Factors Influencing Demand for Life Insurance in India: An Empirical Analysis

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In the backdrop of a staggering market for life insurance in India, this paper explores the responsiveness of India's aggregate demand for life insurance to key macroeconomic and demographic developments, over the period 1991-92 to 2021-22. Structured on the edifice of simple economic models and state-of-the-art techniques that undercuts the bias in extant studies, the results of the study unravel significant long-run relationships underlying both per capita and absolute demand for life insurance in the country. Among other things, the study finds household savings per capita to have an asymmetrical effect on this demand, in terms of both direction and magnitude. While savings and acquisition of funds make life insurance affordable and raise its demand, acquired funds, in the long run, also act as self-insurance, offsetting the very need for insurance altogether. Threat to this self-insurance is a prime driver of demand for market-based life insurance.

***Keywords*: Life insurance, Wealth effect, NARDL, Dynamic multipliers**

Introduction

What life insurance means to an individual is different from what it means to the nation at large. Individuals regard life insurance as a commodity or service, demand for which principally stems from their instinct of stability and concern over the uncertainty of leaving their loved ones deprived of the current standard of living (Hakansson, 1969; Lewis, 1989; Richard, 1975; Yaari, 1965). The nation, however, goes beyond to regard life insurance as a set of financial transactions that mobilize savings, fund capital markets, allow reallocation of resources and reinvestments in private and public sector projects (Beck & Webb, 2002; Ripoll, 1981). Indeed, studies have empirically ascertained the contribution of life insurance in the financial development and economic growth of the country in the long haul (Arena, 2008; Hou et al., 2012; Outreville, 2013; Ward & Zurbruegg, 2002).

The life insurance market in India underwent a sea change with the advent of neoliberal reforms in 1999, which ushered in an era of market orientation, privatization, foreign

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investments, competition and consequent product and distributional innovations. The sector has come a long way today, and in the year 2022 it claimed a market of $100.4 bn. It is further projected to achieve a CAGR of 12% during 2023-27 (Global Data, 2023). These developments, however, do not blur the fact that the sector has been facing a shrinking market since the onset of the Global Financial Crisis. The decadal growth rate of gross life insurance premiums of the country dipped from a sound 23.5% in 2000-2010 to about 4% in 2010-2020. Table 1 outlines how the steady rise witnessed by the country's market for life insurance India in the 2000s, courtesy the supply-side reforms, gets overturned in the post-recession period. Per capita gross life insurance premium (density) registers a decadal growth of 5.1% in 2010-2020, compared to 21% growth in the previous decade. The share of life insurance premium to the country's GDP (penetration) faces a negative CAGR of –4.3 for the decade 2010-2020.

Table 1: Trends in India's Life Insurance Market (CAGR) (1980-2020)

Period	Density	Penetration	Gross Premium
1980-90	15.4	2.4	15.6
1990-00	15.7	3.9	17.6
2000-10	20.9	10.7	23.5
2010-20	5.1	–4.3	3.8

Source: Computed using IRDAI database

Arresting the decline and sustaining the growth of life insurance market is instrumental for a robust savings and investment culture. A flourishing market for life insurance with greater public participation can further ease the state's burden of publicly funding social security and protection schemes, thus allowing efficient resource allocation and economic growth. To this end, it becomes imperative to question what exactly explains the demand for life insurance in India? Although this research question has found frequent attention in the academic space, the current study is fundamentally apart, for it conscientiously shows how the demand for life insurance and the ability to pay for it share a nonlinear, precisely an asymmetrical causal relationship.

The rest of the paper is structured as follows: the next section presents a brief discussion on the prospective determinants of a country's demand for life insurance, as conjectured by the existing literature. Inspired by the literature and then guided by the statistical properties of the empirical data, estimable models are constructed in the subsequent section. The main findings are then presented, followed by a conclusion.

Literature Review

Research on the determinants for life insurance has generally assumed two discernible structures. The dominant stance has been to situate it within the context of consumption demand and maximization of utility over the life cycle of the insured. The less explored stance views life insurance as a form of savings, competing with other saving instruments in the market.

Origins of the consumption-based theoretical premise can be traced back to the works of Yaari (1965), Hakansson (1969), Fischer (1973) and Richard (1975) who construe a household's demand for life insurance as a constrained optimization problem—minimization of uncertainties in a household's income owing to the demise of principal breadwinner, under constraints to rate of income and consumption spending. Naturally then, like demand for any other commodity, the decision to buy life insurance is essentially a function of income. An individual's personal income is the earnings flow that pays the insurance premiums, and so consumption of life insurance purchase is a positive function of income (Campbell, 1980; Cargill & Troxel, 1979; Hakansson, 1969; Hammond et al., 1967; Hwang & Gao, 2003; Lewis, 1989; Li et al., 2007; Liebenberg et al., 2012; Mantis & Farmer, 1968; Mitra & Ghosh, 2010; Outreville, 1996; Showers & Shotick, 1994; Sliwinski et al., 2013; Truett & Truett, 1990; Ward & Zurbruegg, 2002). Even so, Fortune (1973) identifies that if a high income earning individual practices savings, the consequential wealth accumulated will decrease his aversion to risk, in turn causing his need for life insurance to dwindle. Hong and Ríos-Rull (2012) find an adverse effect of income on life insurance purchase of middle-income groups but a positive influence for higher-income groups. With the propensity to save being low and cost of living being high, life insurance premiums might not be attractive options for the middle-class, but might provide attractive tax savings to the rich.

This brings us to the other stance—life insurance as a form of savings. Despite the lack of a unified theory, important conjectures emerge from the existing literature. Should life insurance be viewed as a saving that competes with other forms of saving in the market, then an increase in household savings or accumulated private wealth should deflate the need for life insurance. True to form, Lewis (1989), Mossin (1968), Fischer (1973), and Li et al. (2007) argue that acquisition of funds and private wealth instills a higher level of risk tolerance and/or ends up substituting for life insurance over time. But since saving is a characteristic of high-income groups and accumulated funds represent the ability to pay premiums, more savings and increasing net worth can also stimulate demand for life insurance. Along these lines, Hau (2000), Beck and Webb (2002), and Heo et al. (2013) find a positive impact of savings on purchase of life insurance. Taking a step further, Sen and Madheswaran's (2013) study on select Asian countries deduces life insurance density to be elastic to savings, but penetration to be inelastic, connotating that these economies are not very responsive to changes in aggregate savings. Then again, the study's log transformation of the penetration variable, which is already in percentage terms, renders this inference on elasticity disputable.

Premiums paid are essentially savings which are set aside by the insurer and paid back at a much later stage in the event of death, retirement or disability. Ripoll (1981) observes that a typical insurer calculates the premiums on the basis of interest rates, which is discounted from the investment made by the policyholder. As a result, a high interest rate in the economy ought to result in smaller premiums and hence higher demand for life insurance. But since in practice, most life insurance plans come with pre-fixed premiums, a direct effect of interest rates may not materialize. Nevertheless, high market interest rates on competing and relatively more liquid assets like bank deposits and bonds may indirectly dampen demand for life insurance by encouraging investors to switch to alternate saving options. True to form, studies by Cargill and Troxel (1979), Li et al. (2007), Sliwinski et al. (2013), and Sen and Madheswaran (2013) find a negative effect of interest rate on consumption of life insurance.

Inflation is touted to act as a deterrent to life insurance in the same way as it is a deterrent to any long-term saving plan (Ripoll, 1981). Price hike reduces the real value of the policy cover, thus making life insurance plans less attractive. Likewise, rising prices inflate basic consumption expenditures, which again limits the affordability of investment plans. Accordingly, Beck and Webb (2002), Browne and Kim (1993), Hwang and Gao (2003), Li et al. (2007), Mitra and Ghosh (2010), Outreville (1996), Sen & Madheswaran (2013), Ward and Zurbruegg (2002), etc. evidence a negative effect of inflation and price instability on demand for life insurance.

Finally, by virtue of being a type of social security, demand for life insurance is also influenced by social and demographic factors. In particular, an earning individual's purchase of life insurance over annuities is basically a transaction made on behalf of their beneficiaries—dependent children. Individuals care about their dependent's long-term wellbeing, practice some level of altruism and have an operational bequest motive, as argued by Hakanson (1969) and Hong and Rull (2012). Studies by Beenstock (1968), Hammond et al. (1967) and Lienberg et al. (2012) thus find the number of dependents to be a positive significator of life insurance demand. Browne and Kim (1993), Outreville (1996) and Sen and Madheswaran (2013) lend further support that younger economies offer a larger market for life insurance businesses. Besides dependents, education has also been theorized to play a positive role in demand for life insurances along the notion that more years of formal education provides greater awareness of the need for life insurance and aids meticulous future financial planning. Beck and Webb (2002), Browne and Kim (1993), Burnett & Palmer (1984), Hammond et al. (1967), Truet and Truet (1990), Outreville (1996), Li et al. (2007), etc. do find education to stimulate life insurance purchase. Outreville (1996) estimates a negative impact of education on insurance demand, but acknowledges that the negativity owes to strong multicollinearity between the demographic variables set used, namely, human development index (HDI), life expectancy, health status, dependency ratio and social security. The study by Sliwinski et al. (2013) deserves special mention for taking due cognizance of the bias that plagues most past studies for using a wide range of related economic and demographic variables as regressors. The study uses factor analysis to merge these variables into four independent factors, and the subsequent regression reveals economic and financial factors to be the strongest stimulator of life insurance demand.

