A Rough and Ready Approach to Aging and Cohort Replacement

James A. Davis

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The algebra of Age/Period/Cohort allows one to separate the size of Aging and Cohort Replacement effects although it rules out separate estimates of all three. The notion is tested on 178 variables in the cumulative GSS 1975-2008. Substantively I infer that Cohort Replacement is by far the strongest driver of change in GSS items and attitudes are surprisingly seldom influenced by Aging.

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Introduction

It is a truth universally acknowledged it is impossible to calculate distinct linear regression coefficients when predicting a dependent variable, Y, from Age, Period, and Cohort (date of birth) with Ordinary Least Squares. Granted that, this paper argues it is not only possible but desirable to estimate the *relative* sizes of the two effects Aging and Cohort Replacement in longitudinal - though not necessarily panel - data.

The paper:

Justifies the project

Justifies the suggested procedure

Introduces a collection of test variables from the NORC General Social Survey

Assesses the construct validity of the method using 178 GSS items

Draws inferences about Aging and Cohort effects over 15 content areas

Justification

Compared with the advanced statistical procedures in the literature (Mason and Fienberg 1985, Yang, 2008) the calculations suggested here are literally rough but literally ready at hand. Are they worth the ambiguity?

Impressive as the advanced procedures are, they don't really dodge Glenn's postulate (Glenn, 1976). Although they produce 'legal' results[1], *any* interpretation of a net statistical effect is

[1] Actually, if one shifts Age, Period, and Cohort to vectors of dummy variables, the Statistical multi-colinearity is usually broken. Partial coefficients will emerge but the numbers generally fail to make sense.

some form of the relationship between A and B within values of C. But this is a logical contradiction as such situations simply cannot exist in APC data. On the practical side, the analyst whose primary interest is not in APC itself but who needs to know something about dynamics in the data may not find it cost- effective to execute multiple, complex calculations. When estimating A and P and C is not the main question there is a case for an approach that gives rough though useful insight into dynamic data without slashing the Gordian knot. Since the procedures advanced here are approximate and the interpretations require a bit of judgment, it is necessary to be convinced even a short step forward is worth the trouble.

The technical papers on the APC identification problem may one to lead one to view the matter as a statistical-algebraic crossword puzzle rather than a major issue in Sociological theory. I disagree.

The key idea here is change. In one-time data, it really makes little Sociological difference whether an effect comes from Age or Cohort - the analyst can get away with speaking about the older generation versus the younger generation. Luckily for GSS data, youth and Cohort almost always work in the same direction.[2] That is, older scores on age line up with earlier scores on date of birth. Therefore, one may usually interpret the result as a sum of Age and Cohort effects.

In longitudinal data, however, the difference is crucial. The central issue is level of analysis - individual shifts versus, changes in population means.

Consider first. Age. Many Sociological variables show an Age correlation. Does this

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[2] In the 178 test correlations analyzed below, all reliable linear bivariates for Age and Cohort have opposite signs.

promote change at the group level? It depends on whether the *average* age is changing. In other words we work with a three variable model:

Time -> Age -> mean Y

To say Aging produces change in means is to argue for two empirical results: (1) Time is related to Age (2) Age is related to Y, net of Time. In the words of an anonymous methodologist It takes two to tango.

Consider the NORC General Social Survey 1972-2008, the annual and biennial samples of the U.S. household population with many replicated items (details in the following section). In light of the plethora of attention to an aging population, it may come as a surprise that the bivariate correlation (**r**) between Year and Age in the GSS is virtually nil. Table 1 displays the values

Table 1.

