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Application of the age-period-cohort model for estimating the incidence rate ratio of diabetes among the elderly

CP Prakasam and Manish LekhwaniDOI: <https://www.doi.org/10.22271/math.2025.v10.i12c.2229>**Abstract**

Incidence Rate (IR) is defined as the incidence of new cases of a disease over given time period to the total population exposed. This Incidence rate is not comparable to another group of population. To overcome this, Incidence Rate Ratio (IRR) calculated as the ratio of two different groups rates. To estimate the Incidence rate ratio of Diabetes among elderly, Age-Period-Cohort model used. Data were collected from LASI wave-I and estimated by age group, period (duration of diabetes) and cohort (Birth cohort) by sex. For building the APC model, initially data matrix developed suitable to Lexis diagram frame work and analysed by generalized linear model (GLM) with a *Poisson* family, a log link and log *person-risk-time*. As the dispersion derived from Poisson regression estimates show large variation. Alternatively negative binomial model fitted to APC data and found to be best fit. Results show that for total sample, the risk of diabetes significantly increases in the age groups 55 to 79 and slight decline in 80-85 age group compare to younger age group 45-49. The period (calendar year) has shown an overall significant increase in risk and showed highest risk of Diabetes in the recent period 2005-2014 (IRR=20.17, $p<.001$) when compare to base period. Conversely, the cohort effect suggests that people born more recently may have a lower risk than previous generations, possibly due to increased health awareness and interventions. Stratification by sex, Period effects are large but less than females (e.g., 2005-2014 IRR ~15.6 men vs ~27.8 women) for Men. Cohort effects for men show negative pattern (IRRs < 1 for later cohorts) suggests men of later cohorts may have lower incidence of diabetes relative to baseline after adjustment (or sample artifact). In case of women, Age effects are consistently higher than men and Period increases are larger than men particularly for 2the Periods 2005-2014 and 2015-2020. Further negative binomial model fitted to know the sensitivity of IRR estimates and found to be best fit.

Keywords: LASI data, APC model, generalized linear regression, incidence rate, negative binomial model

Introduction

In Epidemiological studies the onset of diabetes is measured through odds ratio and incidence rate. Incidence Rate (IR) measures the frequency of new cases in a population over a specific time and restricted to single population forms a limitation for comparison. To overcome this limitation Incidence Rate Ratio (IRR) is calculated. Incidence rate ratio is a measure that compares the incidence rates of two different groups by dividing the rate of one group by the rate of another group. Thus, incidence rate ratio is a way to compare two different groups to measure the different risk patten among these groups. In a cross-sectional study data set, the initial value is taken as reference category and incidence rate ratio is calculated, Around 1.4 billion people in India estimated with diabetes adding to global burden (Sekher TV *et al.* 2025, Tandon *et al.* 2018) ^[15, 16]. As on 2019, India is the second largest country where in 77 million people with diabetes affected and estimated to increase (Ravi Prakash Jha, *et al.* 2021). According to the 2019 National Diabetes and Diabetic Retinopathy Survey, prevalence was found to be 11.8% in people over the age of 50 years. The prevalence was similar in both male (12%) and female (11.7%) populations. (Tandon N, Anjana RM, Mohan V, *et al.*) ^[16]. It is an important phenomenon to know the incidence of diabetes and its variation over period.

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In case of diabetes, the rates depend on current age of individual (Age), duration of disease (Period), the birth cohort (Cohort) and also by sex. Age-Period-Cohort (APC) is important because individual chronological age (current age) brings biological changes, the period (period of exposure to disease) effects changes in treatment that could affect all ages and the Cohort (birth cohort in this study) associated with long-term exposure, with different generations being exposed to different risks (Robertson C, Boyle P. 1986) ^[11]. Keeping this concept, the incidence rate ratios (IRR) of diabetes estimated by applying Age-Period-Cohort model using grouped cross-sectional data from Longitudinal Ageing Survey of India (LASI) and IRR estimated by age-period-cohort and by Total, Male, Female sample.

