A Time-Series Analysis of the Demand for Life Insurance in Australia: An Unobserved Components Approach

Liam J. A. Lenten* and David N. Rulli

Department of Economics and Finance
La Trobe University

Abstract

We systematically explore the time-series properties of life insurance demand using a novel statistical procedure that allows multiple unobservable (but interpretable) components to be extracted. This methodology allows the data to be modelled in new and innovative ways. We find univariate series decomposition allows us to more easily explain the behaviour of life insurance demand over the sample period (1981-2003), than would otherwise be possible. A multivariate model (including a number of variables thought to influence demand) produces quite pleasing results overall. A SUTSE model involving demand and each of the explanatory variables in turn shows evidence of common components in all cases but one. Finally, an out-of-sample forecast comparison shows the univariate model to outperform the multivariate model for accuracy.

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* Corresponding author. Address: Department of Economics and Finance, La Trobe University, Victoria, 3086, AUSTRALIA. Tel: + 61 3 9479 3607, Fax: + 61 3 9479 1654. E-mail: l.lenten@latrobe.edu.au
1. Introduction

The importance of life insurance companies (LICs) within Australia’s financial system has increased significantly over the last two decades, now representing around 7 per cent of total assets held in the Australian financial system. Despite this dramatic rise, still not much is known about the structural behaviour of the demand for life insurance and what external factors drive this demand. This study investigates the behaviour of life insurance demand in Australia during a period of deregulation and industry reform, and also explores the relationship between demand and a specified set of explanatory variables over this time.

The paper improves on the existing literature as follows. Firstly, and most importantly, a structural time series model (STM) is applied as a means of portraying the structural behaviour of life insurance demand. The distinguishing feature of the STM is that the time-series data are considered as comprising of distinct components such as the trend, cyclical, seasonal and irregular components, each of which can be modelled separately. This allows us to capture complex dynamic properties of the observed time series and better understand the nature of demand. Secondly, the framework of the STM is applied to other variables thought to have explanatory power over life insurance demand, allowing us to test for common components. This study focuses on the impact of selected variables including the price level, income, interest rate, unemployment and population. Finally, we add depth to the results by contrasting the forecasting power of this multivariate STM with a univariate version. The results presented herein may have some relevance for LICs in Australia.
The remainder of this study is organised as follows. Section 2 considers some of the recent events that have shaped the industry. A detailed review of previous studies in the area of life insurance demand is presented in section 3. Section 4 looks at some factors that are popularly thought to influence demand in detail. Section 5 proceeds to give a more elaborate description of the STM and separately examines each of the various components of a time-series. Section 6 describes the data sources used and defines the measurement of the variables. Also, a report on the results is presented in this section: beginning with a univariate STM analysis on life insurance demand. The various components of life insurance demand are graphed and results are reported on the explanatory power of the model. Then, a seemingly unrelated time series equations (SUTSE) model in testing for common trends and cycles is considered. Complementing those results, section 7 compares the forecasting ability of the univariate STM with the multivariate STM. Section 8 concludes with a general overview of the key findings.

2. A Recent History of the LIC Industry

The decades of the 1980s and 1990s may be recognised as arguably the most eventful in the history of the Australian financial system. During this time the life insurance industry evolved from primarily a risk management and superannuation orientated business, to become a complete player in a broad array of financial services. As well as this, the structural base on which the industry was founded underwent a significant transformation - demutualisation. The story of change in the industry starts with the Campbell report, the proceedings of which had a significant impact on life insurance firms in Australia, ultimately changing the face of the industry. Deregulation brought with it a wave of
competition as both domestic and foreign banks entered the life insurance market. This transition was rapid as they pushed to make up for lost time. Banks also had a number of advantages over life offices - they were able to achieve economies of scale by combining banking and insurance products, they also had lower information costs because of their established customer networks, and had solid marketing strategies (Keneley, 2002).

As a result, a period of industry rationalisation occurred. The larger life offices moved to diversify their services and compete on the same level as the banking sector. For example, AMP attempted a joint venture with Chase Manhattan Bank, and when that fell through, they proceeded to apply for their own banking licence (Blainey, 1999). In effect, the distinction between life insurance offices and other financial institutions such as banks began to erode (Davis, 1997).

Demutualisation can be seen as a direct consequence to the formation of conglomerate institutions within the life insurance industry. In understanding this point, one must recall that since mutuals are owned effectively by their members, profits are often re-invested into the firm, and the build-up of reserves in this way is their main source to build capital. As LICs began looking towards other avenues of business, however, their expansion was restricted by their limited capital base. Thus the process of demutualisation was driven by the need to access external capital to facilitate expansion, diversify activities, and compete more effectively with publicly listed companies in the market (RBA, 1999: 2). In 1985, 58 per cent of industry assets were held by mutuals. However, by 2000, no mutual associations still existed in the life industry.
One of the key observations of the Wallis Report was that although financial products from different institutions had become similar in nature, the regulations governing them were subject to an institutional (rather than product-based) approach. In turn, different regulators supervised similar products issued by banks (for example) vis-à-vis life offices. This meant they had different capital adequacy, disclosure and advice requirements (Rafe, 1997). Therefore, in what the inquiry saw as a significant step towards sweeping reform of the financial system, it recommended the establishment of a single integrated regulatory framework.

Other developments that have occurred during the sample period include: (i) the spectacular growth of the superannuation sector over the same period. These products are often tied to life insurance products, and the institutions are often classified jointly; and (ii) the change in composition of assets, once invested heavily in government sector securities, due to the 30/20 rule. However, most of the assets are now denominated in equities, unit trusts and corporate securities.

3. A Brief Literature Review

As specified earlier, research into the life insurance industry is very limited. Many studies examining life insurance demand have focused on the Asian market, while research into the Australian market is seemingly scarce. Zietz (2003) identifies 26 academic empirical studies that directly examine demand levels for life offices in her summary of existing literature. Although Australian data has been used in a number of cross-sectional studies, no study has been identified that focuses exclusively on the Australian market.
The concept of life insurance demand is not based on a unique and integrated theory. However, according to Outreville (1996), nearly all theoretical work on the demand for life insurance products identify Yaari (1965) as the genesis. Yaari considered the demand for life insurance within the lifetime allocation process of an individual, subject to personal desire to leave funds for dependants and provide income for retirement. Hakansson (1969) extends this, suggesting that the level of demand for life insurance products is also a function of wealth, the individual’s income stream, the level of interest rates, policy premium rates and the assumed discount function for current consumption.