Research Gap

A few studies have empirically explored the demand for life insurance in India using long time-series data. Notwithstanding their pioneering contribution in explaining this demand, their contrasting findings hint at the sensitivity of their explanations to methodological nuances. For instance, the earliest time-series study on probable determinants of life insurance dates back to Sadhak (2006) who computes Pearson's correlation coefficients on the level of variables like personal disposable income, household savings and life insurance funds, thereby generating spurious results, with correlations reaching as high as 0.99. In order to assess the income effect on demand for life insurance under a causal framework, Mitra and Ghosh (2010), Ghosh (2013), Parida and Acharya (2014) and Mathew and Sivaraman (2017) model premium expenditures as a function of gross disposable income. But while the first three studies find a positive income effect on the edifice of spurious regressions that do not factor in short-term error corrections in estimation, the otherwise fine study of Mathew and Sivaraman (2017) concludes a negative income effect, which is discernibly a consequence of the inevitable correlation between inflation and aggregate income.

An inverse relation between income and life insurance penetration also emerges for the time-series study of Sen (2008) that considers GDP per capita, alongside gross domestic savings (GDS) per capita, as explanatory variables. If not collinearity, the inverse effect could be merely the result of the numerator in GDP per capita being the denominator in insurance penetration rate. Similar is the case for inflation and interest rates as explanatory variables. Inflation is touted to act as a deterrent to life insurance in the same way as it is a deterrent to any long-term saving plan (UNCTAD, 1981). However, inflation has a positive sign in the study by Mathews and Sivaraman (2017) and Mitra and Ghosh (2010) and real interest rate has the counter-intuitive positive sign in Sen (2008), and these can be attributed to the inclusion of both inflation and interest rate as regressors. Inflation is also a positive predictor in the study by Ghosh (2013) who reasons it with the plausible existence of money illusion. But then again, there is no strong reason why such an illusion should be a characteristic of an emerging market economy like India. It is more likely that the sign owes to the correlation between inflation and GDP per capita. Last but not the least, almost all the studies employ the rudimentary ADF test to gauge the unit root properties of the variables but deduce the series on inflation, i.e., the change in general price levels to possess a unit root.

It is in this backdrop that the current study finds space. Unlike the unit level studies where findings are bound to be sample-specific and contextual, ambiguity in single-country macro level studies is uncalled for and merits decisiveness to facilitate efficient policy decisions. In what follows, this paper attempts to reconcile some of the methodological oversights in existing studies to definitively identify the prime determinants of absolute and per capita demand for life insurance in India. In particular, it departs from existing studies in terms of representation, factors out bias from collinearity and employs higher power statistical tests to better ascertain and model the time-series properties of the macroeconomic variables. More importantly, it adds to the literature by accounting for the asymmetric association between demand for life insurance and the ability to pay. In doing so, it empirically establishes the theorized duality of life insurance as an item of consumption and a type of saving.

Data and Methodology

The analysis is structured around a partial equilibrium model where a country's demand for life insurance is considered to be a function of income, households' savings, inflation, dependency ratio and attainment of higher formal education. The model is built on annual data spanning the period 1991-92 to 2021-22, thereby making the study fall within the ambit of time-series analysis. The exact econometric specification of the model is subject to the nature of data, variable construction and properties of time-series used.

Data and Variable Description

As mentioned, dependent variable is the demand for life insurance. A country's overall demand for life insurance can be quantified either in terms of total amount insured or total expenditure on life insurance premiums (Duker, 1969; Hamond et al., 1967). In the absence of reliable data on the former, this study employs two distinct measures of premium expenditures as approximations of India's demand for life insurance, viz., life insurance density (*D*) and life insurance penetration (*P*). By definition, insurance density is the ratio of a country's insurance premiums to its population. Penetration rate, on the other hand, expresses insurance premium expenditures as a percentage of gross domestic product (GDP). So, while density indicates the per capita demand for life insurance, the penetration rate serves as a significator of the share of insurance demand in the country's aggregate demand. However, being a percentage, penetration is bounded between 0 and 100. As bounded dependent variables pose estimation issues in linear regression framework, the absolute levels of premium expenditure are retracted from the percentage figures. The resulting series denotes the absolute level of life insurance premium expenditures. The raw data on density, which is available in USD terms for international comparisons, have been converted into rupee figures using the nominal exchange rate (₹ per USD) for consistency with the rest of the dataset.

With regard to the explanatory variables, we deviate from studies like Cargill and Troxel (1979), Sadhak (2006), Parida and Acharya (2014), etc., who have considered personal disposable income over gross income per capita to estimate the income effect on demand for insurance. Taking disposable income inadvertently assumes taxes to have no bearing on life insurance demand when in fact, one of the key reasons behind their purchase is to avail tax concessions. In short, there is no a priori reason to assume that individuals do not take their taxes into account when buying life insurances. Accordingly, this study considers the conventional GDP per capita in current prices and in rupee terms as a measure of personal income. Household savings per capita have been computed using data on gross household savings, as obtained from the RBI Database along with the World Bank's population estimates. The series is denominated in rupees and takes in 2011-12 prices. The country's inflation is captured in terms of annual changes in the wholesale price index (WPI), data for which is sourced from the RBI and back series data have been rebased to 2011-12 prices. To cover the bequest motive behind purchase of life insurance, dependency ratio is used as an explanatory variable. It shows the proportion of young dependent population (<15 years) to the working-age population (15-64 years). The series has been sourced from the World Bank database. Finally, due to a dearth of statistics on high level of educational attainment, the enrollment in secondary education to gross enrollment is considered as a proxy. One can argue that enrollment does not imply attainment and secondary school is not necessarily higher education. But then again, since enrollment is the first step to attainment and secondary schooling is a prerequisite to higher education, the proxy fits the purpose of this study. Data on secondary education enrollment is also drawn from the World Bank. All the level variables—per capita income, savings per capita, density and absolute penetration—have been taken in their natural log forms. Dependency rate, education and inflation continue to be expressed in shares and percentages. Table 2 summarizes the variable construction and their data sources.

Table 2: Variable Description and Data Sources

Variable	Definition	Construction	Data-Sources Used
ln*D*	Per Capita Demand for Life Insurance	Log of life insurance density, post conversion to rupee figures	*Handbook of Indian Insurance*; World Bank Official Exchange Rate (₹ per USD)
ln*P*	Absolute Demand for Life Insurance	Log of the product series of penetration and GDP	*Handbook of Indian Insurance*; World Bank GDP in current prices and rupee terms
ln*Y*	Per Capita Income	Log of GDP per capita	World Bank per capita income in current prices and rupee terms
ln*S*	Savings	Log of per capita household savings	RBI Database, World Bank's population estimates
gWPI	Inflation Rate	Annual growth rate of wholesale price index (2011-12 base)	RBI Database
EDU	Higher Education	Secondary school enrollment as a percent of gross enrollment	World Bank Database
DR	Dependency Ratio	Ratio of young dependents to working-age population (%)	World Bank Database

Table 3 reports the descriptive statistics and distributions of the variables. The sample period reports an average inflation growth rate of a resounding 6% per annum and a secondary school enrollment of 58%. The average dependency ratio is 51% intimating an almost equi-proportionate distribution of young and working-age population for the period. The Jarque and Bera (1981) test statistics reject the null of non-Gaussian distribution for all the variables.

Table 3: Basic Descriptive Statistics of the Variables							
	ln*D*	**ln*P***	**ln*Y***	**ln*S***	***gWPI***	***DR***	***EDU***
Mean	6.75	32.34	10.64	9.08	5.59	51.17	58.01
Max.	8.59	34.4	12.16	10.39	12.99	64.29	78.81
Min.	4.40	29.4	9.03	7.31	–3.65	37.32	36.60
SD	1.38	1.5	0.95	0.92	3.53	8.50	12.81
Skewness	–0.40	–0.44	–0.02	–0.38	–0.06	–0.05	0.16
Kurtosis	1.72	1.82	1.69	1.92	3.34	1.73	1.56
Jarque-Bera	2.94 (0.2)	2.7 (0.2)	2.18 (0.3)	2.24 (0.3)	0.17 (0.9)	2.09 (0.3)	2.79 (0.2)
n	31	31	31	31	31	31	31

Note: Figures in parentheses show exact probabilities of the Jarque-Bera statistics on the null of normal distributions.