Age-Period-Cohort Model

Initially, greater emphasis was placed on cohort studies and Ryder (1965) ^[14] focused on birth cohorts derived social change, thereby contributing to the theoretical concept of APC analysis. APC model has since been effectively used in Cancer registers and registries for other diseases (Eva Negri *et al.*, (1990) ^[4], Clayton, D, Schiffler, S (1987) ^[3] and web-based tool for age-cohort-period analysis have been developed for Cancer incidence and Mortality rates.

Researchers identified that APC model suffers from an *identifiability problem* i.e., that each temporal dimension (Age, Period, Cohort) is a linear function of the others (Glenn 2005) ^[5]. Mason *et al.* (1973) ^[7] suggested a common solution to overcome this problem by imposing constraints that set certain APC parameters equal. Thus, each age, period and cohort group entered into a regression model as a dummy variable, with the assumption that two categories are constrained to be equal (Carstensen, 2007) ^[2].

To overcome the *identifiability problem* Yang, Fu and Land (2004) ^[19] fitted age-period-cohort terms as factors, and a constraint that sets two of the categories from different components equal to one another is applied in the regression. This methodology discussed as *hierarchical APC (HAPC)* model. Further for the repeated cross-sectional study, Yang, Fu and Land (2004) ^[19] developed HAPC-GLMM frame work to overcome the classical identification conundrum. They analysed age-by-cohort and cross level interactions with STATA commands such as *apc_ic* and *apc_cglim*. As extended research Yang, & Land, (2006, 2013) ^[17, 18] developed mixed model for cross-sectional survey data and with empirical applications. Applicability of HAPC model by Yang & Land (2013) ^[18] has been argued by Bell and Jones (2015) suggested modified version by applying BHPS data. Carstensen, (2007) ^[2] identified the problem of *identifiability* which is raised due to age, period and cohort (Cohort=Period-

Age), suggested APC model for continues variables through the use of spline functions and incorporated his method for age-period-cohort model in the Epi package for R. Carstensen (2007) ^[2] introduced a unified Lexis-diagram framework for modeling rates by APC, and analysed by generalized linear model (GLM) with a Poisson family, a log link and log *person-risk-time*. For the Carstensen (2007) ^[2] APC model Rutherford *et al.*, (2010) developed STATA command *apcfit* with *person-risk-time*. Researchers, Glenn (2005) ^[5], Carstensen, (2007) ^[2], argued that there is no *satisfactory* solution to APC collinearity because there is underlying collinearity between A-P-C. However, with necessary assumptions, models have been developed for continuous and grouped data set. Keeping above concepts in view by using APC model, Incidence rate ratio of Diabetes among elderly for total, male, female data set has been estimated.

Data and Methodology

The Longitudinal Ageing Study in India (LASI) is a multidisciplinary, internationally harmonized panel study (IIPS 2020) with a national representative sample of India's population aged 45 and older. The main objective of LASI Wave I (2016-2018) is to provide evidence base on self-reported health and wellbeing of elderly population in India, collected information about demographics, household economic status and health status of elderly. The data covered 30 major states and 6 union territories of India. Further the survey collected a wide range of data on various aspects of health and well-being, including self-reported health status, chronic conditions such as diabetes, heart, lungs, Asthama etc. And disabilities, healthcare utilization and other background information. One can access the data and LASI India Report from IIPS website (IIPS 2020) ^[6].

Out of total sample of 72250 older adults aged 45 and above in the LASI study, data from 65531 elderly population data have been considered for the present research. Among that sample of 64397 elderly between 45 to 85 years of age considered for analysis. To estimate the incidence rate ratio using the APC model, data were further extracted from individuals who reported their "age at last birthday," "ever diagnosed with diabetes (Yes/No)," "year of diabetes diagnosis," "birth year," and sex. Age at last birthday was taken as *Age (A)*, birth year as *Cohort (C)*, and the difference between the year of diagnosis and the survey year was considered as *Period (P)* representing exposure time to diabetes. Respondents reporting "ever diagnosed with diabetes=Yes" were classified as *cases*, while the total respondents (Yes + No) were treated as the *population exposed* to the risk of diabetes.