A number of different models of life insurance demand have been developed and tested, many of these motivated by the existence of varying consumption patterns between different countries. Beck and Webb (2003) highlight the fact that life insurance demand is predominantly low in developing countries, and that even between developed economies there are distinct differences. Given the large variation in indicators of demand across countries, the question arises as to the causes of this variation, and hence, the determinants of life insurance.

Research aimed at explaining international differences in life insurance demand has traditionally involved cross-sectional analysis. Browne and Kim (1993) examine the factors influencing life insurance demand across 45 countries, including both under-developed and developed economies. Beck and Webb (2003) study demand factors using both a cross-sectional data set spanning 63 countries, and a panel data set spanning 23 countries. Outreville (1996) also uses a cross-sectional data set of 48 less-developed
countries in his investigation into the relationship between financial development, and the
development of the life insurance sector.

Two more recent studies in the area, Hwang and Gao (2003) and Lim and Haberman (2004), have directly examined the influence of economic variables on life insurance consumption within single countries, with linkages to economic growth and reform the motivation. Hwang and Gao examine the key determinants of life insurance demand in China, identifying that the main factors contributing to growth in the life industry there can be associated directly with the 1978 economic reforms. These factors include higher incomes, a stronger sense of economic security and improved education levels. Lim and Haberman (2004) focus their study on the influence of the macroeconomic environment on the life insurance industry in Malaysia. While the study aims to link the economic downturn in 1998 to a decline in the performance of the Malaysian life sector, the results do not prove to be completely supportive of the hypothesised relationships.

A common theme regarding research into the variables affecting life insurance consumption is the contradictory nature of results between studies (Zietz, 2003), attributable to differing economic conditions, demographics or geographic factors. Inconsistencies in the findings of different studies make it hard to draw any definitive conclusions regarding the impact of key economic variables. Examples of this common occurrence are exhibited in the following section.
4. Factors Affecting Life Insurance Demand

Factors affecting life insurance demand can be classified generally as being either demographic or economic. While economic factors are predominant in this study, many studies have focused more on demographic variables. Education and the dependency ratio represent two key demographic variables that have been considered in the past. However, the directional relationships associated with these two variables are not conclusive.

(i) Education

Although studies examining the effect of education on life insurance demand generally presume that a positive relationship exists, the ambiguous nature of the variable makes it difficult to fully understand the source of its influence. Truett and Truett (1990) seek to explain the positive impact of education found in results of their study, by suggesting that an increase in the number of educated people in a country may be associated directly with a greater recognition of various types of products offered by life insurance companies, leading to higher levels of demand. Beck and Webb (2003) offer a similar view but also suggest that a better understanding of the benefits of risk management and long-term savings may encourage risk aversion. Alternatively, Browne and Kim (1993) explain the positive influence of education on life insurance demand through its effect on the period of dependency. Individuals educated over longer periods forgo the opportunity of full-time employment, and extend their reliance on the income stream of other working members of the family, increasing the demand for policies. It can also be proposed that these effects are exacerbated by the income effect of education.
Empirically, there has been an inconsistency in results of different studies. Education is found to be positively related to demand in three identified studies (Truett and Truett, 1990; Browne and Kim, 1993; and Gandolfi and Miners, 1996) but is alternatively found to be negatively related in two other studies (Anderson and Nevin, 1975; and Auerbach and Kotlikoff, 1989), although Beck and Webb (2003) find an insignificant relationship.

(ii) Dependency Ratio

The dependency ratio variable represents the demographic structure of the average household in terms of the number of family-members dependant on the main source of income. While studies by Lewis (1989) and Showers and Shotick (1994) demonstrate the effect of the dependency ratio on life insurance consumption to be positive, Auerbach and Kotlikoff (1989) find evidence of an inverse relationship. Lewis’ theoretical explanation of dependency ratio influence (through term-life polices) is that life insurance is purchased to satisfy the needs of dependents, and that individual demand depends on the demographic structure of that household.

Showers and Shotick (1994) expand on this idea by giving reference to a curvilinear relationship. They propose a positive relationship between family dependents and life insurance demand that levels out as dependents grow older and leave home, and then apply a quadratic variable to test for the relationship. Although they find evidence to support their theory, results from Duker’s (1969) similar study produces no evidence of the hypothesised relationship. Studies by Truett and Truett (1990) and Browne and Kim

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1 Statistical measurement of the dependency ratio is typically defined by the ratio of the total number of children under the age of 15 to the number of persons between 15 and 64.
(1993), however, do not consider the possibility of a curvilinear trend. Nevertheless, all provide statistical evidence to support the existence of a positive (linear) relationship between the dependency ratio and life insurance.

In addition to these demographic factors, economic factors are also relevant. As stated by Lim and Heberman (2004), ‘the economic environment may have a profound effect on the growth of the life insurance market’. In Australia, the performance of the life insurance industry during the early 1990s was affected by recession. There is evidence of a strong cyclical influence on net contributions into superannuation during this period, likely to have been caused by the economic downturn. In effect, aggregate net superannuation contributions (following the introduction of the Superannuation Guarantee Charge) did not trend upwards as immediately expected (Edey and Gray, 1996). There is also evidence of a strong cyclical influence on net contributions during the recession of the early 1980s. Findings related to the effect of each of these economic variables are investigated separately forthwith.

(iii) Inflation
The inverse effect of inflation on life insurance demand has been largely documented in past research, and several explanations have been forwarded in an effort to clarify the relationship that exists. Browne and Kim (1993) propose that inflation has a ‘dampening effect’ on demand for products offered by life insurance companies, as it erodes the real value of these products. Leading on from this point, it can be suggested that this dampening effect more likely sources from inflationary expectations. Outreville (1996)
emphasises ‘anticipated’ inflation by highlighting that life insurance is commonly purchased on a level premium plan, with the same price being charged throughout the policy’s duration. Also, with life savings products, monetary uncertainty is said to have a substantial negative effect on the assumed future value (Beck and Webb, 2003). From a supply-side perspective, they also state that ‘inflation can have a disruptive effect on the life insurance industry, when interest rate cycles spur disintermediation’. This occurred in the US during the inflationary period of the 1970s and 1980s as a consequence of fixed interest rates and loan options imbedded in some life policies. These dynamics make inflation an additional encumbrance to product pricing decisions of life insurance firms, possibly reducing supply during times of high inflation.