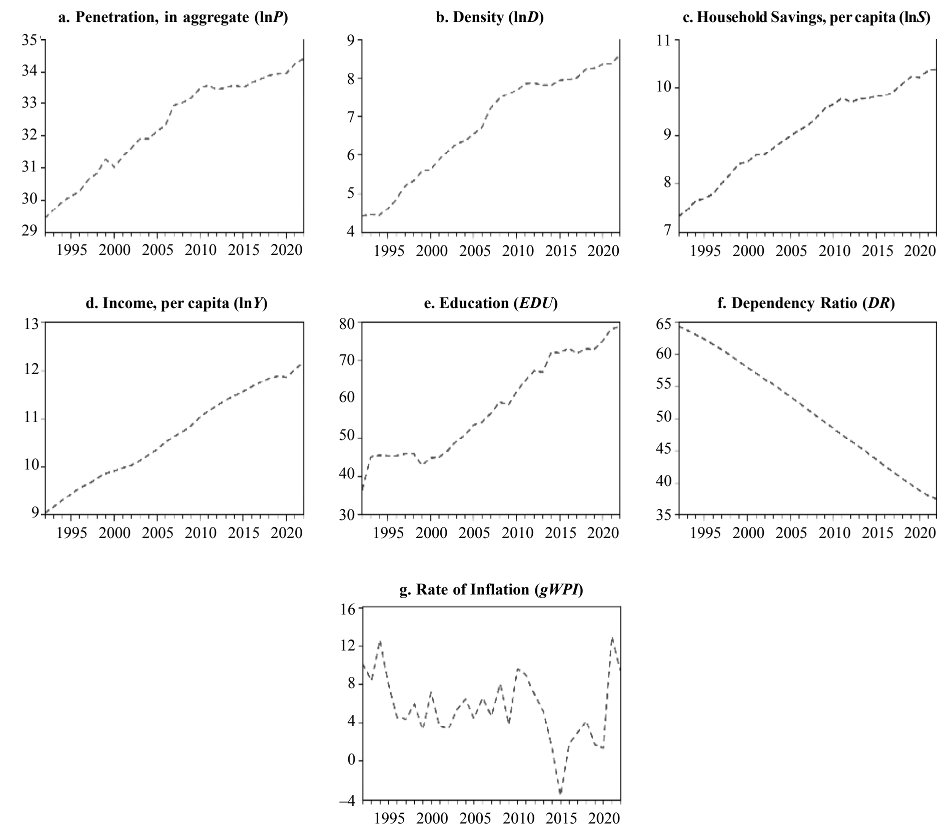
Stationarity and Unit Root Tests

With data spanning a period of 31 years, the foundation of the analytical framework rests on the long-run properties of the time-series used. If autoregressive representations of the variables at levels indicate stationarity, any liaisons between them will be short-lived, and we can test them within the classical regression context, without the danger of spurious judgments (Granger & Newbold, 1974). Conversely, if the series exhibit considerable persistence with unit roots, the prospect of a long-run equilibrium relationship between them cannot be overruled. Indeed, given that the decision to get life insurance is conditional on the effect that the insured's death can have on the future consumption of other household members, it is argued that the existence of a level or long-run association between demand for life insurance and its causal factors merits due attention.

As per the time-paths of the variables plotted in Figure 1, the series on inflation rate (*gWPI*) appears to be mean-reverting or levels stationary, as expected. Life insurance density (ln*D*), aggregate premium expenditure (ln*P*), per capita income (ln*Y*), per capita savings (ln*S*) and education (*EDU*) exhibit strong upward trending behavior along the course of the sample period. Dependency ratio (*DR*), on the other hand, shows a downward trend, clearly a result of the country's achievements in population control and family planning. Formal unit roots and stationarity tests are employed to better delineate whether these trends are deterministic or stochastic. In precise, the variables are subjected to (i) the DF-GLS test by Elliott et al. (1996), built on the null of unit roots; (ii) Lee and Strazicich (2003) test on the null of unit roots with breaks; and (iii) the KPSS test on the null of stationarity by Kwiatkowski et al. (1992).

The choice of DF-GLS over the classic ADF test of unit root accrues from the fact that the former has nearly the same power to the ADF test under the assumption of no deterministics in the underlying series, but is far superior to ADF when the series has any deterministic trends or drifts (nonzero means). And as per the time-plots in Figure 1, the presence of deterministics in the series of choice is fathomable. But although DF-GLS improves on the low power of ADF test due to misperceived trends and means, it has low power in the presence of structural breaks. Since the period of study stretches across some dramatic macroeconomic events in the national and international milieu, the presence of breaks in the variables cannot be undermined. What this implies is that the DF-GLS test runs the risk of wrongly inferring an otherwise stationary process with structural breaks to be a unit root process. As such, the study additionally undertakes the Lee and Strazicich (2003) test of unit root which tests the null of a difference stationary process with structural breaks against a trend stationary process with structural breaks. Variables are further treated to the Kwiatkowski et al. (1992) test of stationarity. This is done under the contention that testing the null of unit root often has low power when compared to testing the alternative null of stationarity. LM statistics for the KPSS test are constructed on the nulls of trend stationarity and level stationarity against the alternative of difference stationarity, such that rejection of the null points to the presence of unit roots.

Figure 1: Time Plots of the Variables (1991-92 to 2021-22)



All the three tests are performed on both the level series and on first differences, in case of unit root detection. The results of the same are presented in Table 4.

Table 4: Testing for Stationarity and Unit Roots

Variables	DF-GLS[a]	KPSS[b]	Lee-Strazicich[c]	Inference
	H_0: *Unit root*	H_0: *Stationary*	H_0: *Unit root despite break(s)*	
	Model: Intercept with Linear Trend			
ln*D*	–0.83	0.15**	–2.94	I(1)
Δln*D*	–4.17***	0.09		
ln*P*	–1.36	0.13**	–3.92	I(1)
Δln*P*	–5.70***	0.08		
ln*Y*	–2.39	0.07	–4.28***	I(0)
Δln*Y*	–3.68**			
ln*S*	–1.23	0.16**	–1.94	I(1)
Δln*S*	–5.44***	0.09		
gWPI	–3.37**	0.10	–5.41***	I(0)
DR	–1.01	0.14**	–3.08	I(1)
Δ*DR*	–3.42**	0.06		
EDU	–2.06	0.10	–3.97	I(1)
Δ*EDU*	–4.95***			

Note: [a] Using McKinnon finite sample critical values; [b] Based on quadratic spectral kernel and automatic bandwidth selection procedure of Newey-West; [c] For SIC based lags for a maximum of 2 lags; and ** and *** indicate significance at 5% and 1% levels, respectively.

True to form, all three tests unanimously identify ln*D*, ln*P*, ln*S* and *DR* as I(1) processes and the series *gWPI* as an I(0) series. The KPSS and Lee Strazicich test jointly infer ln*Y* to be an I(0) process with a deterministic trend, while DF-GLS and the Lee-Strazicich test infer EDU to be an I(1) process. In a nutshell, explanatory variable set comprises both I(0) and I(1) processes, while the dependent variables of choice are exclusively I(1), and short-run coefficients are evaluated by means of the Wald test.

Correlation Matrix

Having identified the statistical and time-series properties of the variable set, next, the study probes into the plausible presence of multicollinearity to skirt biased estimates. Collinearity between two trending time-series cannot be outrightly adjudged from their correlation coefficients, for the latter would be spurious and deceptively high (Vigen, 2015). The same reason renders post-estimation computation of VIFs and tolerances of the variables invalid.

Consequently, for the study's variable set, correlations between the trend stationary form of the I(0) series ln$Y$ and the first differenced forms of all the I(1) series are computed as they all exhibit visible trends. The detrended ln$Y$ series is obtained after procuring its trend (t) using the decomposition technique of Beveridge and Nelson (1981). The subsequent Pearson's correlation coefficients between the variables are presented in Table 5.

Table 5: Correlation Matrix of the Variables

	Δ ln*D*	**Δ ln*P***	**ln*Y*–*t***	**Δ ln*S***	***gWPI***	**Δ *EDU***	**Δ *DR***
Δln*D*	1						
Δln*P*	**0.64**	1					
ln*Y*–*t*	0.07	–0.30	1				
Δln*S*	0.41	0.46	–0.21	1			
gWPI	0.01	0.06	**0.66**	0.10	1		
Δ*EDU*	–0.11	–0.07	0.10	–0.37	0.31	1	
Δ*DR*	0.14	0.09	–0.14	0.02	0.36	–0.19	1

Note: ln$Y$ – t is the detrended per-capita income series.

Predictably, the two dependent variables of choice—life insurance density (ln$D$) and absolute penetration (ln$P$)—are highly and positively correlated with a coefficient of 0.64. Amongst the explanatory variable set, the series on inflation rates ($gWPI$) and per capita income (ln$Y$) share a high correlation of 0.66, thus intimating that the two are collinear. This is taken into consideration in model-building.