Bivariate correlations (r) Among Year, Age, and Cohort/Date of Birth GSS 1972-2008

	Year	Age	Cohort
Year		+.025	+.507
Age			-.849

N = 41,371

The Year/Age relationship is + .025, practically zero.[3] During the GSS years the

[3] There is a telescope-microscope problem here and throughout. With N's in the tens of thousands everything is significant. For example, all regression coefficients of + /- .020 or stronger turn out to be highly significant. Consequently sheer significance will be ignored in drawing inferences about magnitude. Instead, I will use the rule of thumb that coefficients of .10 or stronger are "keepers," smaller ones are nil. In many cases I treat relationships as "keepers" which would not be detected in a conventional sample of 1500 cases. Conversely, these samples are well below Census N's - so some differences (e.g. year and size of place) will be treated as nil, although demographers would consider them worth scrutiny.

adult US population was middle aging, not aging as the baby boom generations moved into mid-life. Bear in mind, however, the GSS population excludes those under age 18 and the elderly in institutions.

Since the arrow from Year to Age is essentially zero, the two-step path is zero and Age has no effect on population means. Thus:

During the GSS years Aging had no effect on sample means whether or not they are correlated with Age.

The pattern for Cohort is the exact opposite. Table 1 showed the bivariate correlation for Year and Cohort to be +.507. This is not only non- trivial, it is by far the largest correlation with Year for any of the hundred or so variables in this analysis.

The difference between aging and cohort replacement may be seen in the difference between a line of people climbing a ladder (The people move up steadily but the rungs stay in place) and a line of people ascending an escalator (the people stand still but the steps move up).[4]

Predicting is always dangerous but this principle gives a handle on forecasting. Since cohort replacement is (and doubtless will continue to be) essentially linear we can comfortably predict the mean date of birth a decade or two from now and hence the mean of any variable related to Cohort but not (one must assume) Year.

Finally, there is Year or Period[5]. A year effect would be one where everybody shifts on some variable regardless of Age or Cohort - like a school of fish changing course *en masse*. We

[4] For some variables a Cohort effect might be construed as an Age/Period/Y interaction - being of an impressionable age at a particular time leaving a permanent mark - true, but not I think, terribly useful for analyses unless one has multiple generations of data.

[5] Period is a bit ambiguous since it can refer to a span of years, e.g. The Middle Ages, as well as the effect of a time process.

will have surprisingly little to say about period effects here because (1) the approach sheds no light on Period effects and (2) The analyses below suggest Period effects in the GSS are surprisingly small.

While American mass society is a strategic sociological research setting, I suspect this approach is applicable well beyond the GSS. Schools are an obvious example - student cohorts change rapidly while the mean student age is nearly constant. The approach might also apply to prison populations, military officers, nursing homes, etc.

In sum when we consider Age/Period/Cohort as a keystone in the demographic theory of social change (Stinchcombe, 1968, Ryder, 1965) a less than exact method for spotting the major variables producing change can be valuable even if it fails to crack the classic APC paradox.

Turning it around - Analysts of aging would like reassurance that their dependent variables are not mere reflections of Cohort differences.

Argument

Shifting from algebra to multiple regression, there is nothing to keep one from using any *two* APC variables as predictors in an OLS regression (temporarily ignoring multi-colinearity). That is, the multiple regression program will run.

But we have not avoided the identification problem. It turns up like this:

> **When one APC variable is controlled, the other two are perfectly confounded - within a value of one A/P/C the other two are strict linear functions of each other.**

Thus:

Within a Year: Age is perfectly related to Cohort
Within an Age: Year is perfectly related to Cohort
Within a Cohort: Age is perfectly related to Year

Restated:

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When one APC variable is entered into a regression controlling for a second, its apparent net effect is actually a linear combination of the predictor's effect and that of the third variable.

Grinding out all the possibilities gives Table 2.

Table 2.
Confoundings in Two- Predictor APC Regressions

Model		Control	Predictor	Apparent Effect on Y	Actual Effect
	Ia	Age	Cohort	Cohort	Cohort + Period
	II a	Age	Period	Period	Period + Cohort
	Ib	Cohort	Age	Age	Age + Period
	IIIa	Cohort	Period	Period	Period + Age
	IIb	Period	Age	Age	Age - Cohort
	IIIb	Period	Age	Age	Cohort - Age

The procedure actually works as shown in Table 3. The dependent variable is a GSS dichotomy 'living on a farm at age 16, yes/no".[6]

[6] Table 3 violates the ▮never use OLS when Y is a dichotomy taboo. Note, however, the taboo is limited to estimates of sampling variances, not estimates of means. With an N of 20,000 or so it is unlikely the coefficients are off by much. Note also: the results only come out exactly with pair-wise deletion because each multiple regression must have identical matrices of APC covariances.

