, which should be of interest. A moment's thought reveals that this probability is 1/3, a figure lower than the 66% occurrence of cycles in the *Combined* data of Table 2, and hence suggestive of evidence for joint cyclicality and persistence. One could counter, however, that persistence is not in question—it has perhaps fewer ramifications for risk management than cyclicality—so that this is not the right metric by which to settle the insurance cycle debate.

An alternative argument is that one should not condition on stationarity at all, but on a wider acceptable domain for the AR(2) parameter space, such as one might find in practical time series modelling. One such domain might be $\mathcal{D}_3 = \{(\phi_1, \phi_2) \in \mathbb{R}^2 \mid \phi_1 \in [-2, 2],\ \phi_2 \in [-1, 1]\}$. The probability of finding both cycles and persistence, conditioned on this 'reasonable' econometric structure, then falls to 1/6. This makes the proportion of 66% of cycles in the *Combined* data of Table 2 appear even more persuasive in favour of cyclicality. Disregarding stationarity may be attractive given that the cointegrated relationships found by Haley (1993), Grace and Hotchkiss (1995) and Choi, Hardigree and Thistle (2002) are founded on individually nonstationary series (see the second section of this paper). On the other hand, Harrington and Yu (2003) find little evidence of unit roots in de-trended profits data, calling into question these cointegrated relationships. Indeed, all but two data points in Figure 3 are located inside the stationarity triangle.

Linearity

We assumed in our analysis that insurance cycles may be described by linear time series, specifically second-order autoregressive processes. In this, we implicitly follow much of the time series literature on insurance cycles. However, insurance cycle theories—reviewed in an earlier section—are not predicated on AR(2) cycles. Arguably, the capital constraint theory of Winter (1994) and Gron (1994a, b), the underpricing hypothesis of Harrington and Danzon (1994), and the financial quality hypothesis of Cummins and Danzon (1997) can explain the asymmetry that is typically observed in the evolution of hard and soft markets. This asymmetry is antithetical to the linearity of autoregressive processes.

More recent work by Wang *et al.* (2010) and Jawadi *et al.* (2009) shows that nonlinear regimes and breaks may provide a better description of insurance profitability data. The pragmatic view of insurance practitioners, who do not necessarily ascribe an AR(2) character to insurance cycles, cannot be dismissed. It is imperative, therefore, to examine the existence of cycles outside the framework of linearity. If cycles do indeed exist in these nonlinear models, then the conventionally accepted estimates of cycle periods—based on autoregressive cycles—may need to be revised. This has important implications for risk management.

Heterogeneity and dependence

The existing studies incorporated in our meta-analysis span several decades, several product lines, and several countries, and report different profitability measures. The commercial and regulatory environment has changed over time, and varies by line of business and by country. Pooling the regression results from so many separate studies may therefore be inconsistent. In particular, stronger evidence of cycles on some lines or at certain periods may be diluted.[9] We stress that we do not pool or combine the data sets themselves, however. The regression results remain discrete, and we examine them separately for significance. Our meta-analysis seeks to capture the overall and cumulative impact of several highly-respected studies.

Any heterogeneity in the data also mitigates against dependence. In other words, whilst one may argue that there is an inevitable degree of overlap between the data which we collate, the diversity across countries, periods and lines supports our comparison with randomly constructed autoregressive processes. Indeed the plot in Figure 1 shows a widespread scatter with little discernable pattern. Nevertheless, it is difficult to argue that there is no commonality in the samples, and they are not independent of each other and identically distributed. In particular, dependence may result from the global nature of the insurance and reinsurance business.

The issue of dependence cuts both ways, however. The profusion of studies claiming both evidence for cycles and estimates for the cycle periods may have led economists and professionals to accept the existence of cycles, without necessarily questioning the dependence in the data.

Conclusion: are underwriting cycles really cryptids?

The purpose of this short article was to offer a challenge to the popular view that the property and casualty insurance industry is characterized by profitability cycles akin to real business cycles in the economy. We performed a meta-analysis of several studies in this field, these studies being arguably the most influential in the insurance economics literature on underwriting cycles. The papers which we used are certainly well-respected and authoritative. They also span different lines of insurance, different countries, different samples, different time frames, and different second-order autoregressive specifications.