Sign-wise, growth rate of household savings per capita (ln$S$) appears to be negatively associated with growth of income per capita, which could be the consequence of higher propensity to consume in the country. The magnitude of association between the two at –0.21 is not very high, but credibly explains the negative albeit low association between income and life insurance penetration (ln$P$). If saved funds denote ability to pay premiums, then a country with low savings rate will exhibit an inverse relation between incremental income and purchase of life insurances. Again, the negative association between EDU variable on one side and ln$S$, ln$D$ and ln$P$ on the other side serves as a reminder that higher education in India is a costly affair that constrains household's savings. Correspondingly, education costs form a part of child-rearing cost, which explicates the negative correlation coefficient of –0.19 between EDU and DR. The more the number of children, the greater their educational expenses and the lesser their enrollment in higher levels of schooling. This association could also work the other way round—educated people, by virtue of being more aware of family planning and the cost of rearing children, may settle for smaller families and thus contribute to a contraction in the total number of young dependents in the country.

We do not find any strong association (>|0.5|) between the dependent variables (ln*D* or ln*P*) and the explanatory variables of choice per se. But since correlation fall shorts of projecting causality and/or demarcating between long-run and short-run dynamics between trending variables, a causal analysis befitting to the purpose of this study is undertaken.

Model and Estimation

The demand for life insurance is modeled using single-equation estimation techniques befitting I(1) dependent variable and a mix of I(0) and I(1) explanatory variables. Precisely, the ARDL bound testing approach of Pesaran et al. (2001) is employed, for it can identify the presence of long-run relationship between a variable and a set of regressors, "irrespective of whether the underlying regressors are I(0), I(1) or mutually cointegrated", and also simultaneously provide the short-run estimates. The ARDL procedure involves building a 'conditional' reduced-form short-term error correction model (ECM) where the causality is assumed to be unidirectional, such that the parameters are corrected for weak endogeneity. It is on this ECM that *F*-test statistics are constructed on the nulls of no levels relationship, and then tested against a set of two critical values that serve as 'bounds' each for purely I(0) and purely I(1) processes, such that if the values of the statistics cross the critical I(1) bound, then the null stands rejected.

Demand for life insurance is first modeled as linear functions of their *p*-lagged AR terms and *q*-lagged explanatory variables. Per capita income (ln*Y*), as an explanatory variable, is dropped owing to its collinearity with the country's inflation rate (*gWPI*). Nonetheless, since savings is a function of income and a high propensity to save is characteristic of higher income, the savings per capita variable (ln*S*) is expected to also cover for the income effect.[1] Thus, ultimate models hypothesize life insurance density (ln*D*) and absolute penetration (ln*P*) as functions of two economic and two demographic variables, namely, savings per capita (ln*S*), rate of inflation (*gWPI*), higher education (*EDU*) and young dependency ratio (*DR*). The order of the lags (*p,q*) is determined using Schwarz information criteria (*SIC*), with a maximum lag length of (1, 2), keeping in mind the shorter time-frame of the study with only 31 observations.

The parsimonious ARDL models, as chosen by SIC, for life insurance density (ln*D*) and absolute penetration (ln*P*) can be written as:

Model 1.1

$$\ln D_t = \alpha + \phi.\ln D_{t-1} + \beta_1.\ln S_t + \beta_2.gWPI + \beta_3.DR + \beta_4.EDU + v_t$$

and

Model 2.1

$$\ln P_t = \alpha + \phi.\ln P_{t-1} + \beta_1.\ln S_t + \beta_2.gWPI + \beta_3.DR + \beta_4.EDU + v_t$$

[1] A similar approach has been taken by Sen (2008) who argues that as income grows, it will add to insurance demand only via the rising savings component.

where α is the intercept, ϕ is the coefficient to the AR term, β_i shows the marginal effect of the i^{th} explanatory variable and v_t represents deviations from equilibrium in time t.

According to Pesaran et al. (2001), the dynamic form of ARDL model conceives consistent OLS estimates of short-run parameters that converge at the standard rate of $\sqrt{T}$ and so are asymptotically normal, while long-run estimates are T consistent and have mixed normal distributions. It is on the estimated conditional ECMs underlying Models 1.1 and 2.1, that the F-bounds statistic on the dual null hypotheses of (i) joint significance of the long-run coefficients; and (ii) significance of the equilibrium adjustment parameter (v_{t-1}) are tested.

Now, implicit in Models 1.1 and 2.1 is the idea that demand for life insurance has a symmetric response to changes in the explanatory variables across all time-periods, irrespective of whether t entails a positive change in the variable or a negative change. This assumption is restrictive when it comes to the impact of income or savings on demand for life insurance because it rules out the possibility of ratchet and demonstration effects. It is also palpable that the economy responds strongly to an increase in savings than to a decrease, as the process of discontinuing or surrendering purchased life insurances entails costs on the insured. Furthermore, how an agent responds to an incremental income or savings can vary in terms of the nature of response too, for incremental savings are not just increased avenues to pay out premiums, but also increased wealth, which can substitute for market insurance altogether.

Given these qualifications and possibilities, Models 1.1 and 2.1 are lent asymmetric constructions in which the variable $\ln S_t$ is decomposed into its partial sum processes of positive and negative changes, thereby begetting a nonlinear ARDL (NARDL) model of the forms:

Model 1.2

$$\ln D_t = \alpha + \phi.\ln D_{t-1} + \theta^{+}.\ln S_t^{+} + \theta^{-}.\ln S_t^{-} + \beta_2.gWPI + \beta_3.DR + \beta_4.EDU + v_t$$

and

Model 2.2

$$\ln P_t = \alpha + \phi.\ln P_{t-1} + \theta^{+}.\ln S_t^{+} + \theta^{-}.\ln S_t^{-} + \beta_2.gWPI + \beta_3.DR + \beta_4.EDU + v_t$$

where

$$\ln S_t^{+} = \sum\nolimits_{j=1}^{t} \Delta \ln S_t^{+} = \sum\nolimits_{j=1}^{t} \max\left(\Delta \ln S_t, 0\right)$$
$$\ln S_t^{-} = \sum\nolimits_{j=1}^{t} \Delta \ln S_t^{-} = \sum\nolimits_{j=1}^{t} \min\left(\Delta \ln S_t, 0\right)$$

The long-run Models 1.2 and 2.2 now employ two different filters allowing insurance demand to respond differently to positive growth and negative growth in savings per capita.

If indeed this response differs rightly such that $\left(\theta^{+}=\theta^{-}\right)$, and if $v_t \sim I\left(0\right)$, then it is implied that savings is asymmetrically cointegrated with demand for life insurance.[2] To test the dual null hypotheses of no asymmetry $\left(\theta^{+}=\theta^{-}\right)$ and no cointegration $\left(v_t \sim I\left(1\right)\right)$, the NARDL F-bounds statistic of Shin et al. (2014) is employed, which is basically a nonlinear extension of the ARDL bound tests.

Furthermore, the NARDL model can generate information about the cumulative dynamic multiplier effects of $\ln S_{t-1}^{+}$ and $\ln S_{t-1}^{-}$ on $\ln D_t$ (or $\ln P_t$) over some forecast time horizon, say, h such that they show how the dependent variable responds and adjusts to a positive or negative unitary shock in savings per capita, over the horizon. In the event of significant long-run relationship, the cumulative dynamic multipliers are extracted as

$$mh^{+}=\sum_{i=o}^{h}\frac{\partial \ln D_{t+i}}{\partial \ln S_{t-1}{}^{+}} \text{ and } mh^{-}=\sum_{i=o}^{h}\frac{\partial \ln D_{t+i}}{\partial \ln S_{t-1}{}^{-}}$$

for the density model or,

$$mh^{+}=\sum_{i=o}^{h}\frac{\partial \ln P_{t+i}}{\partial \ln S_{t-1}{}^{+}} \text{ and } mh^{-}=\sum_{i=o}^{h}\frac{\partial \ln P_{t+i}}{\partial \ln S_{t-1}{}^{-}}$$

for the penetration model, where mh^{+} and mh^{-} capture the dynamic response of the system to a positive shock and a negative shock in savings per capita, respectively. The statistical significance of the impulse response asymmetry can be judged by mapping whether the difference between the two cumulative dynamic multipliers mh^{+} and mh^{-} is significantly different from zero for 95% confidence intervals.

The post-estimation diagnostic tests that have been followed up include normality tests of Bai and Serena (2005), Breusch-Pagan serial correlation test and heteroskedasticity tests of Breusch-Pagan-Godfrey. Stability of the models are judged from the CUSUM and CUSUM-SQ tests of Brown et al. (1975), which plot the cumulative sums and cumulative sum of squares of the recursive residuals against 95% confidence bands for assessing the stability of the model parameters and residual variances, respectively.