A key study that demonstrates the detrimental influence of inflation on demand is Babbel (1981). In an effort to mitigate the value erosion caused by inflation, many life offices offer indexed life insurance products. However, as Babbel identifies empirically, life insurance sales in Brazil were still affected by inflationary expectations even after policies were linked to a price index. It is suggested that anticipated inflation can lead to higher perceived real costs of life insurance, even when policies are index-linked. However, given Brazil’s hyperinflationary economy during the sample period, caution should be exercised when considering this result. Nevertheless, the findings of Browne and Kim (1993) and Outreville (1996) support Babbel’s conclusions, although the results of Cargill and Troxel (1979) and Rubayah and Zaidi (2000) imply an insignificant relationship. Hwang and Gao (2003) also find little evidence to conclude that the life industry suffered adverse impacts over inflationary periods in China but suggest this was
due to coinciding high economic growth. Inconsistencies between the various conclusions may be related to those factors mentioned earlier. However, another possible reason may be differences in methodologies – anticipated inflation (impossible to measure without robust survey data) can be proxied in many different ways.

(iv) Income

The impact that the level of income has on life insurance consumption may be considered the most palpable of all the economic variables explored in past research. Several reasons explain why life insurance consumption should rise with income. Firstly, there is no reason to believe that insurance is anything other than a normal good, in the sense that consumption is rising in income. Also, if consumption levels fall relative to income, there follows a need for financial instruments to absorb surplus funds, enabling greater accumulation of wealth (Hwang and Gao, 2003). As LICs offer a variety of financial products with an array of functions, they offer a possible avenue for these surplus funds. Secondly, as a person’s level of income rises, so too does the opportunity cost of dying. Thus, the desire to maintain living standards of dependents generates larger policies.
Most studies apply GDP per capita as the standard measure of income, although Browne and Kim (1993) first deduct depreciation and indirect business taxes from GNP. They argue that such a measure more accurately reflects the amount of disposable income in a country, because it measures income earned by factors of production.

(v) Interest Rates

There is some disagreement over the effect of interest rates on demand. Results depend partly on the definition of the variable. Both Outreville (1996) and Beck and Webb (2003) anticipate the demand for life insurance products to be related to the real interest rate. As the latter explains, ‘a higher real interest rate increases LIC investment returns and thus their profitability, in turn offering greater profitability of financial relative to real investments for potential purchases of life insurance policies’. However, results of neither study offer any evidence to support the hypothesised relationship. Conversely, higher interest rates might be expected to reduce demand as higher yields on alternative savings products makes life insurance less attractive (Lim and Haberman, 2004).

Empirical difficulties experienced by Outreville (1996) may suggest that various limitations exist in using a cross-national study sample, such as finding consistent data sets and variable definitions across countries. Inter alia, Cargill and Troxel (1979) represent the competing rate of return on alternative instruments as the yield on newly issued AAA utility bonds, while Lim and Haberman (2004) use the savings deposit rate. Rubayah and Zaidi (2000), though, use the short-term (3-month Treasury bill) and current

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2 This point seems debatable considering a high level of LIC assets may be invested in these ‘alternative savings products’.
interest (bank loan) rate, as well as the savings deposit rate. Hence, trying to estimate a consistent variable that can be applied globally may diminish the legitimacy of results.

Results of the distributed lag study by Cargill and Troxel (1979) support the theory that the competing yield is negatively related to the demand for life insurance. Rubayah and Zaidi (2000) also identify significant negative relationships between the demand for life insurance and both interest rate measures. However, the significant positive relationship identified in results of Lim and Haberman (2004) proves to be contrary to the findings of the other studies, as well as their own hypothesised proposition.

(vi) Unemployment
Evidence on the effect of unemployment on demand is limited, and only one study (Mantis and Farmer, 1968) has been identified that examines the relationship between the two variables directly. Results of the early study suggest that unemployment has a negative influence on the demand for life insurance. However, it may be questioned why other studies in the area have not considered this relationship.

One explanation may be that the anticipated effect of employment on life insurance demand is assumedly reflected through the income variable. However, given the recent developments in the industry, the anticipated ‘income effect’ may not explain the relationship fully. Rather, it may be suggested that employment has maintained a more direct relationship with life insurance demand in Australia, since the introduction of policies aimed at encouraging saving, the SGC above all. More salient results on the
impact of employment have been found in the context of occupational class (Duker, 1969; and Fitzgerald, 1987) with some linkage back to the income effect.

5. Methodology

The majority of previous studies exploring the variables significant in determining life insurance demand have applied models based on ordinary least squares regression (OLS) estimates (Truett and Truett, 1990; Browne and Kim, 1993, and Hwang and Gao, 2003). We strongly argue that this type of statistical analysis oversimplifies the nature of the relationships by accommodating only for a deterministic trend, presuming that the relationship is constant and invariable. Furthermore, treatment of cyclical behaviour in past research is something that has yet to be explored with LIC data, and the failure to account for this cyclical behaviour may greatly harm the validity of results.

In an effort to provide an original perspective towards the study of life insurance demand and overcome inadequacies in previous research, this study employs the STM based on the methodology suggested by Harvey (1985, 1989). As opposed to traditional methods, this methodology is based on representing explicitly the components of a series. These components, while unobservable directly, do have a direct and useful economic interpretation. See Flaig and Ploetscher (2000) for a comprehensive list of advantages associated with this framework.

The simplest interpretation of the model is represented by the decomposition of a time series into its unobservable components, and is written as
\[ y_t = \mu_t + \phi_t + \gamma_t + \varepsilon_t \]  \hspace{2cm} (1)

where \( y_t \) is the observed series, \( \mu_t \) is the trend component, \( \phi_t \) is the cyclical component, \( \gamma_t \) is the seasonal component, and \( \varepsilon_t \) is the random component. The trend, cyclical and seasonal components are assumed to be uncorrelated, while \( \varepsilon_t \) is white noise.

The trend component represents the long-term movement in a series and is assumed to have the following stochastic process:

\[ \mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t \] \hspace{2cm} (2)

\[ \beta_t = \beta_{t-1} + \xi_t \] \hspace{2cm} (3)

where \( \eta_t \), and \( \xi_t \) are themselves white noise. Here, \( \mu_t \) follows a random walk with a drift factor, \( \beta_t \), which follows a first-order autoregressive process as represented by equation (3). This process collapses to a simple random walk with a drift if \( \sigma_{\eta}^2 = 0 \), and to a deterministic linear trend if \( \sigma_{\eta}^2 = 0 \) as well. However, if \( \sigma_{\eta}^2 = 0 \) while \( \sigma_{\xi}^2 \neq 0 \), the process will have a trend which changes relatively smoothly. \( \mu \) and \( \beta \) represent the level and the slope of the trend series respectively, and are equivalent to the constant term and the coefficient on a time variable in a conventional regression equation.