The main conclusion of this paper is that the existence of underwriting cycles is far from obvious. The standard error on parameter estimates in many of these studies is large enough that the presence of cycles is not statistically significant. When a proper statistical test on the AR(2) regression parameter values is conducted (a Bonferroni test to be exact, or a more stringent Student test), we find that a cycle is likely to be observed in less than a quarter of the studies on the topic.

This is far from the 65% to 70% likelihood that is generally presented in the literature. This generally reported probability range is, in fact, close to the probability of finding a cycle by drawing the two AR(2) parameters randomly from a uniform distribution. The success rate for the existence of cycles in the data is therefore commensurate with the probability of cycles occurring in appropriate statistical processes with randomly chosen parameter values.

Of course, our analysis is based on regression results that have already been published in the literature, without verifying directly the validity of these regressions. Also, we used only a subset of the results that

[9] The authors wish to thank an anonymous reviewer for raising this issue.

may be found in the insurance economics literature. Only rigorous and peer-reviewed studies, which provided estimates of the standard errors of the AR(2) regression parameters, were included in our meta-analysis.

Insurance profitability cycles may of course exist in some lines, countries and for some time periods. However, the evidence is that they are not of the predictable linear autoregressive character that is ascribed to them. And even if there are instances where the absence of a cycle can be rejected, there is no evidence whatsoever that the trend superposed on the cycle is predictable (see Boyer *et al.*, 2012, for more on this topic). This means that those insurers which "have simply accepted the insurance cycle, seeing it as a force of nature with an uncontrollable impact on their business"[10] may have been justified. Insurance cycles may simply be a 'force of nature' akin to capital market cycles[11] which uncontrollably buffet a pension plan.

The belief that predictable underwriting cycles exist leads to the perception that the insurance market is plagued with imperfections. The supposed presence of underwriting cycles can then become the basis for government intervention (Gron, 2010), or can become part of financial stability regulation to control insolvency (European Commission, 2002), even though solvency regulation may actually exacerbate cycles (Winter, 1991). Perhaps we would be wise to heed the conclusion of Baker (2005) who argues that "leaving the insurance cycle alone would be the wiser course for now".

[10] Lloyd's (2006). Annual Report - Strategy.
http://www.lloyds.com/Lloyds/Press-Centre/Press-Releases/2006/12/Seven_steps_to_managing_the_cycle}

[11] Using monthly data, we calculate a cycle period of 4.69 months for total returns on the S&P500 from April 1993 to June 2012 (or 7.22 years when using yearly total returns over the same period), a cycle of 4.15 months for the total returns on the FTSE100 from July 1984 to June 2012, and a cycle of 4.16 months for the total return on the 30-year Treasury bond from May 1977 to June 2012.

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Appendix

Table 2. Summary statistics of cycles in the different samples and subsamples

	Combined	SE available *ALL*	*Signif.*	*Bonf.*	*Stud.*	*LTW*	*Random*	*Trunc.*
Total observations	194	98	98	98	98	96	700*200	140,000
Number with cycles	128	69	30	21	11	59		91000
Proportion with cycles	66%	70%	31%	22%	11%	61%	66% (3%)	65%
Mean period	7.62	8.11	7.03	6.89	6.08	7.05	8.6 (1.2)	7.50
Median period	6.90	7.70	6.95	6.51	6.11	6.15	6.0 (0.3)	5.95
St.Dev. of period	3.37	3.51	1.31	1.32	0.57	3.12	9.8 (9)	4.25
Skewness of period	3.08	3.33	0.43	0.89	0.94	2.89	5 (2.2)	2.3
Kurtosis of period	13.83	16.44	-0.66	0.28	1.24	10.54	35 (30)	6.1
Longest period	28.40	28.40	9.92	9.92	7.35	21.97	10,000	30
Shortest period	4.09	4.36	5.17	5.24	5.39	4.09	4	4
Gaussian (JB-test)	Fail	Fail	Pass	Pass	Pass	Fail	Fail	Fail
Gaussian (KS-test)	Fail	Fail	Pass	Pass	Pass	Fail		
Gaussian (SW-test)			Pass	Pass	Pass			

LTW refers to the results from Lamm-Tennant and Weiss (1997).