Results and Discussion

Determinants of Life Insurance Density

Table 6 presents the results of the ARDL and NARDL bounds tests built on the conditional ECMs of the models for life insurance density ($\ln D$).

As reported, the asymptotic critical bounds for the computed F-statistics on the ARDL model resoundingly rejects the null of no levels relationship at 1% level of

[2] Since the dependent variables ($\ln D$ and $\ln P$) and the key asymmetric explanatory variable ($\ln S$) are all I(1) processes, the PSS' F-test for long-run level relationship translates into a test for cointegrating relationship (Pesaran et al., 2001).

Table 6: Bound Testing for Long-Run Relation in Density Model								
ARDL Model 1.1					NARDL Model 2.1			
Statistic[a]	Estimate	Critical Bounds			Estimate	Critical Bounds		
		Significance	I (0)	I (I)		Significance	I (0)	I (I)
		10%	2.20	3.09		10%	2.08	3.0
F_{PSS}	12.4***	5%	2.56	3.49	16.9***	5%	2.39	3.38
		1%	3.29	4.37		1%	2.7	3.7
		10%	2.45	3.46		10%	2.4	3.5
$F_{NG,n=30}$	12.4***	5%	2.97	4.08	16.9***	5%	2.8	4.0
		1%	4.09	5.53		1%	4.1	5.7

Note: [a] Models have a maximum of 2 lags and restrict the intercept to enter the level equation.

significance, and this is confirmed further by the finite sample critical values of Narayan (2005). Thus, the variables ln*D,* ln*S, EDU, DR* and *gWPI* share a long-run equilibrium relationship where the causality runs from the latter four to ln*D*. More importantly, the NARDL *F*-bounds statistics also assert the presence of a levels relationship, while also rejecting the null of no significant asymmetrical effect of savings on life insurance density ($\theta^+ = \theta^-$) at 1% level of significance. To this end, it can thus be inferred that per capita savings and life insurance density are asymmetrically cointegrated.

That the variables in question share a long-run equilibrium relationship implies that their short-run dynamics is characterized by adjustments to this equilibrium. The *t*-bounds statistics on the coefficients of the error-correction term v_{t-1}, as reported in Table 7, also reject the

Table 7: Estimates of Life Insurance Density Model				
	ARDL Model 1.1		NARDL Model 2.1	
Variable	Coefficient	Std. Error	Coefficient	Std. Error
Long-Run Estimates				
c	–18.5***	4.75	6.76**	2.97
gWPI	–0.01**	0.008	–0.03***	0.007
DR	0.10**	0.04	–0.05	0.04
EDU	0.02**	0.01	0.03***	0.009
ln*S*	2.10***	0.23		
$\ln S_t^+$			0.84***	0.29
$\ln S_t^-$			13.44***	2.98

Table 7 (Cont.)

ARDL Model 1.1			NARDL Model 2.1	
Variable	Coefficient	Std. Error	Coefficient	Std. Error
Short-Run Estimates				
c	–9.3**	4.44	4.09	2.61
v_{t-1}	–0.50***	0.16	–0.60***	0.18
$gWPI$	–0.009	0.005	–0.01**	0.006
ΔDR	0.05	0.03	–0.034	0.038
ΔEDU	0.01	0.01	0.02*	0.01
$\Delta \ln S$	1.06***	0.36		
$\Delta \ln S_t^+$			0.51	0.40
$\Delta \ln S_t^-$			8.14**	2.27
$\Delta \ln S_{t-1}^-$			–2.89	1.81
Diagnostics Tests				
R^2	0.49		0.66	
$\overline{R^2}$	0.49		0.64	
χ^2_{AC}	1.07 (0.35)		2.53 (0.18)	
χ^2_{HET}	0.23 (0.94)		1.28 (0.30)	
χ^2_{BNG}	1.56 (0.45)		1.31 (0.51)	
F_{FF}	0.94 (0.34)		1.07 (0.36)	

Note: 1. $\overline{R^2}$ is the adjusted R^2 of the conditional ECM.

2. χ^2_{AC}, χ^2_{HET} and F_{FF} are test statistics for nulls of no serial correlation, no homoskedasticity and no functional form misspecification.
3. χ^2_{BNG} reports the Bai-NG statistic on the null of residual normality.
4. *, ** and *** indicate significance at 10%, 5% and 1% levels, respectively.

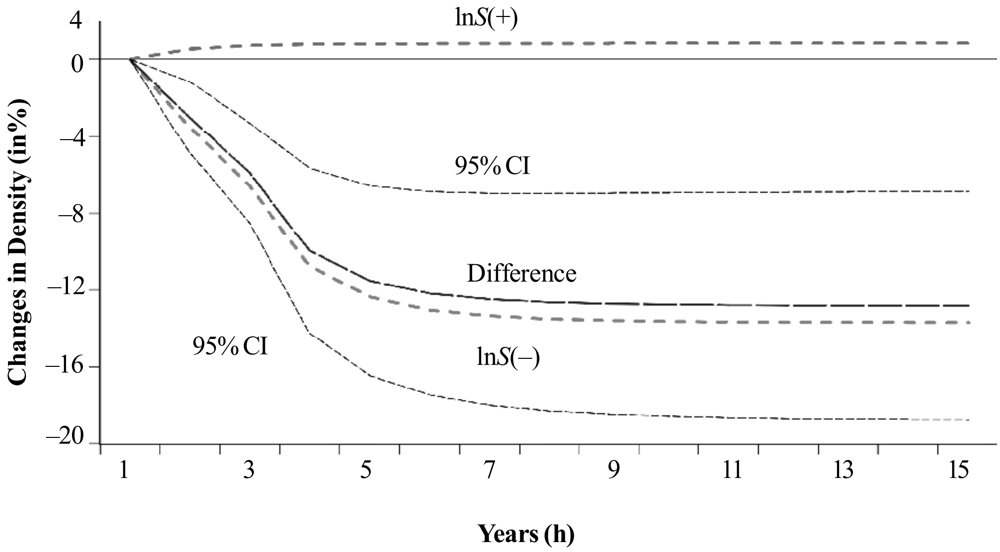
null of no levels relationship for both the symmetric and asymmetric models. The speed of adjustment is found to be –0.5 for the ARDL model and –0.6 for the NARDL version. Between the two, the NARDL model offers a stronger joint explanatory power with an adjusted R^2 of 64%. The strong significance of the NARDL bounds statistic and the better fit of its ECM reiterates that the long-run relation between India's per capita savings and life insurance density, ceteris paribus, is best defined as asymmetric, wherein over the long run, density responds differently to an increase in savings than to a decrease. The results of both models are robust to the various diagnostic tests mentioned in the bottom panel of Table 7. Recursive estimations of this underlying ECMs suggest that the estimated parameters are stable over the sample period, and the CUSUM and CUSUM square plots of these residuals do not show any significant breaks in the model for 5% level of significance (Appendix).

The overall inference from the estimates can be surmised as follows: Per capita demand for life insurance (ln*D*) in India is elastic to availability of funds or household savings, but this elasticity is asymmetric in terms of both magnitude and direction. In essence, density tends to rise by 0.84% to a percent increase in savings in the long run, but rises manifold (13.44%) to a percent decrease in savings (Table 7). Simply put, the country's per capita demand for life insurance is positively inelastic to a rise in savings, but negatively elastic to a decrease in savings. This connotes that accumulated savings serves more as an end than as a means to financial or social security. Basically, Indian households do not just view their accumulated savings as the means to finance life insurance investments but also as wealth that can altogether substitute for social and financial security alternatives, so much so that a dip in this wealth risks their security, thus pushing them to go for life insurance. The long-run coefficients for inflation rate and higher education are –0.03 and +0.03, respectively. They both have expected signs. It is implied that soaring commodity prices require shelling out more funds/income on basic consumption expenses, such that less of it is available for investing in insurance. Also, to the extent that there exists no money illusion, structurally increasing inflation rates imply devaluation of the future insurance payback or benefits, thus making life insurance less lucrative for buyers. Accordingly, a percent increase in the country's rate of inflation causes per capita demand for life insurance to dip by –2.95%.[3] Other things being equal, higher education generates greater awareness about the risk and the need to hedge against lost family income over time. The more educated the population, the greater the demand for life insurance. Elasticity-wise, a percent increase in enrollment to higher education causes a 3.04% increase in life insurance density in the long run.[4] Similar inferences can be drawn from the short-run estimates, except that although per capita demand for life insurance is reactive to an instantaneous decrease in per capita savings, it does not significantly respond to a contemporaneous increase, essentially conveying that the positive influence of wealth (or savings) on demand for life insurance is a long-run phenomenon. In other words, per capita life insurance expenditure is more a function of permanent wealth rather than current wealth holdings.