Table 3
Predicting Y = Farm16 from Age/Period/Cohort

(GSS 1975-2008, N=39,926)

Model	Control	Predictor	b	Beta	R	Estimates
Ia	Age	Cohort	-.0049	.2378	.245	C+P
IIa	Age	Year	-.0049	-.1259	.245	C+P
Ib	Cohort	Age	.0001	.0081	.245	A+P
IIIa	Cohort	Year	.0001	.0047	.245	A+P
IIb	Year	Age	.0051	.2132	.245	A-C
IIIb	Year	Cohort	-.0051	-.2471	.245	C-A

With raw regressions the calculations follow the arithmetic precisely, but the standardized coefficients do not. The discrepancy is because betas are sensitive to unequal standard deviations among the predictors. This is not fatal and will be dealt with below.

Table 4 rearranges the numbers in Table 3.

Table 4.
Raw Coefficients in Table 3 Rearranged

Model	Control	Prediction		Raw	Std.	Estimates
Ia	Age	Cohort		-.0049	-.2378	C + P
Ib	Cohort	Age		.0001	.0081	A + P
			Abs difference	.0048	.2297	
			Ratio	49.0	29.36	
IIa	Age	Year		-.0049	-.1259	C + P
IIIa	Cohort	Year		.0001	.0047	A + P
			Abs Difference	.0048	.1212	
			Ratio	49.0	26.79	
IIb	Year	Age		- .0048	-.1630	A - C
IIIb	Year	Cohort		+.0048	+.1875	C - A

The big question is the relative sizes of the Cohort effect, and the Age effect. They never appear alone but their *difference* appears in six forms:

Ia - Ib
Ia - IIIa
IIa - Ib
IIa - IIIa
- IIb
IIIb

In each case here C is larger than A, i.e. the Cohort minus Age difference is positive. – as one would expect. Having lived on a farm at age 16 is more strongly related to Cohort than to Age, a single number capturing a huge social change. Note also the Betas for A+P are very small (more on this later).

From all this Rule I:

(Rule 1)

The difference in absolute value, Ia - Ib, gives the size of the Cohort versus Age statistical effect

. The interpretation is straight forward: One year's difference in Cohort makes about half a year's larger difference in farm origins more than does a year in Age. However, this is not directly comparable to, say, a raw Ia-Ib difference of +.954 on a three point misanthropy scale (After adjustment they turn out to be about the same) . Standardized coefficients (**Betas**), of course, put effects on a comparable and familiar zero/one scale but Table 4 displays more than one because of variation among the standard deviations of Age, Cohort and Year. By equalizing the standard deviations we can get a plausible **Beta** difference. One could set both SDs to a common value or set one to the variability of the other. A reasonable rule would be to reset **Beta Ib** to the variability of **Beta Ia** [7]. Thus:

[7] Arbitrary, but no more arbitrary, than setting standard deviations to one. In any case the correction does not seem to have a big impact. In the data analyzed here the raw and adjusted **Beta** differences correlate +.827.

(Rule 2)

To adjust Ia-Ib for differences in variabilities
Divide abs(bIa) by abs(bIb)
Divide Beta Ia by the ratio
Substitute that for Ib.
Subtract abs(Ia) - abs(Ib adjusted)

In our example . .0049 / .0001 = 49
.2378/49 = .0049
.2378 - .0049 = .2329

We conclude: in standardized terms the Cohort effect on farm origins is something like 23 correlation points larger than the Age effect and at least 23 points in magnitude. (This is quite strong as we shall see).

For simplicity I will use the following notation

C= absolute(bIa)
A = absolute (Ib adjusted)

Examples

To assess face validity of the technique and then, if the approach seems plausible, explore substantive results, I worked with 178 [8] items from among the five thousand plus variables in the cumulative NORC General Social Survey.