Table 1: Data Structure for APC Model (LASI)

OBS	A (Age)	P (Period)	C (Cohort)	CASET	POPT	CASEM	POPM	CASEF	POPF
1	75-79	1957-1994	1939-1948	17	2065	13	1056	4	1009
2	80-85	1957-1994	1939-1948	18	2385	15	1137	3	1248
3	75-79	1995-2004	1939-1948	56	2065	38	1056	18	1009
4	80-85	1995-2004	1939-1948	32	2385	15	1137	17	1248
5	75-79	2005-2014	1939-1948	141	2065	81	1056	60	1009

A: Age, P: Period, C: Cohort, CASET: Case count for the total sample, POPT: Total population exposed, CASEM / CASEF: Case count for males and females, respectively, POPM / POPF: Population exposed for males and females, respectively

Initially frequency of A, P, C CASE, POP, SEX has been prepared. Among these 8332 elderly reported diabetes (yes) 7156 have had reported their year of onset of diabetes

(diagnosis). Since the objective of the present research is to estimate Incidence rate ratio by applying APC model, only 7156 (P) elderly considered as study sample. A new file for

A, P, C, CASE, POP, SEX for 7156 elderly has been generated. AGE (A) has been grouped in to 5-years age group as 45-49, 50-54.....80-85 and coded as 1, 2,...8. Similarly, P into three groups 1,2,3 (1995-2004, 2005-2014, 2015-2020) and C into three groups (1949-1958, 1959-1968, 1969-1979). From this coded data for each A, P, C corresponding CASES

and POP, data matrix has been prepared. Sample data matrix for N=5 is listed in Table 1. By using the reconstructed data in suitable matrix format (Table 1), a GLM fitted by using the STATA 16.1 version. Core STATA commands given in Table 2

Table 2: List of core STATA commands for APC model used

Command Category	STATA Code	Description / Purpose
Data Preparation	gen poprisktime=popt	Creates a variable for population at risk.
	gen logpopt=log(poprisktime)	Generates the log of population for the offset.
Document Export	putdocx begin	Initializes a new Word document export.
Poisson Model	glm caset i.a i.p i.c, family(poisson) link(log) offset(logpop) vce(robust) eform	Runs the Base Poisson APC model with robust standard errors and exponentiated coefficients (IRR).
	putdocx table reg1=etable, title (Table 1: Base Poisson APC-robust)	Exports the Poisson results to a Word table.
Negative Binomial	nbreg caset i.a i.p i.c, offset(logpop)	Runs a Negative Binomial model as a sensitivity check.
	putdocx table reg6=etable, title (Table 2 Negative binomial-sensitivity Total)	Exports the Negative Binomial results to a Word table.
NB with IRRs	nbreg caset i.a i.p i.c, irr	Runs the Negative Binomial model and reports Incidence Rate Ratios directly.
	putdocx table reg7=etable, title (Table Negative binomial-sensitivity total)	Exports the IRR-specific results to a Word table.

Initially the population exposed has been transferred to *log* logpopt generated. Further with glm for the cases of diabetes *a*, *p*, *c* with family *poisson*, link *log*, *logpop* and *robust* with *eform* fitted the reg equation to derive Incidence rate ratio by age, period and cohort for total sample, male, female separately. Results are listed in Table 3, 4, 5.

Results

The Incidence rate ratio has been derived by APC model for the data described in Table 3 for total sample, male, female separately and given in Table 4, Table 5.