Now although the coefficient of the error correction term v_{t-1} in the NARDL suggests that around 50% of the disequilibria is adjusted every year, there are significant asymmetries in this adjustment too, as given by the cumulative dynamic multiplier graphs in Figure 2. First, the multiplier for positive changes in savings ln*S*(+) is positive, but so is the multiplier for negative changes in savings ln*S*(–), throughout the 15-year forecast horizon, reaffirming that while an increase in savings causes demand for life insurance to increase, a fall in savings also causes demand to increase. Second, equilibrium adjustments are significantly

[3, 4] Log-level interpretation of coefficients, i.e., $\{\exp(\beta)-1\}\times 100$.

Figure 2: Asymmetric Dynamic Cumulative Multipliers (ln*S* → ln*D*)



asymmetric for the 95% confidence bands, for the difference graph between the two multipliers does not cover the value zero for any *h*, meaning that the difference is statistically different from zero. Finally, the multiplier graphs show that negative shocks to savings are more domineering and long-lasting, and it is not until the fifth year that the shock is absorbed and a new equilibrium is achieved. Adjustment of density to positive shock in savings is relatively faster.

Determinants of Life Insurance Penetration

The results for the life insurance penetration model offer similar inference. As reported in Table 8, both the ARDL and NARDL bound tests for long-run relationship between ln*P*, *gWPI*, ln*S*, *EDU* and *DR* yields *F*-statistics of values 13 and 12, respectively, which when compared to asymptotic and finite sample critical values, reject the null of no levels relationship at 1% level of significance. The NARDL *F*-statistics further rejects the null of no asymmetries, thus intimating, once again, that demand for insurance is asymmetrically cointegrated to per capita savings, other things being equal.

The underlying conditional ECMs can hence be tested and long-run estimates can be drawn. Table 9 reports the model estimates for both the ARDL and NARDL specifications. As enclosed in the bottom panel of table, the validity of the model estimates is corroborated by the diagnostics tests. Proceeding to the coefficient estimates, the error correction terms are statistically significant and have a value of around –0.8, implying that adjustments of disequilibrium in aggregate demand for insurance is relatively fast than in the case of per capita demand.

Table 8: Bound Testing for Long-Run Relation in Penetration Model								
ARDL Model 1.1					NARDL Model 2.1			
Statistic[a]	Estimate	Critical Bounds			Estimate	Critical Bounds		
		Significance	I (0)	I (I)		Significance	I (0)	I (I)
		10%	2.20	3.09		10%	2.08	3.00
F_{PSS}	13.01***	5%	2.56	3.49	12***	5%	2.39	3.38
		1%	3.29	4.37		1%	2.70	3.70
		10%	2.45	3.46		10%	2.40	3.50
$F_{NG,n=30}$	13.0***	5%	2.97	4.08	12***	5%	2.80	4.00
		1%	4.09	5.53		1%	4.10	5.70

Note: [a] Models have a maximum of 2 lags and restrict the intercept to enter the level equation.

Table 9: Estimates of Life Insurance Penetration Model				
Variable	ARDL Model 1.1		NARDL Model 2.1	
	Coefficient	Std. Error	Coefficient	Std. Error
Long-Run Estimates				
c	4.20	3.66	22.7**	2.44
$gWPI$	–0.003	0.005	–0.007	0.007
DR	0.11***	0.03	0.07**	0.02
EDU	0.03***	0.01	0.03***	0.01
$\ln S$	2.24***	0.16	2.64***	0.54
$\ln S_t^+$			1.96***	0.20
$\ln S_t^-$			5.53***	2.05
Short-Run Estimates				
c	3.53	3.58	18.2***	4.08
v_{t-1}	–0.84***	0.18	–0.80***	0.18
$gWPI$	–0.002	0.007	–0.005	0.41
ΔDR	0.09**	0.03	0.064	0.44

Table 9 (Cont.)

Variables	Coefficient	Std. Error	Coefficient	Std. Error
ΔEDU	0.02*	0.01	0.03**	0.01
$\Delta \ln S$	1.88***	0.45		
$\Delta \ln S_t^+$			1.57***	0.49
$\Delta \ln S_t^-$			4.43**	1.75
Diagnostics Tests				
R^2	0.53		0.57	
$\overline{R^2}$	0.53		0.57	
χ^2_{AC}	1.32 (0.28)		2.3 (0.11)	
χ^2_{HET}	0.56 (0.72)		0.76 (0.60)	
χ^2_{BNG}	1.56 (0.45)		0.64 (0.71)	
F_{FF}	1.57 (0.12)		1.57 (0.12)	

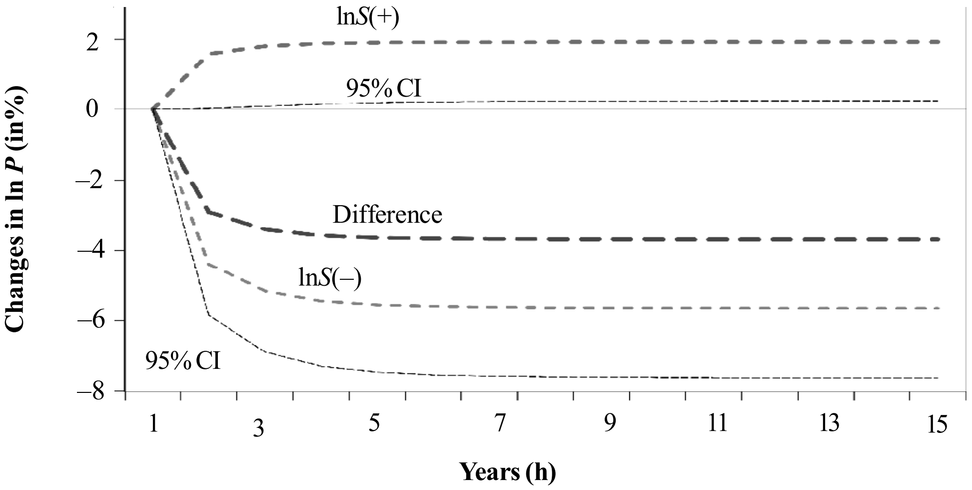
Note: 1. $\overline{R^2}$ is the adjusted R^2 of the conditional ECM.

2. χ^2_{AC}, χ^2_{HET} and F_{FF} are test statistics for nulls of no serial correlation, no homoskedasticity and no functional form misspecification.
3. χ^2_{BNG} reports the Bai-NG statistic on the null of residual normality.
4. *, ** and *** show significance at 10%, 5% and 1%, respectively.

Economic intuition secured from the rest of estimates goes as follows: The country's household savings per capita (ln*S*) has an asymmetric effect on aggregate demand for life insurance (ln*P*). Demand responds strongly and inversely to a fall in savings per capita (5.56%), and positively to an increase in savings (1.96%) (Table 9), thereby reaffirming the conjecture that saved funds do not just raise the ability to pay premiums but act more fervently as wealth capital and self-insurance, thus, eroding the need for market life insurance. The coefficient on *EDU* variable reestablishes that demand for insurance is elastic to higher education, ceteris paribus. A percent rise in secondary education enrollment raises the economy's aggregate expenditure on life insurance premiums by 3.04%.[5] Aggregate premium expenditure does not seem to be significantly affected by inflation rate (*gWPI*) for the sample period, albeit having the correct negative sign. Markedly, the increasing number of young dependents (*DR*) in the country swells consumption of life insurance, conveying that the bequest motive behind life insurance purchase stands. Perhaps, the insignificance of dependents in the density model is due to the per capita construction

[5] Log-level interpretation of coefficients, i.e., $\{\exp(\beta)-1\}\times 100$

Figure 3: Asymmetric Dynamic Cumulative Multipliers (ln*S* → ln*P*)



of the density variable, wherein the effect of increasing number of young children on premium expenses is offset by its impact on population size.

The narrative secured from the dynamic cumulative multiplier graphs from the penetration model is consistent with that of the density model. As Figure 3 illustrates, both a positive and a negative shock to savings bring forth a positive change in aggregate demand for life insurance, with the effect of the latter being stronger and longer-lasting. The difference in multiplier is not statistically different from zero as per the interval plots, but we believe it holds significance for 90% intervals, considering the small margin for which the significance stands rejected by the 95% bands.

In sum, between the model on life insurance demand per capita (ln*D*) and demand in aggregate (ln*P*), the former offers better fit and stability. The stability diagnostics of the NARDL model for ln*P* (Appendix) hints at the presence of intercept-type structural breaks for the sample period. Since stability is imperative for validity, inferences are drawn from the model on life insurance density, which reveals that per capita demand for life insurance in India is a negative function of inflation rate, a positive function of higher education, and an asymmetric function of household savings per capita or the ability to pay for life insurance.