The GSS is an annual/biennial personal interview area-probability sample of US householders carried out 27 times from 1972 to 2008 with completion rates from 70 to 75 percent.

Notes:

1) 1972-1974 was a modified probability sample. Full probability samples began in 1975 with a split half design. Since results might be sensitive to extreme years I limited the set to full probability cases

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[8] The 178 items do not match 178 GSS mnemonics because some are multi-item scales and some are multiple dichotomizations of categorical variables such a marital status. I will use CAPS for mnemonics from the GSS file, lower case for author’s recodes.

reducing the time span to 1975-2008.

2) I re-weighted the data to make them representative of individuals rather than households.

3) Because the shape of age effects is often strikingly different in the early adult years (e.g. attendance at bars increases from age 18 to 25 and decreases steadily thereafter) I excluded those 18 to 24.

4) The GSS commenced interviewing in Spanish in 2006. Of 6,533 respondents in 2006- 2008, 769 reported their national background as Mexico, Puerto Rico, Spain and Other Spanish. 344 of them (45 per cent) were interviewed in Spanish, For the variable Spanish origins I excluded cases prior to 2006.

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Consequently my working data set had a weighted N of 41,371 as shown in Table 5.

Table 5
Constitution of the Analysis Sample

Total cases in the 1972-2008 cumulative file = 53,043

Of these:	6,818 modified probability samples (excluded) 46,225 probability sample (included)
Of these	4,826 ages 18-24 (excluded) 41,399 probability sample and age 25+ (included)
	41,371 after adjustment to represent persons (included) 28 difference

The GS has two unique features relevant to this essay.

First, it was deliberately designed to cover an unusually wide range of Sociological topics. The original questionnaire drew on informal surveys of potential users and the project is monitored by a committee of social scientists. No survey can be totally comprehensive and the GSS core is thin in several areas - e.g., mass and high culture, media usage, health behavior and politics - the latter skimped because of extensive (though rarely longitudinal) coverage in the Michigan Election Studies. I chose items with good time spans, extensive publication by GSS users and, in some cases, potential sensitivity to Age versus Cohort differences. Appendix 1 gives examples from fifteen common sense categories.

Second, the GSS is the only national attitude study that stresses exact replication of items year after year in its "permanent core." The core is far from perfectly permanent, however. Many "permanent core" items began and ended in different years, and until 1993 some items were on a rotation scheme, appearing in two years out of three, such that the any bivariate could be calculated somewhere during a three year interval. Consequently, of 178 test items:

Years Spanned (range = 14 to 33, median = 33)

33 =	121
30-32 =	34
20-29 =	11
14-19 =	12
	178

Yearly Data Points (range =6 to 24, median = 24)

24 =	95
20-23 =	43
10-19 =	37
<10 =	3
	178

I examined both linear (OLS) patterns and non-linear ones using dummy variables, 24 dummies for Year, 15 for Age in five year intervals, 13 for Cohort[9] (date of birth) in equal N categories. The dummy versions give a better fit to the data points, introduce non-linearity as a finding and reduce multi-colinearity among the APC variables. Unless otherwise noted the results reported are for the dummy versions.

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[9] Cohort has 13 dummies, not 15, because it was constructed on the complete 1972-2008 data set. This is unlikely to make any difference in the analyses.

Construct Validity

The algebra and results in Table 3 give the index **C-A** face validity but one would be still happier if they behaved the way they should in actual data; i.e. they should show construct validity.

To proceed:

First, I ran and saved the predicted values for each of the 178 variables against Year, giving 178 measures of change. (For example, the correlation for Farm origins and Year is +.143.) The changes have a range from +.018 to +.418 with a median of +.084[10].

Second, I calculated **C, A,** and **C-A** each of the 178 items.