Total sample APC: IRR estimates

Age effect shows the IRR for the total study sample rises (Table 3) with age up to 75-79 having peak IRR 1.6-2.6, then declined slightly for 80-85. This reveals that increasing diabetes incidence with age in the elderly having a peak in the oldest-old group in India (Table 3). Period effect also shows statistically significant increase for the periods 1995 onwards having peak in the recent periods 2005-2014 (IRR=2017, $p<.01$). Further Cohort effect found to be weak or no significant effect in the cohort group for this cross-sectional data. That suggest after adjusting for the age & period, birth cohort don't show higher IRR than base cohort but not statistically significant (Table 3). Graphical presentation with 95% confident intervals in Figure 1 shows predicted incidence

rate peak in middle age group and declines later. Period wise the Upper and lower limits of confidence interval found to be close to estimated Incidence rates and peat at middle period. Cohort wise the IRR steep declining trend observed with wider CI (Fig 1).

Sex wise APC: IRR estimates

Male Elderly

Table 4 shows IRR of diabetes among elderly males reveals that the rates are >1 but not significant when compared with 45-49 age group except in the age group 60-64 years. Period effects are large but somewhat smaller than females (e.g., 2005-2014 IRR ~15.6 men vs ~27.8 women). Cohort effects for men show some negative pattern (IRRs <1 for later cohorts) and are sometimes statistically significant-suggests men of later cohorts may have lower incidence relative to baseline after adjustment (or sample artifact), (Figure 2).

Female Elderly: IRR estimates

Analysis in Table 5 show that IRR increases Period wise larger than men, particularly strong for 2005-2014 and 2015-2020. Age effects among women are consistently higher than men (women show stronger age gradient), (Figure 3). This points to stronger secular rise in diabetes detection/incidence among older women in recent periods (or cohort-specific care effects).

Table 3: APC Incidence rate ratio of diabetes among elderly in India: LASI data analysis. (Robust)

APC model: Total	IRR	Std. Err.	[95% Conf. Interval]	
a				
50-54	1.46529	.290528	.993466	2.161196
55-59	1.658598	.2791783***	1.192519	2.306838
60-64	1.845298	.315233***	1.320247	2.579156
65-69	1.791762	.3115662***	1.274285	2.519383
70-74	1.864827	.4237341***	1.194607	2.911068
75-79	1.656083	.4019058*	1.029221	2.664744
80-85	1.23334	.3525881	.7042725	2.159856
p				
1995-2004	4.727778	1.206817**	2.866676	7.797143
2005-2014	20.16667	4.419003**	13.12548	30.9851
2015-2020	13.87222	3.211509**	8.812262	21.83759
c				
1949-1958	.9320113	.1668515	.6562004	1.32375
1959-1968	.8527052	.185834	.556279	1.307089
1969-1979	.7991003	.1784967	.5157825	1.238044
_cons	.002103	.0007326**	.0010625	.0041625
logpop	1	(offset)		