Conclusion

This study looked at selected macroeconomic and demographic influences on India's demand for life insurance for the period 1991-92 to 2021-22. The time-series analysis identified significant long-run relationships underlying both per capita demand and absolute demand for life insurance, and the behavioral elasticities procured reveal interesting findings. Among other things, results show that demand for life insurance is positively inelastic to a rise in per capita savings, but negatively elastic to a decrease in these savings. Indian households do view their saved funds as the means to pay premiums, but they also view accumulated savings as wealth that can altogether substitute for social and financial security alternatives, so much so that a dip in this wealth risks their security and drives them to get life insurance. The finding that life insurance consumption rises more fervently when personal savings contract also suggests that demand for life insurance is not as much a function of income as it is a function of risk aversion. Future research scope lies in delineating the wealth or income effect from the implied risk aversion effect on insurance demand.❖

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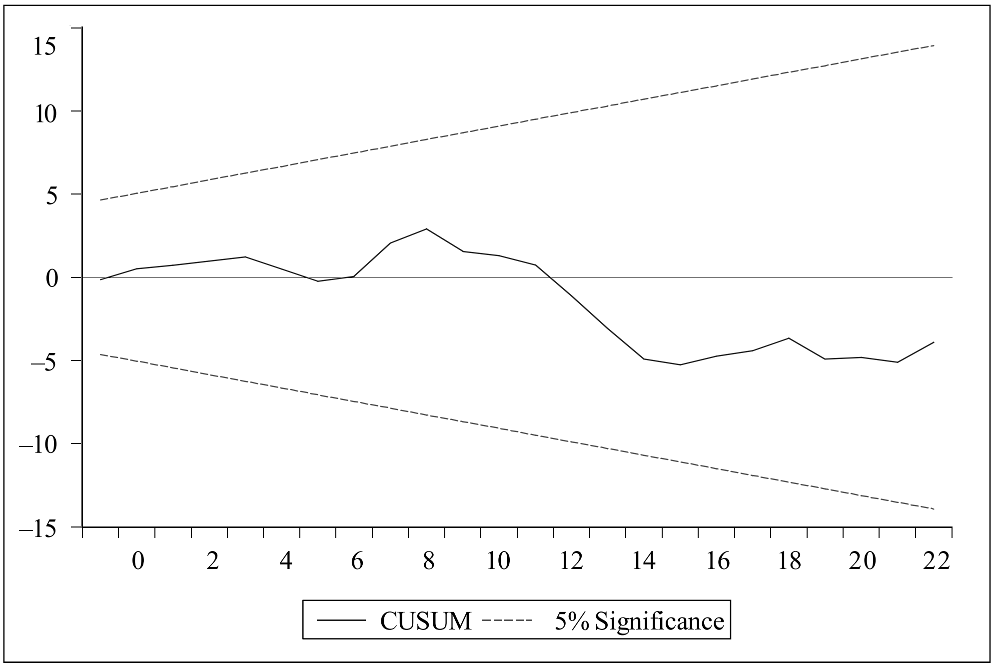
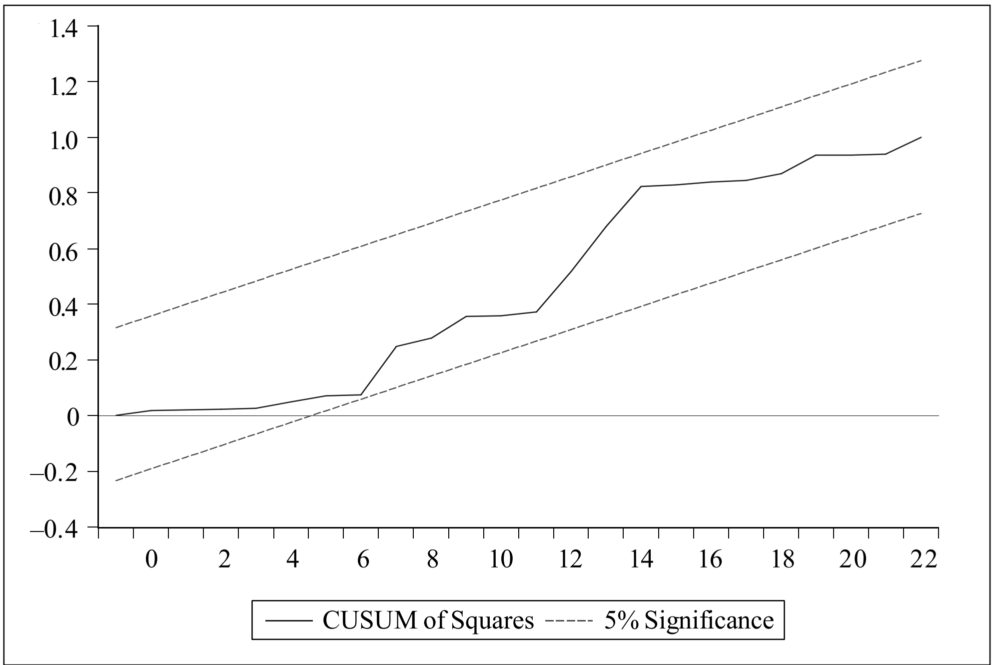
Appendix

Figure A1: Stability Tests: Life Insurance Density Model

ARDL Model

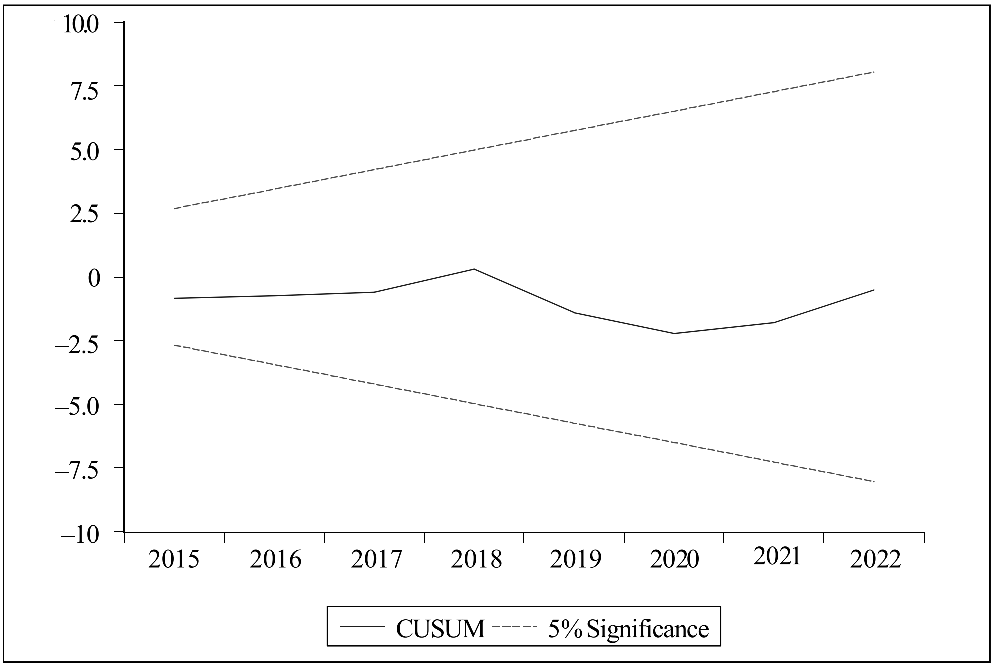


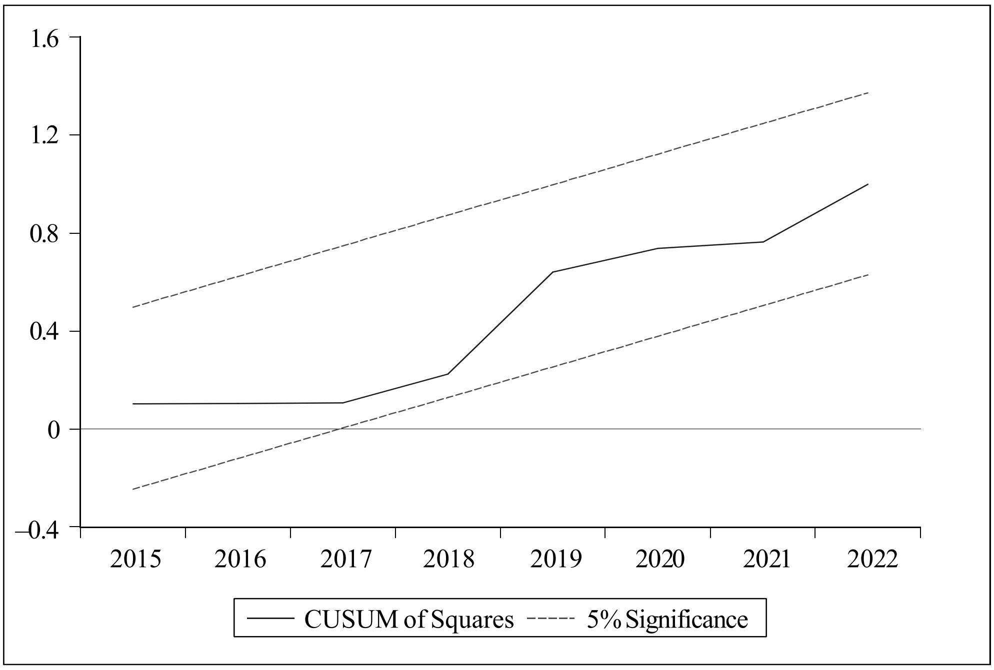


Appendix (Cont.)