The cyclical component, which is assumed to be a stationary linear process, can be represented by

\[ \phi_t = a \cos \theta t + b \sin \theta t \] \hspace{2cm} (4)

In order to make the cycle stochastic, the parameters \( a \) and \( b \) are allowed to evolve over time. If disturbances and a dampening factor are also introduced, we obtain
\[ \phi_t = \rho(\phi_{t-1} \cos \theta + \phi^*_{t-1} \sin \theta) + \omega_t \]  

(5) and

\[ \phi^*_t = \rho(-\phi_{t-1} \sin \theta + \phi^*_{t-1} \cos \theta) + \omega^*_t \]  

(6)

where \( \phi^*_t \) appears by construction such that \( \omega_t \) and \( \omega^*_t \) are uncorrelated white noise disturbances with variances \( \sigma^2_\omega \) and \( \sigma^2_\omega^* \) respectively. The parameters \( \theta \) and \( \rho \) are the frequency of the cycle and the dampening factor on the amplitude, respectively. In order to make numerical optimisation easier, the constraint \( \sigma^2_\omega = \sigma^2_\omega^* \) is imposed.

Although a number of different specifications exist for seasonality, the trigonometric version is the most preferred. Where \( s \) is the number of seasons per year (four for quarterly data), the seasonal component is written as

\[ \gamma_t = \sum_{j=1}^{s/2} \gamma_{jt} \]  

(7)

where \( \gamma_{jt} \) is given by

\[ \gamma_{jt} = \gamma_{jt-1} \cos \lambda_j + \gamma^*_{jt-1} \sin \lambda_j + \kappa_{jt} \]  

(8)

\[ \gamma^*_{jt} = -\gamma_{jt-1} \sin \lambda_j + \gamma^*_{jt-1} \cos \lambda_j + \kappa^*_{jt} \]  

(9)

where \( j = 1, \ldots, s/2 - 1, \lambda_j = \frac{2\pi j}{s} \) and

\[ \gamma_{js} = -\gamma_{js-1} + \kappa_{js} \]  

(10)

where \( \kappa_{jt} \) and \( \kappa^*_{jt} \) are also white noise, and \( \sigma^2_\kappa = \sigma^2_\kappa^* \). One advantage of this specification is that it allows for smoother changes in seasonals. The extent in which the trend, cyclical and seasonal components evolve over time depends on the hyperparameter
values of $\sigma^2_\eta$, $\sigma^2_\xi$, $\sigma^2_\omega$ and $\sigma^2_\kappa$. These can be estimated by maximum likelihood once the model has been written in state space form.

In order to include explanatory variables, the model represented in equation (1) must be modified and expressed as

$$y_i = \mu_i + \phi_i + \gamma_i + \mathbf{X}_i \mathbf{B} + \varepsilon_i$$

where $\mathbf{X}_i$ is a $k \times 1$ vector that contains $k$ explanatory variables and $\mathbf{B}$ is a $k \times 1$ vector of estimated coefficients. If the included economic variables in $\mathbf{X}$ have high explanatory power for the dependent variable, $y_i$, they should be able to explain its trend, cyclical and seasonal variation.

6. Data Particulars and Results

The results presented in this paper are based on a sample of quarterly, seasonally unadjusted Australian data covering the period 1981Q2–2003Q4, resulting in 90 observations in total. The main advantage of using quarterly data, as opposed to annual data, is that it allows us to address possible seasonal fluctuations appropriately. However, the drawback is that the dependency ratio must be excluded from the study as the data is available only on an annual basis.\(^3\) The demand for life insurance is proxied by the asset base for all LICs in Australia (taken from the RBA Bulletin database). This is a superior measure to the number of policies, as the latter does not discriminate between large and

\(^3\) Education is also missing from the study because of measurement difficulties.
small policies. Data used to represent the price level, income, unemployment and interest rate variables are taken from *ABS Time-Series Statistics Plus*, and the population data is sourced from *ABS Demographic Statistics*. The variables are modelled in terms of their natural logs, with the exception of the interest rate (already a flow variable).

From an informal examination of figure 1, several observations can be made. Firstly, it is clear that the asset-base of life offices, price level, income and the size of the population all display positive trends. In the case of unemployment, the trend changes during the 1980s, shows a steep increase in the early 1990s that can be linked to the recession, and then levels off. The short-term interest rate has a seemingly flat trend, with a structural break in the early 1990s. It is also visually obvious that there is seasonal behaviour in both the unemployment rate and GDP per capita. This type of behaviour is less evident in the other variables. With all of this in mind, we now turn to a more formal examination of the data, beginning with a univariate analysis.

Before considering the effect of macroeconomic variables, the demand for life insurance as the underlying variable will be examined separately in terms of its unobservable components. The expression of the univariate time series model is as outlined in equation (1). The behaviour of the different components is shown graphically in table 1 (first column), which reports the estimated hyperparameters, as well as the relating $q$-ratios. In describing the graphical representation of the various components, we refer to figure 2.

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4 Another valid issue is why the asset base is preferred to total liabilities. This may be an empirical issue. However, an intuitive explanation is that marginal premiums generated by a new policy immediately become an asset. Contingent liabilities are then assumed. Hence, the causal link with assets is more direct.

5 The interest rate is the 90-day bank accepted bill rate. The other variables are self-explanatory.
From table 1, it can be determined that the seasonal component relating to life insurance
demand is deterministic. The high values of $\sigma^2$, $\sigma^2_\omega$ and $\sigma^2_\epsilon$ imply that the level, cyclical
and irregular components are stochastic. In figure 2, the trend component shows a
constant rise in life insurance demand that levels off in the late 1990s and then begins to
decline slightly, possibly due (among other reasons) to the collapse of HIH or the
implications of the 11 September 2001 terrorist attacks. From the slope component (see
top-left panel of figure 2), we are able to better observe the rate of growth in demand over
time. During the mid 1980s, growth was at its strongest, which may be partly a reflection
of sales-related factors relating to the structure of the industry at the time. At the time
(before demutualisation and institutional conglomeration), self-employed brokers and
agents played a more predominant role in the market, spurring the sale of life insurance
products. The strong growth may also be linked to reform and policies relating to the
treatment of superannuation. In 1986, the Industrial Relations Commission endorsed the
employer provided superannuation benefit, set initially at 3 per cent. At the same time
personal superannuation was maintained as a tax deduction until the mid 1990s, when it
was removed for those receiving employer superannuation contributions\(^6\).