'SE available' refers to those studies where the standard errors of the two AR(2) regression coefficients are available. *ALL* uses all the data points; *Signif.* uses all data points where the two coefficients are significantly different from zero; *Bonf.* uses the data points where the two coefficients pass the Bonferroni test, and *Stud.* uses the data points where the two coefficients pass the Student test. *Combined* combines the 98 observations where standard errors are available with the 96 observations presented in Lamm-Tennant and Weiss (1997).

Random and *Trunc.* refer to the case where ϕ_1 and ϕ_2 were each randomly drawn from a uniform distribution. The values under the *Random* column are the average values for each statistical moment using 700 series of 200 draws with the standard deviation in parentheses. The values under the *Trunc.* column were obtain using the same 140,000 draws, but limiting the maximum period to 30 years.

The Jarque-Bera test examines whether the observation are distributed normally based on the observed skewness and kurtosis. The JB statistic is given by $JB = \frac{n}{6}\left(S^2 + \frac{(K-3)^2}{4}\right)$, with n being the number of observations and S and K being the third and fourth moment of the empirical distribution (not the kurtosis which is the fourth central moment from which we substract $\frac{3(n-1)^2}{(n-2)(n-3)}$). The JB statistic follows a $Chi2$ distribution with two degrees of freedom.

The Kolmogorov-Smirnov test of normality is valid only for a number of observations between 10 and 1024. We present the 5% test here so that we cannot reject the normality distribution assumption with a 95% confidence interval.

The Shapiro-Wilk test of normality is valid only for a small number of observations (between 5 and 38). We present the 5% test here so that we cannot reject the normality distribution assumption with a 95% confidence interval.

Table 1. Source of the AR(2) results in the literature on P&C insurance underwriting cycles and value of the coefficient and its standard deviation

Source	Type of test	Specific regression	Φ_2	SD(Φ_2)	Φ_1	SD(Φ_1)
Cummins Outreville (T2)	t-stat(23, 5%, two-tail)=2,069	Canada	**-0,635**	0,169	**0,851**	0,170
Cummins Outreville (T2)	t-stat(23, 5%, two-tail)=2,069	France	**-0,431**	0,165	**0,946**	0,197
Cummins Outreville (T2)	t-stat(23, 5%, two-tail)=2,069	Italy	**-0,612**	0,152	**1,261**	0,166
Cummins Outreville (T2)	t-stat(23, 5%, two-tail)=2,069	Sweden	**-0,397**	0,190	**0,816**	0,216
Cummins Outreville (T2)	t-stat(23, 5%, two-tail)=2,069	Suisse	**-0,409**	0,182	**0,445**	0,201
Cummins Outreville (T2)	t-stat(23, 5%, two-tail)=2,069	U.S.	**-0,653**	0,140	**0,735**	0,153
Cummins Outreville (T1)	t-stat(23, 5%, two-tail)=2,069	Australia	**-0,411**	0,212	0,294	0,209
Cummins Outreville (T1)	t-stat(23, 5%, two-tail)=2,069	Canada	**-0,670**	0,161	**0,959**	0,159
Cummins Outreville (T1)	t-stat(23, 5%, two-tail)=2,069	Denmark	0,109	0,229	**0,477**	0,230
Cummins Outreville (T1)	t-stat(23, 5%, two-tail)=2,069	Finland	-0,029	0,213	**0,490**	0,227
Cummins Outreville (T1)	t-stat(23, 5%, two-tail)=2,069	France	**-0,392**	0,166	**0,904**	0,202
Cummins Outreville (T1)	t-stat(23, 5%, two-tail)=2,069	Germany	-0,406	0,209	**0,879**	0,207
Cummins Outreville (T1)	t-stat(23, 5%, two-tail)=2,069	Italy (1)	-0,253	0,181	**0,865**	0,181
Cummins Outreville (T1)	t-stat(20, 5%, two-tail)=2,086	Italy (2)	-0,346	0,206	**0,775**	0,223
Cummins Outreville (T1)	t-stat(23, 5%, two-tail)=2,069	Japan	-0,349	0,173	**0,812**	0,177
Cummins Outreville (T1)	t-stat(23, 5%, two-tail)=2,069	NewZealand	**-0,397**	0,199	**0,694**	0,208
Cummins Outreville (T1)	t-stat(23, 5%, two-tail)=2,069	Norway	0,233	0,217	**0,515**	0,222
Cummins Outreville (T1)	t-stat(23, 5%, two-tail)=2,069	Sweden	-0,434	0,229	**0,714**	0,211
Cummins Outreville (T1)	t-stat(23, 5%, two-tail)=2,069	Suisse	-0,210	0,225	**0,355**	0,220
Cummins Outreville (T1)	t-stat(23, 5%, two-tail)=2,069	U.S.	**-0,767**	0,129	**0,904**	0,132