If the prior argument is valid:

C should correlate with change
C should predict change better than **A**

Third, I ran **C** and **C-A** against the 178 changes. The bivariate correlations are:

C = +.823
C-A = +.540

Inference: **C** is a very good predictor of change and a better predictor than **A.**

These results have two substantive implications:

First: Cohort replacement is probably the best driver of change among the 178 GSS variables. Consider:

The saved predictions for Cohort->Y
The saved predictions for Year->Y (i.e. change in the variable)

[10] Since the predictors are dummies, all bivariates are positive.

The two correlate +.868 (N-178). That is, Items correlated with Cohort are highly likely to change. No other driver of change in the data set comes close.

Second, Year (Period) effects seem to contribute little to social change in the GSS. The **A** values are not impressive (range = .022 to .556, median = .050, upper quartile = .104). Since **A** is the sum of the Age and Year effects, either the Age and Year effects have opposite signs producing a suppressor variable, or both are nil. Since Year and Age are essentially uncorrelated in the GSS the former seems more likely.

Shifting from the general to the specific:

No one knows which variables are actually age or cohort driven - if so, we wouldn't be doing this research. However, common knowledge and sociological wisdom give us some purchase.

Common observation suggests using items "known" to be permanently tied to date of birth, i.e. fixed items. But it's not that simple because: (a) fixed items need not be related to cohort - gender is awfully permanent, but in populations without horrific battle casualties the sex ratio. changes very little from cohort to cohort and (b) analysts claim some non-fixed items, e.g. Party Preference, are set in early adulthood.[11] (c) social psychology is leery of long term memory (We just might embellish memories of family background as time /age proceeds).

So:

> Fixed items may or may not have positive values of **C-A** but should *not* have negative ones.
>
> Non-fixed items can have any value of **C-A** but should not produce only

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[11] In the analyses here PartyID does come out on the cohort side (**C-A = +** .065), but it is among the least dynamic variables (**R=**.065**)** .

positive values of C-A. (It is unlikely that *all* GSS variables are Cohort driven.)

Given that the test turns on the absence of differences not their presence and the validity of fixity coding begs the very question being addressed, the “rough” in “rough and ready” in the title seems well warranted.

Nevertheless, I proceeded as follows:

First, I coded items that on logical grounds should *not* change with a respondent’s age after age 18. Examples would be biological properties such as sex and race, characteristics of the respondent’s *parental* family (e.g. parents’ level of schooling) and all items pegged to when you were 16 years of age. I judged 38 of 178 to be fixed[12].

Second, If **C** and **A** should be both very small, e.g. with Betas of .0003 and .0002, their relative difference would be an impressive +.1.5 but the proper interpretation would be neither variable has a non-trivial Cohort or Age effect (or Period effect). Thus, we should avoid cases where neither **C** nor **A** is worth noting. Of necessity all three multi-variate regression set ups (Age & Cohort, Age & Year, Year& Cohort) give identical values of **R.** Therefore, non-trivial values of **R** satisfy us that something is going on though it does not tell us ‘what”. I ignored all cases where **R** was less than .10. Sixty-one of 178 (34%) had such low values. I I I I I ignored all cases where R was less than .10. Turning it around, two thirds of the test cases show dynamics worth scrutiny.[13]

Table 5 displays the basic distributions.

[12] I did not assess coding reliability. Readers may gain an impression from the results following.

[13]. Of the 12 least dynamic items (**R** <..02) eight are size of place, current or at age 16, and four are religious denominations.

Table 5.
Distribution of C-A results

	R			
Value	<.10	>= .10		% >=.10
+.30 or larger		7		
+.20 to +.29		7		
+.10 to +.19		19		
			33	28%
+.05 to +.09	9	15		
.00 to +.04	36	15		
			20	26%
-.01 to -.04	16	17		
-.05 to -.09	9	9		
			26	22%
-.19 to -.10		11		
-.29 to -.20		5		
-.30 or smaller		12		
			28	24%
	61	117		1005

The 117 non-trivial dynamic variables fall into four essentially equal groups

One quarter definitely Cohort
One quarter mildly Cohort
One quarter mildly Age
One quarter definitely Age

Tables **6** and **6a** displays the results of the construct validity test.