It is obvious from figure 2 that the strong growth in life insurance demand was not
sustained. Two periods can be identified in which the rate of growth in demand declined
significantly. Firstly, in the period between the late 1980s and the early 1990s, caused
possibly in part by the October 1987 sharemarket crash. A major implication of the crash
was that people lost faith temporarily in the finance industry in general. Poor returns in

\(^6\) The removal of tax deductibility meant that people receiving employer superannuation contributions were
now less inclined to take out an additional policy with life offices, thus impacting demand.
superannuation funds exacerbated by the recession of the early 1990s meant that people began to question whether the savings instrument was the safe haven it was thought to be.

A second major period of decline can be identified in the latter years of the sample (1997-2002). Towards the turn of the century, the positive trend in life insurance demand began to level off and then turn downwards, partly a consequence of the financial services reform (FSR) following the Wallis Inquiry and the formation of APRA. During this period, regulations and reforms were imposed on LICs, aimed at improving industry integrity. For example, insurance agents and financial advisers were required to have a minimum level of education before they could provide advice, and privacy laws were introduced restricting the flow of information between LICs on one hand, and agents and advisers on the other. Further, insurance agents and providers were required to hold a dealing licence. These impositions, which may also be considered supply-side effects, lead to the exit of many insurance dealers from the industry. This may be a possible reason for the fall in the asset-base of life offices in more recent years.

It is also observed in figure 2 that the seasonal component of life insurance demand is fixed (deterministic). Referring to the panel (bottom-right) that maps out the individual seasonals, it can be seen that demand for life insurance peaks in quarter 1 (January to March), falls moderately in quarter 2 (April to June), then increases by approximately the same factor in quarter 3 (July to September). Demand then declines to its lowest point in quarter 4 (October to December) of each year.
This ‘summer effect’ may be used to explain the decline in life insurance demand during quarter 4. During this period, people may be less inclined to purchase life insurance products because of additional costs associated with the festive season. People may also be generally more optimistic during this period, and less interested in LIC services and products. It may be considered a particular point of interest that life insurance demand is considerably higher in quarter 1 than it is in quarter 4. With people returning from their holiday break and recommencing work, the focus may be re-directed to the financial welfare needs associated with life insurance products.

In some cases, taking out life insurance policies in the months leading into June (end of the financial year) also provides tax relief. It is well known in the industry that life insurance companies use tax-deductibility as a focal point in marketing campaigns launched during this period. However, even though this is the case, demand declines in quarter 2. This may suggest one of two possibilities; firstly, that tax relief is not a significant motive in taking out life insurance polices after all, and that other more effective means exist. Secondly, it may suggest that most people begin planning for the end of the financial year during the first quarter, and therefore, life offices would benefit most from their marketing campaigns if they were launched at the beginning of the year.

The results of estimating the univariate time series model for demand are presented in table 2. The table reports the estimated components of the state vector and their respective $t$-statistics, while model validation is based on various goodness of fit and
diagnostic test statistics. The coefficients $\mu_t$, $\beta_t$, $\phi_t$, $\phi^*_t$, $\gamma_{1,t}$, $\gamma^*_{1,t}$ and $\gamma^*_{2,t}$ indicate the final state values of their relating components. The model has a moderate level of explanatory power as shown by $R^2$ and a relatively low standard error term. Further, the model seems to be well specified. Although the $Q$ statistic is significant, the $DW$ test statistic indicates the null of no serial correlation cannot be rejected. The model also succeeds in passing the diagnostic test for heteroscedasticity. However, the $N$ statistic does suggest a statistically significant departure from normality. These results indicate that life insurance demand can be explained to some extent by its estimated components.

We now consider a multivariate model involving the components of demand, and the specified set of macroeconomic variables. Before testing for common components, the independent variables included in the study are first considered individually and within the univariate model represented by equation (1). Table 1 reports the estimated hyperparamaters $\sigma_\eta^2$, $\sigma_\varepsilon^2$, $\sigma_\omega^2$, $\sigma_\kappa^2$ and $q$-ratios of all the variables included in the model. From the table, it can be seen that both the trend and cyclical components are stochastic for all six series. The results show relatively substantial cyclical behaviour for all the variables except population. It is also clear from the value of $\sigma_\kappa^2$ that seasonality is stochastic for the price level, income, interest rate and population variables.

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7 The goodness of fit measures include the adjusted (seasonal) coefficient of determination ($R^2$) and the standard error of the equation ($\hat{\sigma}$). The diagnostic test statistics include both the Durbin-Watson test ($DW$) and the Ljung-Box (1978) $Q$ statistic for serial correlation, as well as the Bowman-Shenton (1975) test for normality ($N$), and a test for heteroscedasticity ($H$).

8 This is most likely due simply to outliers in the data, and hence is not really a problem.
Table 2 reports the estimated components of the state vector as well as goodness of fit and diagnostic test statistics for all variables included in the study. Equation (1) seems to fit well for the price level, income and population variables, with $R^2$ values of 0.47, 0.61 and 0.56 respectively. This is not the case for the interest rate variable - with an $R^2$ value close to zero and a markedly higher $\tilde{\sigma}$, the model has inferior goodness of fit. The estimated equations of all the independent variables pass the diagnostic tests for serial correlation and heteroscedasticity. However, the price level, interest rate and unemployment variables fail the diagnostic test for normality.

From tables 1 and 2 it is evident that the time-series of all the variables, even the interest rate, can be described to some extent by the behaviour of their different components. Knowing this, we can pose the question as to whether any relationship exists between the components of life insurance demand and the components of these macroeconomic variables. Particularly, we are interested in addressing whether the cyclical components between life insurance demand and each of the economic variables included in this study in any way related, mutatis mutandis for the trend components.

The behaviour of both the trend and cyclical components of all the time series can be observed directly in figures 3 and 4, respectively. Although it is difficult to be conclusive in the interpretation of these figures, a few distinctive observations can still be made. Firstly, it can be verified that the trend and cyclical components are stochastic for all the time-series. This means that it would be fallacious to presume a fixed relationship between life insurance demand and any of the economic variables. For the trend
components of the time series, it is clearly shown that apart from the interest rate, each of these trends rise over time. Although it is harder to identify any similarities in the cyclical behaviour of the variables, it may be noted that the amplitude of the cycles, particularly for life insurance demand, interest rates and unemployment was larger in the late 1980s and early 1990s than it was towards the latter part of the sample.

Rounding out the empirical section, we now consider a SUTSE model, providing a more appropriate framework for testing for commonalities between the components of variables. SUTSE models represent a multivariate generalisation of STMIs. Unlike simple OLS estimation, SUTSE models do not test implicitly for a causal relationship between the dependent and independent variables, but rather for the presence of common factors. In particular, the model allows us to test for common trend (level) components and common cyclical components. In addition, from the results obtained, it is possible to gain an extended understanding as to whether the relationship between demand and the macroeconomic variables in question, is in fact long-term and/or short-term in nature. Specifically, the presence of common factors implies cointegration, which means that the presence of common cycles (but not common trends) suggests a short-term relationship, and the presence of common trends (but not cycles) suggests a long-term relationship.