The numbers in bold are those that are statistically different from zero using the appropriate test.

Table 1. Source of the AR(2) results in the literature on P&C insurance underwriting cycles and value of the coefficient and its standard deviation (cont'd)						
Source	**Type of test**	**Specific regression**	**Φ_2**	**SD(Φ_2)**	**Φ_1**	**SD(Φ_1)**
Harrington Niehaus	t-stat(25, 5%, two-tail)=2,060	U.S. 5579 (with trend)	**-0,790**	0,142	**0,940**	0,132
Harrington Niehaus	t-stat(25, 5%, two-tail)=2,060	U.S. 6084 (with trend)	**-0,580**	0,229	**1,210**	0,201
Harrington Niehaus	t-stat(25, 5%, two-tail)=2,060	U.S.6589 (with trend)	**-0,590**	0,199	**1,090**	0,172
Harrington Niehaus	t-stat(25, 5%, two-tail)=2,060	U.S. 7094 (with trend)	-0,260	0,167	**0,730**	0,155
Harrington Niehaus	t-stat(40, 5%, two-tail)=2,021	U.S. 5594 (with trend)	**-0,320**	0,144	**0,840**	0,132
Harrington Niehaus	t-stat(42, 5%, two-tail)=2,020	U.S. 5596 (with trend)	**-0,310**	0,134	**0,840**	0,129
Chen et al. (app)	** et *** in Chen paper	Singapore All	-0,290	0,232	**0,744**	**0,222**
Chen et al. (app)	** et *** in Chen paper	Singapore MAT	-0,018	0,257	**0,440**	**0,249**
Chen et al. (app)	** et *** in Chen paper	Singapore Fire	0,086	0,166	0,265	0,227
Chen et al. (app)	** et *** in Chen paper	Singapore Motor	**-0,534**	0,190	**1,001**	**0,191**
Chen et al. (app)	** et *** in Chen paper	Singapore Oth	-0,132	0,167	**0,820**	**0,163**
Chen et al. (app)	** et *** in Chen paper	Malaysia All	-0,350	0,252	**1,024**	**0,221**
Chen et al. (app)	** et *** in Chen paper	Malaysia MAT	0,160	0,209	0,194	0,212
Chen et al. (app)	** et *** in Chen paper	Malaysia Fire	-0,061	0,203	**0,400**	**0,222**
Chen et al. (app)	** et *** in Chen paper	Malaysia Motor	0,070	0,222	0,258	0,223
Chen et al. (app)	** et *** in Chen paper	Malaysia Oth	0,582	1,039	**0,570**	**0,222**
Chen et al. (app)	** et *** in Chen paper	South Korea All	0,348	0,206	**0,433**	**0,220**
Chen et al. (app)	** et *** in Chen paper	South Korea MAT	0,151	0,240	**0,421**	**0,239**
Chen et al. (app)	** et *** in Chen paper	South Korea Fire	-0,204	0,180	0,338	0,205
Chen et al. (app)	** et *** in Chen paper	South Korea Motor	-0,039	0,195	**0,465**	**0,198**
The numbers in bold are those that are statistically different from zero using the appropriate test.						