Table 6.
C-A Values by “Fixity” Coding > = .10)

	Fixed			
C-A	No		Yes	
.30 or larger	4		3	
.20 -.29	6		1	
.10 -.19	12		7	
		22		11
.05 - .09	9		6	
.00 - .04	14		1	
		23		7
-.01 to -.04	16		1	
-.05 to -.09	9		0	
		25		1
-.10 to -.19	11		0	
-.20 to -.29	5		0	
-.30 or smaller	12		0	
		28		0
		98		19

Table 6a.
Results in Table 6 Collapsed

Coded	-.10 or smaller	-.09 to +.09	+.10 or larger	Total
Fixed	0	8	11	19
Other	28	48	22	98
Total	28	56	33	117

Table 6 supports the argument because:

No Fixed item seems Age driven (**C-A** -.10 or lower)..
Fixed items appear across the range.

Substantive Results

Assuming the method is persuasive, the 178 results provide perspectives on the forces involved and not involved in social change from 1975 to 2008. Appendix 2 displays the variables with the most clear cut results.

Table 7 displays a typology of possibilities using the convention that an absolute magnitude of .10 or more in standardized regression units is a “keeper”:

Table 7.

Results Typology

Type	R	C-A	absC	absA	N	
I. Definitely cohort	>= .10	>=+.10	>=.10	<.10	30	
II. Relatively Cohort	>=.10	>=+.10	>=.10	>=.10	3	33
III. Relatively Age	>=.10	<= -.10	>=.10	>=.10	2	
IV. Definitely Age	>=.10	<= -.10	<.10	<= -.10	25	27
V. Ambiguous	>=.10	<.abs.10				57
VI. Static	<.10					61
						178

Type I variables (30 items) are definitely Cohort driven: **R** and **C-A** are keepers, **A** is not. Appendix 2 displays the fifteen Type I items with the highest values of **C-A**. The **A** coefficients are all less than .10 (by definition) and 11 of the 15 are less than .05.

Can we infer not only that the Cohort effect is strong but that the Age coefficient is essentially zero? As noted above, **A** is the sum of two forces, Year and Age, and when it is nil, either both are zero or there is a suppressor effect. However, in the GSS the correlation between Age and Year is essentially zero, ruling out suppression. Consequently we infer type I items vary with Cohort but not with Age.

Six of the type I's are classic family background measures, and the remainder are well known, strong, long run liberal attitude trends such as free speech, marijuana, and tolerance of homosexuality (Fischer and Hout, Chapter 9) Although one associates crabbiness with Aging, the Misanthropy scale (are people fair, can people be trusted, are people helpful) is clearly type I with the newer generations more mistrustful (**C-A** = +.186).

Types II (three items) and III (two items) have *both* C and A keeper effects but one is clearly stronger. Both population change and individual charge are at work here. The Cohort effect is stronger for three well known liberal attitude trends (racial attitudes among whites, feminism, and acceptance of homosexuality); the Age effect is stronger for two Labor Force status items.

Type IV (25 items) comprises those variables where Age is stronger than Cohort. Unlike Type I we cannot automatically assume the smaller effect is nil because Cohort and Year are definitely related. All fifteen are home focused, basically the shrinkage of family sizes, labor force participations and libido over the adult lifetime.

Type V cases are ambiguous with keeper values of **R** but non-keeper **C-A** differences. They could come either from strong but equal effects of Cohort and Age or from strong Year effects with trivial magnitudes for C *and* A, i,e, pure Period effects. . The 57 cases in Type V remind us the method is not one for estimating magnitudes but estimating differences. When the difference is small, the method is insensitive. Here the arbitrary .10 point cutting point makes a difference. With such a large sample, almost every one of the 178 items would show a statistically discernable C-A difference. Granted, but significant differences of two or three regression points have little or no Sociological relevance.