The presence of a common factor implies that the variance matrix of disturbances of the relevant factor has a rank of $K$, less than full rank ($N$), and therefore, that component is driven by disturbance factors with only $K$ elements (as opposed to $N$) elements. In testing
for common cycles and trends for each of the specified explanatory variables and life
insurance demand \((DEM)\), we express the vector of variables as follows

\[
x_t = \begin{bmatrix} z_t \\ DEM_t \end{bmatrix}
\]

(12)

where \(z_t\) represents the explanatory variable in question. When testing for common
factors, this regular SUTSE model becomes the ‘unrestricted’ model. However, where
common trends (for example) are present, the true rank of \(\Omega_\eta\), will in this case be \(K<N\)
\((K=1, N=2)\), and the model has 1 common trend. Therefore, the restriction of the common
trend is imposed on the model by reducing the rank of \(\Omega_\eta\), a \(K\times1\) vector, from 2 to 1,
and re-estimating the now ‘restricted’ model, which can be written as

\[
x_t = \Theta \mu_t^* + \mu_0 + \varphi_t + \gamma_t + \epsilon_t
\]

(13)

\[
\mu_t^* = \mu_{t-1} + \eta_t
\]

(14)

subject to \(\epsilon_t \sim NID(0, \Omega_\epsilon)\) and \(\eta_t \sim NID(0, \Omega_\eta)\), where \(\Theta\) is an \(N\times K\) standardised
factor loading matrix (not reported), with ones in the diagonal positions and zeros in all
elements above and to the right of the diagonals. Also, \(\mu_0\) is an \(N\times1\) vector with the last
\(K\) elements being contained in a vector, \(\bar{\mu}\), and all other (upper) elements being zeros.

The statistical test for commonality of factors is the Likelihood Ratio test, \(LR\), which is
simply a ratio of the likelihoods of the restricted and unrestricted models, calculated as

\[
LR = -2(LL_R - LL_U)
\]

(15)

where \(LL_R\) and \(LL_U\) are the log-likelihoods of the restricted and unrestricted models
respectively, distributed as \(\chi^2(r)\), where \(r\) is the number of restrictions imposed (one).
Table 3 reports the $LR$ test results. It is apparent that the evidence is consistent for each of the economic variables apart from the interest rate variable. For the price level, income, unemployment and population variables, $LR$ is insignificant for both the trend and cyclical components, meaning that the null hypothesis of the restriction of the rank of $\Omega_{n}$ and $\Omega_{o}$ to be equal to one cannot be rejected at the 5 per cent level. This allows us to conclude that both common trends and cycles exist between each of these variables and life insurance demand. However, for the interest rate variable, although $LR$ is insignificant for the cyclical component, it is significant for the trend component, implying that the null hypothesis is rejected. Thus, we can conclude here that there exist common cycles, but not common trends between the interest rate and life insurance demand, suggesting that any relationship is short-term in nature. Referring back to figure 3, this result is not at all surprising considering the obvious difference in the graphical representation of the trend components when visually comparing the two series.

It is difficult; however, to directly compare results obtained using the SUTSE model, with the findings of previous studies that have examined these relationships, especially those that employ various OLS methodologies. Common factors, as acknowledged earlier, indicate that the time-series are related and move together in a dynamic structural sense, though none of them necessarily causes the other in a statistical sense.

7. A Comparison between Forecasting Models
The purpose of this section is to contrast the out-of-sample forecasting power of a multivariate STM (where $y_t$ is based on the components of explanatory variables) to a univariate STM (where $y_t$ is based on its own components) by generating two sets of forecasts for both of these methods over the period 1999:1-2003:4. The first set consists of one-step ahead forecasts, while the second consists of multi-step ahead forecasts.\footnote{The simple difference is that for one-step, the model is re-estimated each subsequent period prior to the calculation of the forecast for the following period. This is not the case with multi-step forecasts.}

Figure 5 exhibits the one-step and multi-step forecasts of life insurance demand in comparison to the realised values, based on both the multivariate and univariate STM respectively. It is not surprising when comparing panels that the one-step forecasts are more accurate than the multi-step forecasts. It is clear from the figure that the multi-step forecasts of both the multivariate and univariate models over-estimate the actual value of the series systematically. This reinforces the fact that demand has declined in more recent years because of factors unforeseeable in 1998 (possibly a reflection of the FSR). Also, the univariate model appears to have better predictive power than the multivariate model.

To further examine the forecasting accuracy of the different models, several relevant quantitative measures are presented in table 4. These include (i) the sum of absolute errors ($SAE$); (ii) the mean absolute error ($MAE$); (iii) the sum of squared errors ($SSE$); (iv) the mean squared error ($MSE$); (v) the mean absolute percentage error ($MAPE$); (vi) the root mean squared error ($RMSE$); and (vii) Theil’s inequality coefficient ($TIC$);\footnote{$TIC$ is a ratio of $RMSE$ from the generated forecasts to $RMSE$ using random walk forecasts.} While most of the measures are self-explanatory, it may be noted that the $RMSE$ is a...
measure particularly important to practitioners, because by measuring the squared forecasting error, it takes into consideration the fact that large errors are disproportionately more ‘expensive’ than small errors.

In reviewing the reported accuracy measures, it becomes apparent that for both the one-step and multi-step forecasts, the forecasting errors generated by the multivariate model are generally larger than those produced by the univariate model. In theory, one might expect the multivariate model to have superior predictive power. However, this result may indicate that during the forecast period, the relationship between life insurance demand and the variables included in the model changed, giving rise to a structural break in the series (again possibly due to the FSR). Also, the TICs for the one-step forecasts fall between 0 (perfect foresight) and 1 (as good as a random walk). However, the TICs for the multi-step forecasts of both the univariate and multivariate models are greater than 1, indicating that the forecasts are less accurate than using random walk forecasts.