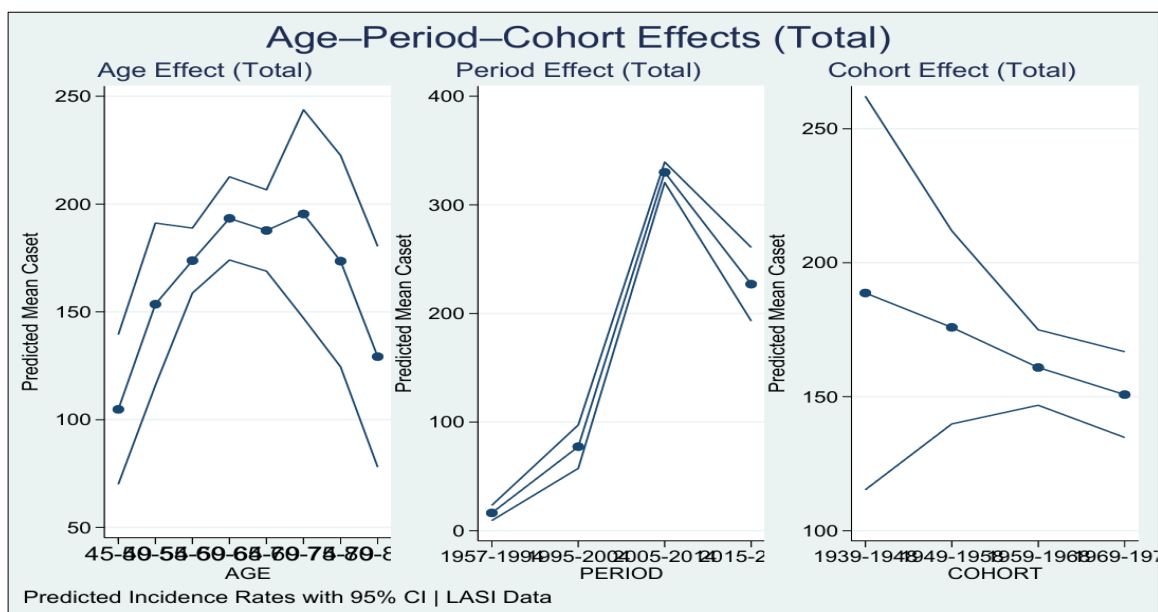


Fig 1: Age-Period-Cohort model for Total sample (LASI data)

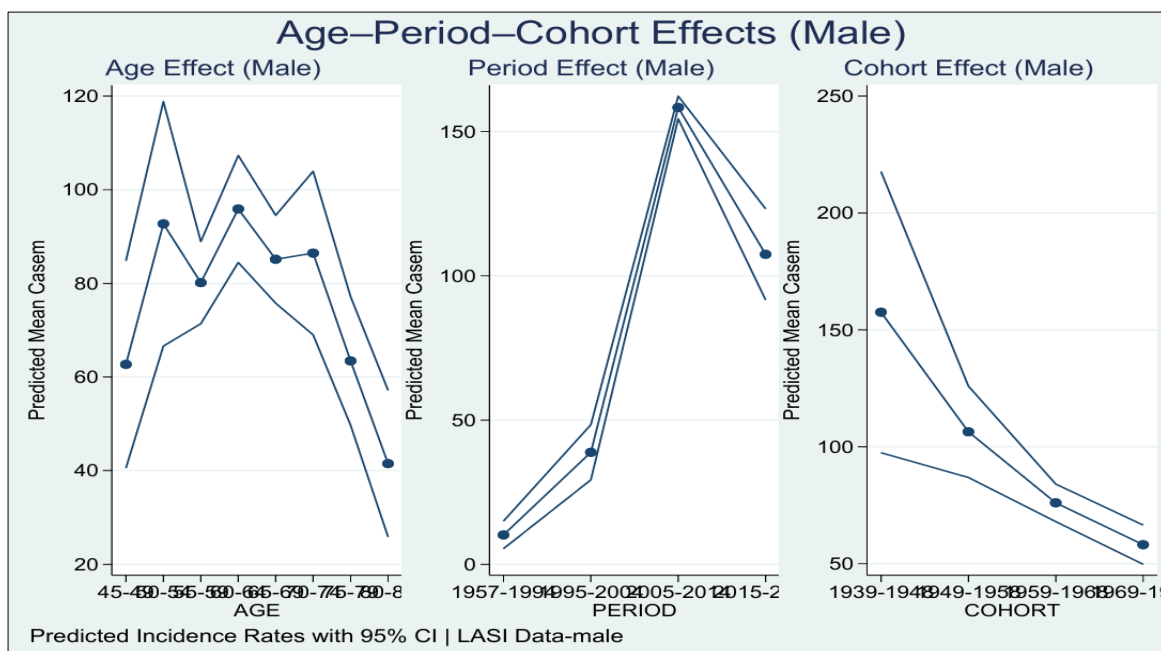


Fig 2: Age-Period-Cohort Model: Male (LASI Data)