Figure A1 (Cont.)

NARDL Model

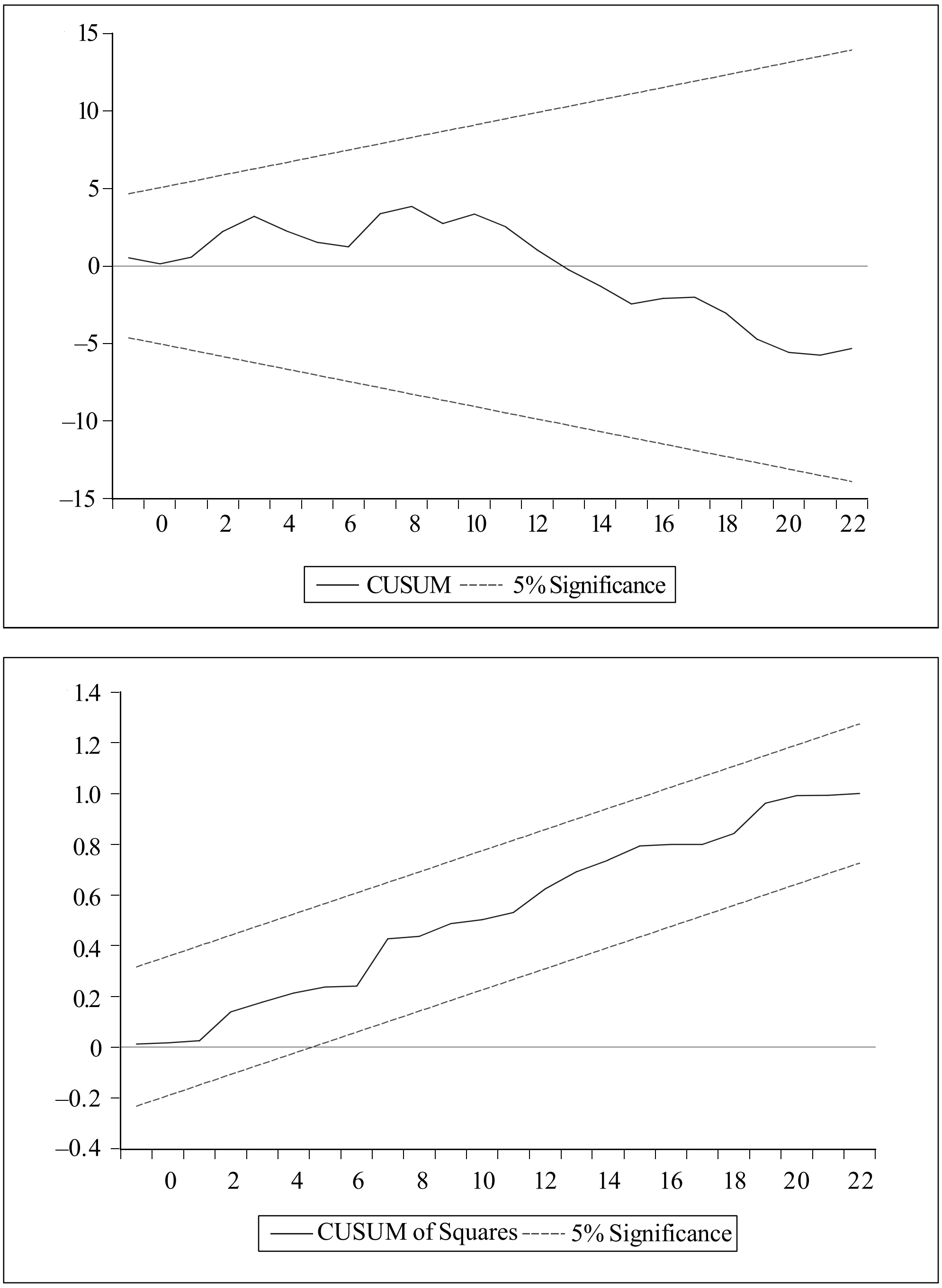




Appendix (Cont.)

Figure A2: Stability Tests: Life Insurance Penetration

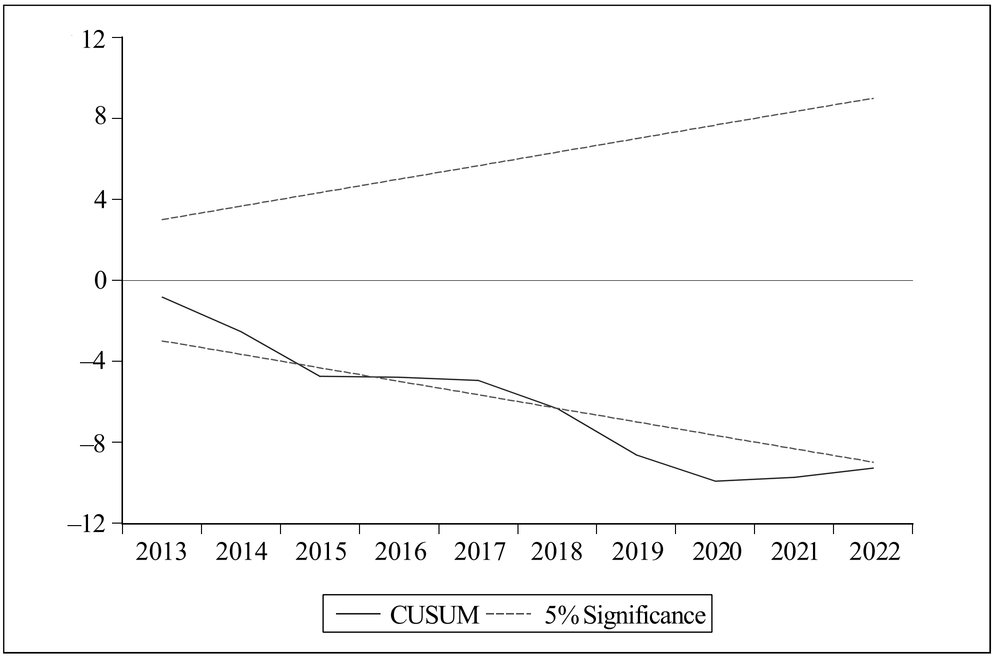
ARDL Model

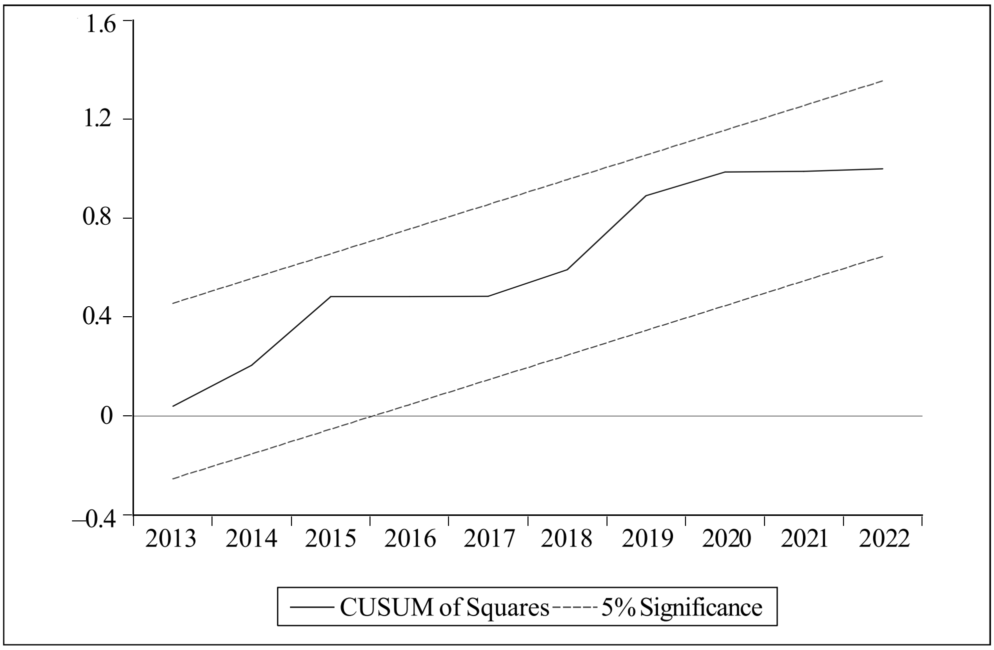


Appendix (Cont.)

Figure A2 (Cont.)

NARDL Model





Reference # 05J-2025-07-04-01