Type VI, the 61 cases (34 percent) where R is less than .10, remind us that before untangling dynamics, one should be assured that there is something to untangle. The majority of the Type Vis are religious affiliations, region, and size of place. Among the interesting stable attitudes and their **Rs** are respondent's occupational prestige (.092) biblical inerrancy (.091), abortion attitudes (.075), Partyid (.065), happiness (.050) and capital punishment (.042).

Do any themes emerge from the typology?

Noting the Type I examples have many attitudes and the Type III none, it suggests that attitude change is mostly Cohort driven - or more exactly, rarely Age driven. To nail this down I coded the items as attitudes if they concern favorability or unfavorability toward something and got the following table:

Table 9
C-A Results for Attitudes and Not Attitudes

Content	<= -.10	-.0999 to +.0999	=> .10	Total
Attitudes	1	17	16	34
Other	26	40	17	83
Total	27	57	33	117
			R <.10	61
				178

Of the 34 keeper attitude items, sixteen were coded as Cohort driven, just one as Age driven. The sole Age related item is TEENSEX (approve of premarital sex if ages 14-16), a sub-question for PREMARSX (approve of premarital sex - no age specified). Approval of teen age sex declines with age (linear trend = -.131) and has a **C-A** of -.131. PREMARSX itself is Type V (**C-A= +**.082, **C**= +.187, **A=** +.105). Approval increases with newer Cohorts and declines with Age.

At the opposite pole, despite the plethora of popular and academic scrutiny of "changing Families", it is a surprise that the family structure variables are concentrated in Type IV, Age driven, and scarce among the Cohort driven..

Table 10 breaks the results out according to the 15 content categories.

The left hand column gives percent with **R** values of .10 or more. Geography (regions and city sizes) Religion (mainly denominations) and Life and Death (abortion, capital punishment, mercy killing) stand out as the least dynamic - although all are major foci of sociological research on change.

Table 10.

Results by Topic

Topic	% R.10+	Below -.10	-.09 to +.09	.10 or More	Median
Family Attitudes	100	0	1	3	+.151
Parental Family	90	0	4	6	+.123
“Red/Blue” Attitudes	85	0	6	7	+.116
At Birth	50	0	4	2	+.068
Between 16 and 24	91	0	8	4	+.059
Politics	54	0	10	3	+.050
Life & Death	25	0	7	1	+.024
Misc. Attitudes	83	0	4	2	+.017
Religion	38	1	21	2	+.008
Geography	15	0	17	3	+.009
Well Being	67	1	8	0	-.000
Socio-Economic	70	2	8	0	-.013
Sociability	75	2	2	0	-.064
Sex	94	8	9	0	-.081
Family Structure	100	13		0	-.111

Among the dynamic topics, family attitudes (feminism, fertility attitudes), “Red/Blue” attitudes, and parental family characteristics are the most Cohort driven; family structure (marital status, labor force status) and sex *behavior* (sex attitudes tend to be Cohort driven) are the most Age linked.

Conclusions

In the main, I judge the empirical results to be favorable to the scheme in that:

1) Specific results can emerge from a single OLS two- variable regression.

2) The approach does not fly in the face of "Glenn's Postulate".

3) Analyses here produce plausible results for background variables and intriguing results for attitude variables.

But there is a downside:

1) It is of little use when the two effects, Cohort and Age, are small or their difference is small.

2) It has only indirect information about Period effects.

3) It does not produce adjusted net Age or Period variables that can be fed as predictors into multiple regression coefficients.

4) It is helpless in the face of one-time data.

And an equivocal result: Simply subtracting the Age bivariate from the Cohort bivariate gives pretty much the same conclusion as the proposed calculations. The two correlate at +.793 and there were no cases of contradictory results. Nevertheless, (A) This is an empirical result and need not hold in other data (B) It is not the best estimate of separate group and individual level effect sums.

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References Cited

Fischer, Claude S. and Michael Hout (2006) *Century of Difference: How America Changed in the Last One Hundred Years.* New York. Russell Sage Foundation

Glenn, Norval. (1976) 'Cohort Analysts' futile quest: Statistical attempts to separate age, period and cohort effects.' *American Sociological Review.* 41:900-904

. Mason, Karen Oppenheim, William H. Mason, Halliman H. Winsborough, and W. Kenneth Poole (1973) "Some methodological issues in cohort analysis of archival data." *American Sociological Review* 38: 242-258.