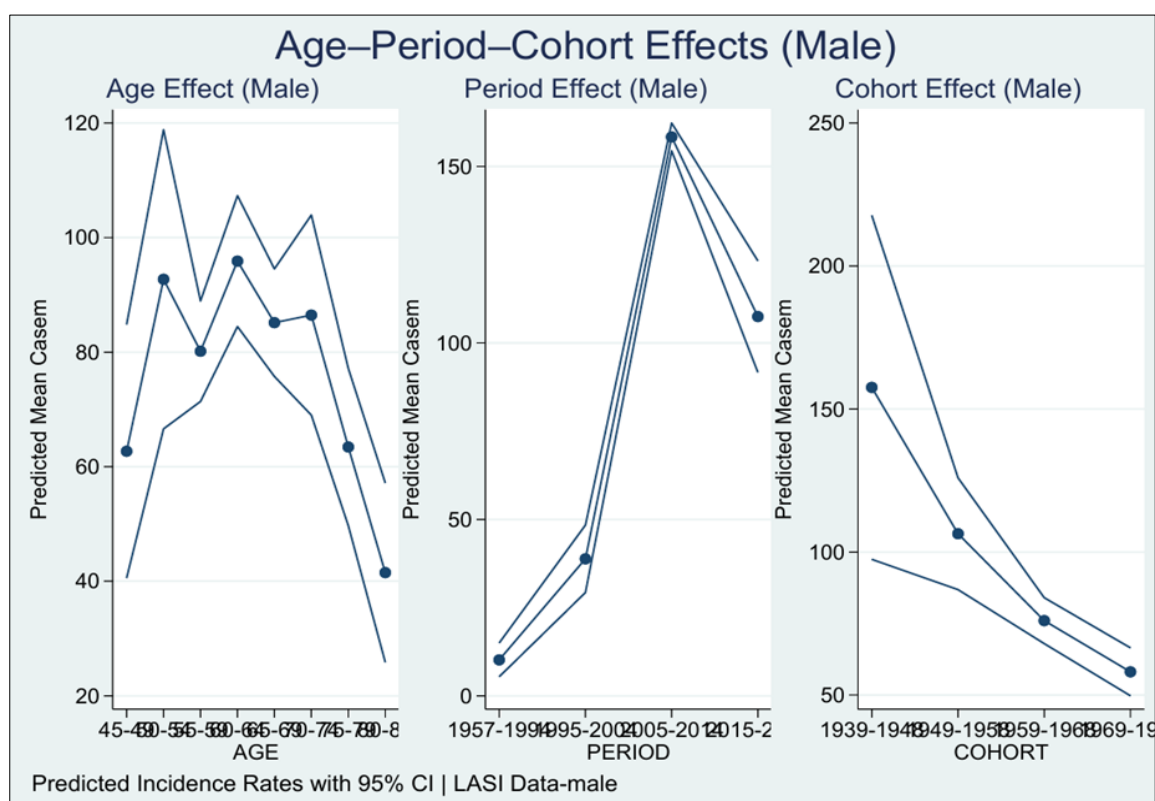
Table 4: APC Incidence rate ratio of diabetes among elderly male in India: LASI data analysis-APC-model (Robust)

Cases-Male	IRR	Std. Err.	[95% Conf. Interval]	
a				
50-54	1.445406	.289095	.9766559	2.139136
55-59	1.319467	.2454881	.9162872	1.900052
60-64	1.558643	.2959399**	1.074308	2.261333
65-69	1.427156	.2731512	.9807429	2.076766
70-74	1.479242	.3316103	.9532794	2.295398
75-79	1.196962	.2796746	.7571711	1.892199
80-85	.8400843	.2451123	.4742058	1.48826
p				
1995-2004	3.8125	1.031946***	2.242908	6.480496
2005-2014	15.55357	3.734317***	9.715426	24.89995
2015-2020	10.55357	2.651207***	6.450087	17.26765
c				
1949-1958	.7563885	.1335164	.5351706	1.069049
1959-1968	.626329	.1257513*	.4225736	.9283306
1969-1979	.4975656	.110856**	.321518	.7700082
_cons	.0045033	.0016695***	.0021776	.0093131
logpopm	1	(offset)		