The measures imply that the univariate model outperforms the multivariate model in terms of forecasting accuracy. However, we cannot tell from these results alone if the differences in these measures are statistically significant. For this reason, we apply the Ashley, Granger and Schmalensee (1980) AGS test to test for the difference of the RMSEs between the univariate and multivariate models. The AGS test requires the estimation of the linear regression

\[
D_t = \alpha_0 + \alpha_1 (S_t - \bar{S}) + u_t
\]  

(16)
where \( D_t = w_{tt} - w_{2t} \), \( S_t = w_{tt} + w_{2t} \), \( \bar{S} \) is the mean of \( S_t \), \( w_{tt} \) is the out-of-sample error at time \( t \) of the model with the higher \( RMSE \), \( w_{2t} \) is the out-of-sample error at time \( t \) of the model with the lower \( RMSE \), and \( t = 1, 2, \ldots, 20 \).

The estimates of the intercept term \( (\alpha_0) \) and the slope \( (\alpha_1) \) are used to test the statistical difference between the \( RMSE \) of the multivariate and univariate models. If the estimates \( \alpha_0 \) and \( \alpha_1 \) are both positive, then an \( F \)-test of the joint hypothesis \( H_0 : \alpha_0 = \alpha_1 = 0 \) is appropriate. However, if one of the estimates is negative and statistically significant, then the test is inconclusive. Finally, if the estimate is negative and statistically insignificant, the test remains conclusive and significance is determined by the upper-tail of the \( t \)-test on the positive coefficient estimate.

Results of the \( AGS \) test are presented in table 5. For the one-period forecast, since one of the estimates is negative and statistically insignificant, the upper-tail of the \( t \)-test on \( \alpha_1 \) indicates that the null hypothesis (that the forecasting power of the multivariate model is not significantly different from that based on the univariate model) cannot be rejected. The coefficients are both positive for the multi-step forecasts, so a Wald test is used. It is obvious here that the null hypothesis can be rejected, indicating that in this case the univariate model does outperform the multivariate model for forecasting accuracy.

8. Conclusion
In this paper, a structural time series model has been utilised to provide an original perspective to the study of life insurance demand. In attempting to describe the structural behaviour of life insurance demand in Australia, and in answering questions as to the relationship between the cyclical and trend components of demand and the specified set of economic variables used in this study, the following conclusions can be stated.

Firstly, it is clear from a univariate model that the cyclical and trend components of life insurance demand are stochastic. This may imply that over the sample time period, life insurance demand was influenced by certain environmental effects most likely related to deregulation and industry reform. The strong growth in demand during the mid 1980s may be viewed in contrast with the levelling off of demand in more recent years. The various effects of demutualisation, the formation of APRA, self-employed brokers and agents, and the FSR, were also addressed. Secondly, it can be inferred that life insurance demand has a deterministic seasonal component to it, with a surge in demand in the first quarter of each year, and the subsequent fall in the fourth quarter. The possible causes of this summer effect were also examined.

Another formal method was then applied – a SUTSE model to test for the presence of common factors. We can conclude from the results that the price level, income, unemployment and population variables all have trends and cycles common to those of demand, implying cointegrating relationships within the time-series of these variables. This finding was the case across the board except in the case of interest rates, which may be viewed as having only a short-term relationship with demand. These results lead us to suggest an associative relationship between each of the reference variables and demand,
though it would be wrong to conclude that the relationship is causal. Finally, the forecasting power of a univariate model as opposed to a multivariate model including explanatory variables was investigated. The fact that the univariate model had stronger forecasting power (multi-step case) leads us to suggest that the relationship between the explanatory variables and demand changed at some point.

Unlike previous studies in the area, we were able to capture dynamic properties of the observed time series and gain an extended understanding into some of the key effects on the life insurance industry over the sample period. Hopefully, findings of the study may be useful in assisting life insurance companies in various areas of their corporate strategy - for example, the seasonal issues. Further research in the area would be of interest to similar institutions. For example, it might be useful to generalise the results of the comparison of forecasting models to other categories of financial intermediaries.
References


Table 1: Estimated Hyperparameters for all Variables

<table>
<thead>
<tr>
<th></th>
<th>DEM</th>
<th>PRL</th>
<th>INC</th>
<th>IRT</th>
<th>UNE</th>
<th>POP</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\sigma^2_\eta$ (Level)</td>
<td>0.0000 (0.0000)</td>
<td>0.0000 (0.0000)</td>
<td>0.0000 (0.0000)</td>
<td>0.8818 (1.0000)</td>
<td>0.0002 (1.0000)</td>
<td>$3.31 \times 10^{-10}$ (0.0336)</td>
</tr>
<tr>
<td>$\sigma^2_\delta$ (Slope)</td>
<td>$8.17 \times 10^{-6}$ (0.2173)</td>
<td>$4.27 \times 10^{-7}$ (0.1372)</td>
<td>$1.63 \times 10^{-8}$ (0.0013)</td>
<td>0.0000 (0.0000)</td>
<td>$2.25 \times 10^{-5}$ (0.1119)</td>
<td>$9.86 \times 10^{-9}$ (1.0000)</td>
</tr>
<tr>
<td>$\sigma^2_\omega$ (Cycle)</td>
<td>$2.70 \times 10^{-6}$ (0.7175)</td>
<td>$4.27 \times 10^{-7}$ (1.0000)</td>
<td>$1.63 \times 10^{-8}$ (1.0000)</td>
<td>$1.478 \times 10^{-5}$ (0.1676)</td>
<td>$3.93 \times 10^{-5}$ (0.1956)</td>
<td>$2.66 \times 10^{-10}$ (0.0270)</td>
</tr>
<tr>
<td>$\sigma^2_\kappa$ (Seasonal)</td>
<td>0.0000 (0.0000)</td>
<td>6.08 $\times 10^{-9}$ (0.0020)</td>
<td>$3.11 \times 10^{-6}$ (0.0365)</td>
<td>0.0000 (0.0000)</td>
<td>0.0000 (0.0000)</td>
<td>$1.06 \times 10^{-10}$ (0.0108)</td>
</tr>
<tr>
<td>$\sigma^2_\epsilon$ (Irregular)</td>
<td>$3.76 \times 10^{-5}$ (0.0000)</td>
<td>$7.67 \times 10^{-7}$ (0.2467)</td>
<td>0.0000 (0.0000)</td>
<td>0.0000 (0.0000)</td>
<td>0.0000 (0.0000)</td>
<td>$1.97 \times 10^{-9}$ (0.2001)</td>
</tr>
</tbody>
</table>