Table 1. Source of the AR(2) results in the literature on P&C insurance underwriting cycles and value of the coefficient and its standard deviation (cont'd)						
Source	**Type of test**	**Specific regression**	**Φ_2**	**SD(Φ_2)**	**Φ_1**	**SD(Φ_1)**
Chen et al. (app)	** et *** in Chen paper	South Korea Oth	0,178	-0,233	**1,041**	**0,230**
Chen et al. (app)	** et *** in Chen paper	Taiwan All	0,049	-0,211	**0,568**	**0,224**
Chen et al. (app)	** et *** in Chen paper	Taiwan MAT	**0,361**	0,175	0,273	0,176
Chen et al. (app)	** et *** in Chen paper	Taiwan Fire	**0,044**	0,017	-0,019	0,186
Chen et al. (app)	** et *** in Chen paper	Taiwan Motor	**-0,351**	0,182	**0,494**	**0,189**
Chen et al. (app)	** et *** in Chen paper	Taiwan Oth	0,047	0,218	0,345	0,217
Chen et al. (app)	** et *** in Chen paper	Japan All	-0,242	0,222	**0,885**	**0,217**
Chen et al. (app)	** et *** in Chen paper	Japan MAT	**-0,673**	0,232	**1,075**	**0,232**
Chen et al. (app)	** et *** in Chen paper	Japan Fire	-0,306	0,247	**0,723**	**0,245**
Chen et al. (app)	** et *** in Chen paper	Japan Motor	**-0,807**	0,164	**1,179**	**0,163**
Chen et al. (app)	** et *** in Chen paper	Japan Oth	-0,162	0,285	**0,936**	**0,253**
Meier (1) (T1)	t-stat(41, 5%, two-tail)=2,021	Switzerland	-0,192	0,167	**0,726**	**0,160**
Meier (1) (T1)	t-stat(41, 5%, two-tail)=2,021	US(1)	-0,328	0,171	**0,900**	**0,167**
Meier (1) (T1)	t-stat(41, 5%, two-tail)=2,021	US(2)	-0,294	0,170	**0,906**	**0,166**
Meier (1) (T1)	t-stat(28, 5%, two-tail)=2,048	Japan	-0,240	0,194	**0,925**	**0,197**
Meier (1) (T1)	t-stat(31, 5%, two-tail)=2,042	Germany	-0,180	0,188	**0,701**	**0,189**
Meier (2) (T2)	t-stat(37, 5%, two-tail)=2,022	Suisse	-0,160	0,193	0,570	0,186
Meier (2) (T2)	t-stat(37, 5%, two-tail)=2,022	U.S.	-0,350	0,229	0,670	0,169
Meier (2) (T2)	t-stat(27, 5%, two-tail)=2,052	Japan	0,060	0,250	0,730	0,203
Meier (2) (T4)	t-stat(36, 5%, two-tail)=2,022	Switzerland	-0,070	0,212	**0,690**	**0,197**
The numbers in bold are those that are statistically different from zero using the appropriate test.						

Table 1. Source of the AR(2) results in the literature on P&C insurance underwriting cycles and value of the coefficient and its standard deviation (cont'd)

Source	Type of test	Specific regression	Φ_2	SD(Φ_2)	Φ_1	SD(Φ_1)
Meier (2) (T4)	t-stat(36, 5%, two-tail)=2,022	U.S.	-0,270	0,186	**0,790**	**0,178**
Meier (2) (T4)	t-stat(26, 5%, two-tail)=2,056	Japan	0,250	0,269	**0,680**	**0,215**
Meier Outreville (T3)	t-stat(20, 5%, two-tail)=2,086	France	-0,270	0,250	0,180	0,261
Meier Outreville (T3)	t-stat(20, 5%, two-tail)=2,086	Switzerland	**-0,610**	0,223	**1,030**	0,199
Meier Outreville (T3)	t-stat(20, 5%, two-tail)=2,086	Germany (1)	-0,070	0,167	0,130	0,228
Meier Outreville (T3)	t-stat(20, 5%, two-tail)=2,086	Germany (2)	-0,150	0,211	0,400	0,253
Meier Outreville (T4)	t-stat(20, 5%, two-tail)=2,086	France (1)	-0,040	0,222	0,290	0,240
Meier Outreville (T4)	t-stat(20, 5%, two-tail)=2,086	France (2)	-0,080	0,242	0,220	0,259
Meier Outreville (T4)	t-stat(20, 5%, two-tail)=2,086	France (3)	-0,160	0,229	0,160	0,235
Meier Outreville (T4)	t-stat(20, 5%, two-tail)=2,086	France (4)	-0,210	0,239	0,120	0,255
Meier Outreville (T4)	t-stat(20, 5%, two-tail)=2,086	Switzerland (1)	**-0,480**	0,217	**1,010**	0,188
Meier Outreville (T4)	t-stat(20, 5%, two-tail)=2,086	Switzerland (2)	-0,310	0,218	**0,720**	0,224
Meier Outreville (T4)	t-stat(20, 5%, two-tail)=2,086	Switzerland (3)	**-0,510**	0,223	**0,990**	0,191
Meier Outreville (T4)	t-stat(20, 5%, two-tail)=2,086	Switzerland (4)	-0,440	0,232	**1,010**	0,193
Meier Outreville (T4)	t-stat(20, 5%, two-tail)=2,086	Germany (1)	0,060	0,273	**0,640**	0,228
Meier Outreville (T4)	t-stat(20, 5%, two-tail)=2,086	Germany (2)	0,060	0,286	**0,650**	0,269
Meier Outreville (T4)	t-stat(20, 5%, two-tail)=2,086	Germany (3)	0,100	0,286	**0,630**	0,238
Meier Outreville (T4)	t-stat(20, 5%, two-tail)=2,086	Germany (4)	0,240	0,202	0,150	0,217
Meier Outreville (WPA2)		LR(1)	-0,130		0,630	
Meier Outreville (WPA2)		CR(1)	-0,150		0,610	