Table 5: APC Incidence rate ratio of diabetes among elderly female in India: LASI Data Analysis-APC-model (Robust)

Cases-Female	IRR	Std. Err.	[95% Conf. Interval]	
a				
50-54	1.481358	.2935885*	1.004527	2.184533
55-59	1.939695	.3201749***	1.403557	2.680628
60-64	2.052354	.3480599***	1.471962	2.861594
65-69	2.091998	.3700768***	1.479049	2.958965
70-74	2.195682	.5609432**	1.330786	3.622686
75-79	2.144398	.5920419**	1.248243	3.683932
80-85	1.781016	.5537766	.9682801	3.275928
p				
1995-2004	6.235294	1.650686***	3.711214	10.47606
2005-2014	27.76471	6.208499***	17.91245	43.03594
2015-2020	19.33824	4.557464***	12.18465	30.69167
c				
1949-1958	1.207283	.226296	.8360996	1.743253
1959-1968	1.226178	.3070274	.7506166	2.003038
1969-1979	1.275334	.322586	.7768172	2.093769
_cons	.0009356	.0003395***	.0004595	.0019052
logpopf	1	(offset)		

Note= LASI data

**Fig 3:** Age-Period-Cohort Model: Female (LASI Data)

After fitting the Poisson model and estimated IRR for Total, Male and Female, the results are tested for its normality. Poisson Model assumes $\text{Var}(Y)=E(Y)$. But expected variance calculated for the Poisson Model fit has been observed as Deviance=468, Chi square=497 for DF=30 and the calculated dispersion was 16.5, which was very high. This large dispersion is an indication of strong over dispersion, thus Poisson Model underestimates standard errors leading to extreme IRR values. To overcome the large dispersion, Negative Binomial model has been applied to estimate IRR.

Negative Binomial Model: (NBM): The negative binomial model has been fitted by STATA 16.1 and the commands are

listed in box 1. The IRR by age, period and cohort for total, male and female are given in Table 6.

The Negative Binomial model for total sample data (Table 6) indicates that age effects show a decreasing incidence rate ratio (IRR) (50-54, IRR= 1.28, NS) with increasing age (55-59, IRR=.4148, $p<.001$), unlike the Poisson model pattern, suggesting that over dispersion adjustment changes age-related associations considerably.

Period effects (IRR=4.80, $p<.001$) remain strong and highly significant, with the diabetes incidence increasing substantially across later periods-particularly during 2005-2014 (IRR=19.57) and 2015-2020 (IRR=13.34), confirming rising diabetes burden over recent years.

Table 6: Incidence rate ratio (IRR) estimates of Diabetes among elderly: Negative Binomial model: Age-Period-Cohort analysis: LASI Data