Table 2: Results of Estimated Univariate Time-Series

<table>
<thead>
<tr>
<th>State Variable</th>
<th>DEM</th>
<th>PRL</th>
<th>INC</th>
<th>IRT</th>
<th>UNE</th>
<th>POP</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu_t$</td>
<td>5.2901* (609.06)</td>
<td>2.1556* (427.87)</td>
<td>3.9920* (591.46)</td>
<td>5.1345* (5.0723)</td>
<td>2.7730* (127.98)</td>
<td>7.3010* (1.02 $\times 10^{-5}$)</td>
</tr>
<tr>
<td>$\phi_t$</td>
<td>0.0039 (-0.0009)</td>
<td>0.0005 (0.7999)</td>
<td>0.0000 (8.289)</td>
<td>-0.0104 (-0.0564)</td>
<td>-3.35 $\times 10^{-6}$ (-0.0410)</td>
<td></td>
</tr>
<tr>
<td>$\phi^*_t$</td>
<td>0.0022 (-0.0028)</td>
<td>0.0008 (0.0000)</td>
<td>0.4680 (0.0000)</td>
<td>-0.0167 (-3.5058)</td>
<td>4.57 $\times 10^{-6}$ (-1.6249)</td>
<td></td>
</tr>
<tr>
<td>$\gamma_{1,t}$</td>
<td>0.0017 (1.1893)</td>
<td>0.0003 (0.7999)</td>
<td>0.0136 (8.289)</td>
<td>-0.0743 (-0.0564)</td>
<td>-0.0145 (-8.508)</td>
<td>-1.36 $\times 10^{-6}$ (-0.0410)</td>
</tr>
<tr>
<td>$\gamma^*_{1,t}$</td>
<td>-0.0003 (-0.2420)</td>
<td>1.08 $\times 10^{-5}$ (-0.0025)</td>
<td>-0.0059 (0.1313)</td>
<td>0.0486 (19.686)</td>
<td>0.0333 (19.686)</td>
<td>4.7116</td>
</tr>
<tr>
<td>$\gamma_{2,t}$</td>
<td>0.0003 (0.2480)</td>
<td>-0.0003 (-0.8674)</td>
<td>0.0084 (-3.5058)</td>
<td>-0.0153 (-0.0564)</td>
<td>-0.0152 (-8.508)</td>
<td>-3.88 $\times 10^{-6}$ (-0.0410)</td>
</tr>
<tr>
<td>$\gamma^*_{2,t}$</td>
<td>0.1965 (0.4673)</td>
<td>0.6062 (0.4673)</td>
<td>0.0694 (0.4673)</td>
<td>0.2324 (0.4673)</td>
<td>0.5611 (0.4673)</td>
<td></td>
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<tr>
<td>$\sigma$</td>
<td>0.0130 (0.0030)</td>
<td>0.0054 (0.0030)</td>
<td>1.0801 (0.0030)</td>
<td>0.0187 (0.0030)</td>
<td>0.0002 (0.0030)</td>
<td></td>
</tr>
<tr>
<td>$DW$</td>
<td>1.9568 (1.9538)</td>
<td>1.9428 (1.9538)</td>
<td>2.0114 (1.9538)</td>
<td>1.8866 (1.9538)</td>
<td>1.9854 (1.9538)</td>
<td></td>
</tr>
<tr>
<td>$N$</td>
<td>78.319* (12.369)</td>
<td>3.1171 (3.1171)</td>
<td>21.794* (3.1171)</td>
<td>10.522* (3.1171)</td>
<td>1.9810 (3.1171)</td>
<td></td>
</tr>
<tr>
<td>$H$</td>
<td>0.2852 (0.9237)</td>
<td>0.4044 (0.9237)</td>
<td>0.0637 (0.9237)</td>
<td>0.4600 (0.9237)</td>
<td>0.7801 (0.9237)</td>
<td></td>
</tr>
</tbody>
</table>

* Significant at a 5 per cent level. The $t$-statistics are given in parentheses.
### Table 3: LR Statistics for Common Trend and Common Cycle Tests

<table>
<thead>
<tr>
<th>Variable</th>
<th>Trend</th>
<th>Cycle</th>
</tr>
</thead>
<tbody>
<tr>
<td>PRL</td>
<td>0.0100</td>
<td>0.4400</td>
</tr>
<tr>
<td>INC</td>
<td>-0.3040</td>
<td>-0.3120</td>
</tr>
<tr>
<td>IRT</td>
<td>521.69*</td>
<td>-2.3880</td>
</tr>
<tr>
<td>UNE</td>
<td>0.0020</td>
<td>-0.0150</td>
</tr>
<tr>
<td>POP</td>
<td>-5.5200</td>
<td>0.0200</td>
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</tbody>
</table>

*Significant at a 5 per cent level.

### Table 4: Measures of Forecasting Accuracy

<table>
<thead>
<tr>
<th>Measure</th>
<th>One-step Forecast</th>
<th>Multi-step Forecast</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Multivariate</td>
<td>Univariate</td>
</tr>
<tr>
<td>SAE</td>
<td>0.1752</td>
<td>0.1639</td>
</tr>
<tr>
<td>MAE</td>
<td>0.0088</td>
<td>0.0082</td>
</tr>
<tr>
<td>SSE</td>
<td>0.0022</td>
<td>0.0021</td>
</tr>
<tr>
<td>MSE</td>
<td>0.0001</td>
<td>0.0001</td>
</tr>
<tr>
<td>MAPE</td>
<td>0.0017</td>
<td>0.0016</td>
</tr>
<tr>
<td>RMSE</td>
<td>0.0104</td>
<td>0.0103</td>
</tr>
<tr>
<td>TIC</td>
<td>0.6386</td>
<td>0.6337</td>
</tr>
</tbody>
</table>

### Table 5: Results of the AGS Test

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>One-period forecast</th>
<th>Multi-step forecast</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha_0$</td>
<td>-0.0028</td>
<td>0.0934*</td>
</tr>
<tr>
<td></td>
<td>(0.9490)</td>
<td>(0.0000)</td>
</tr>
<tr>
<td>$\alpha_1$</td>
<td>0.0004</td>
<td>0.0207*</td>
</tr>
<tr>
<td></td>
<td>(0.6350)</td>
<td>(0.0000)</td>
</tr>
<tr>
<td>Wald ($\alpha_0 = \alpha_1 = 0$)</td>
<td>0.2369</td>
<td>528.79*</td>
</tr>
<tr>
<td></td>
<td>(0.8880)</td>
<td>(0.0000)</td>
</tr>
</tbody>
</table>

*Significant at a 5 per cent level. The p-values are given in parentheses.
Figure 1: Time-Series Data (Original Series)
Figure 2: Components of Life Insurance Demand
Figure 3: Trend Components of All Variables

- **DEM**
- **PRL**
- **INC**
- **IRT**
- **UNE**
- **POP**
Figure 4: Cyclical Components of All Variables
Figure 5: Multivariate and Univariate Forecasts

One-Step Forecast

Multi-Step Forecast