The numbers in bold are those that are statistically different from zero using the appropriate test.

Table 1. Source of the AR(2) results in the literature on P&C insurance underwriting cycles and value of the coefficient and its standard deviation (cont'd)						
Source	**Type of test**	**Specific regression**	**Φ_2**	**SD(Φ_2)**	**Φ_1**	**SD(Φ_1)**
Venezian	t-stat(15, 5%, two-tail)=2,131	Fire	**-0,554**	0,210	**0,847**	0,209
Venezian	t-stat(15, 5%, two-tail)=2,131	HMP	**-0,742**	0,186	**0,728**	0,189
Venezian	t-stat(15, 5%, two-tail)=2,131	CMP	**-0,473**	0,220	**0,617**	0,226
Venezian	t-stat(15, 5%, two-tail)=2,131	OM	-0,284	0,249	**0,832**	0,249
Venezian	t-stat(15, 5%, two-tail)=2,131	IM	**-0,860**	0,279	**1,278**	0,272
Venezian	t-stat(15, 5%, two-tail)=2,131	WC	-0,436	0,251	**1,122**	0,246
Venezian	t-stat(15, 5%, two-tail)=2,131	NBIL	-0,418	0,247	**1,054**	0,236
Venezian	t-stat(15, 5%, two-tail)=2,131	ABIL	**-0,891**	0,185	**1,000**	0,176
Venezian	t-stat(15, 5%, two-tail)=2,131	APDL	**-0,541**	0,206	**0,535**	0,213
Venezian	t-stat(15, 5%, two-tail)=2,131	COLL	**-0,612**	0,195	**0,616**	0,200
Venezian	t-stat(15, 5%, two-tail)=2,131	FTC	**-0,790**	0,154	**0,728**	0,154
Venezian	t-stat(15, 5%, two-tail)=2,131	ALL	**-0,815**	0,140	**0,919**	0,142
(Self here): 1986-2006	t-stat(20, 5%, two-tail)=2,086	Canada all	-0,030	0,273	**0,908**	0,254
(Self here): 1986-2006	t-stat(20, 5%, two-tail)=2,086	Canada Auto	-0,081	0,261	**0,642**	0,260
(Self here): 1986-2006	t-stat(20, 5%, two-tail)=2,086	Canada Com. Prop.	0,047	0,283	0,465	0,291
(Self here): 1986-2006	t-stat(20, 5%, two-tail)=2,086	Canada Liab. ex-auto	0,051	0,330	0,488	0,326
(Self here): 1969-2004	t-stat(36, 5%, two-tail)=2,022	U.S. all	-0,215	0,166	**0,905**	0,171
(Self here): 1969-2004	t-stat(36, 5%, two-tail)=2,022	U.S. all with trend	-0,304	0,181	**0,870**	0,173

The numbers in bold are those that are statistically different from zero using the appropriate test.