AGE	Total			Male			Female		
	IRR	LL	UL	IRR	LL	UL	IRR	LL	UL
45-49									
50-54	1.2796	0.8008	2.0446	1.2762	0.8002	2.0354	1.2411	0.8333	1.8485
55-59	0.4148**	0.2551	0.6746	0.3159*	0.1902	0.5250	0.4861**	0.3191	0.7404
60-64	0.6934	0.3521	1.3657	0.5635	0.2818	1.1267	0.7469	0.4176	1.3358
65-69	0.2192**	0.1102	0.4365	0.1640**	0.0805	0.3343	0.2501**	0.1376	0.4547
70-74	0.2513***	0.1086	0.5816	0.1661**	0.0705	0.3914	0.3229*	0.1550	0.6726
75-79	0.0444**	0.0189	0.1047	0.0249**	0.0102	0.0608	0.0699**	0.0328	0.1493
80-85	0.0372**	0.0136	0.1018	0.0184**	0.0065	0.0522	0.0698**	0.0284	0.1725
PERIOD									
1957-94									
1995-2004	4.7999***	3.4591	6.6604	3.7873**	2.6716	5.3688	6.5913**	4.6587	9.3256
2005-2014	19.5753***	14.1764	27.0307	15.3657**	10.9444	21.5731	27.5607**	19.7352	38.4891
2015-2020	13.3422***	9.6127	18.5188	10.4110**	7.3795	14.6879	18.4623**	13.1892	25.8437
COHORT									
1939-48									
1949-1958	0.4963**	0.2917	0.8444	0.3453**	0.1972	0.6045	0.8658	0.5249	1.4282
1959-1968	0.2325**	0.1127	0.4796	0.1245**	0.0586	0.2647	0.5627	0.2914	1.0868
1969-1979	0.08217**	0.0342	0.1974	0.0362**	0.0145	0.0904	0.2377*	0.1086	0.5204
_cons	210.38**	81.4624	543.2980	289.693*	108.2820	775.0324	31.20617*	13.0561	74.5880
ln alpha	-2.2516	-2.8037	-1.6994	-2.3300	-2.9977	-1.6624	-2.7415	-3.3786	-2.1045
alpha	0.1052	0.0606	0.1828	0.0973	0.0499	0.1897	0.0645	0.0341	0.1219
* $p < .05$, ** $p < .01$, *** $p < .001$			LL=95% CI Lower limit, UL=95% CI Upper limit						

Cohort effects show a declining IRR for more recent birth cohorts (Table 6) implying that individuals born after 1949 may have relatively lower diabetes incidence (IRR=0.4963, $p < .001$) compared to older cohorts, possibly due to better health awareness and medical advancements. The presence of a significant dispersion parameter (alpha=0.105) confirms that Negative Binomial is more appropriate than Poisson due to over-dispersion in the data.

Conclusion and Discussions:

In this research, the Age-Period-Cohort (APC) analysis indicates that age and period effects substantially increase the risk of diabetes among the elderly, while cohort effects show considerable influence among males but remain statistically insignificant among females. Age continues to be a dominant risk factor, with diabetes incidence rising sharply in older age groups. Period results show a consistent increase in risk over the years, likely reflecting lifestyle transitions toward urban, sedentary behaviours. Further, cohort effects suggest that individuals born more recently may have slightly better risk profiles compared to earlier generations, potentially due to increased healthcare access, early diagnosis, and improved awareness of lifestyle-related risks although these trends differ between sex groups and geographic regions.

Both Poisson and Negative Binomial APC models show strong and statistically significant period effects, with peak incidence observed during 2005-2014. Poisson suggests a progressive rise in diabetes risk with advancing age, whereas NB reduces age intensity, implying over-dispersion in the data. Cohort influence appears weak in Poisson but markedly protective in NB, indicating generational improvement effects. The significant alpha parameter confirms NB as a superior fit over Poisson. These differences demonstrate the need to report APC outcomes from both models for robust epidemiological insight.

The APC framework is an important analytical tool that helps disentangle the temporal dynamics of disease occurrence by quantifying independent effects of aging, historical changes, and generational differences. However, researchers have highlighted that APC components are linearly dependent

(Cohort=Period-Age), leading to an *identifiability* problem that requires appropriate constraints or advanced modeling strategies. Proper preparation of the dataset-including its structure as cross-sectional, cohort-based, or repeated survey design-is crucial for valid APC modelling. After establishing the data framework, selecting an appropriate regression approach such as generalized linear models (GLM), polynomial models, or non-linear regression techniques remains a key step supported by strong theoretical justification.

By keeping necessary precaution, the APC model provides several analytical benefits: 1). It helps visualize how disease burden is shifting across generations. 2) It reveals whether rising prevalence (IRR) is driven more by aging, behavioural changes, or exposure differences at birth cohorts. It supports health policy by identifying high-risk cohorts for targeted interventions.

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