Ryder, Norman B. (1965) "The Cohort as a Concept in the study of Social Change." *American Sociological Review. 30:* 843-861.

Schuman, Howard S., Charlotte Steeh, Lawrence Bobo, and Maria Krysan. (1985) *Racial Attitudes in America: Trends and Interpretations.* Cambridge MA. Harvard University Press.

Stinchcombe, Arthur L. (1968) *Constructing Social Theories* pp. 60-79. Chicago. University of Chicago Press.

Yang, Yang. (2008) "Social Inequalities in Happiness in the United States, and Age-Period-Cohort Analysis." *American Sociological Review* 73. no. 2: 2004-226.

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Appendix 1.
Topical Areas and Representative items

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1) FAMILY ATTITUDES: should divorce be harder, ideal number of children, gender roles (4 items)
2) PARENTAL FAMILY: parents' schooling, parent's occupational prestige, siblings (10)
3)RED/BLUE ATTITUDES: marijuana, free speech, prayer in schools, gun control (13)
4) AT BIRTH: gender, race, born in US, ethnic origins (6)
5) BETWEEN 16 AND 24: ever divorced, age at 1st marriage, education (12)
6) POLITICS: party id, national spending priorities, redistribution (13)
7) LIFE AND DEATH: abortion, capital punishment, mercy killing (8)
8) MISC. ATTITUDES: work values, misanthropy, racial prejudice among whites (6)
9) RELIGION: denomination, belief in God, church attendance (24)
10) GEOGRAPHY: region, size of place (20)
11) WELL BEING: happiness, health, changes in income (9)
12) SOCIO-ECONOMICS: income, occupational prestige, self-rated class
13) SOCIABILITY: frequency of socializing with friends, family, etc. (4)
14) SEX: frequency, partners' genders, approve of premarital sex (17)
15) FAMILY STRUCTURE: marital status, labor force, household composition (22)

Appendix 2.
Examples of Results

Item#	C-A	C	A	R	Linear Trend
Type 1: Definitely Cohort: - Fifteen largest values of C-A					
Pared (mean of mo & fa school years)	+.378	.390	.012	.382	More
MAWORK (mother in labor force after marriage)	+.366	.370	.004	.374	Yes
ParsDead (if orphaned, because of divorce versus deaths)	+.342	.378	.036	.404	Divorce
TolAth (free speech for atheists: 3 item scale)	+.311	.330	.019	.317	Liberal
HiGrad (education = high school or more)	+.305	.349	.044	.321	More
TolMil (free speech for militarists: 3 item scale)	+.291	.294	.003	.296	Liberal
EDUC (school years completed)	+.289	.351	.062	.311	More
Tolcom (free speech for communists: 3 item scale)	+.264	.303	.039	.277	Liberal
RES16 (living on a farm at age 16)	+.233	.238	.005	.240	Less
HOMOSEX (homosexuality - how wrong)	+.209	.306	.097	.256	Liberal
NATEDUC (favor national spending on Education)	+.187	.266	.079	.222	Liberal
Misanthropy (3 item scale on trust, etc.)	+.186	.186	.000	.186	Mistrust
GRASS (legalize marijuana)	+.184	.217	.033	.198	Liberal
AGED (should elders live with grownup children)	+.180	.207	.027	.227	Yes
NATENVIR (favor national spending on environment	+.170	+.193	.023	.2209	Liberal

#CAPS=mnemonic in GSS cumulative file; lower case = author’s recode

TypeIV: Definitely Age - Fifteen most negative values of C-A

Item*	C-A	C	A	R	Linear Trend
Labor force1*	-.534	-.020	.554	.663	Negative
Labor force2*	-.511	.045	.556	.708	Negative
Sex1**	-.449	.043	.492	.555	Negative
Sex2**	-.429	-.029	.448	.482	Negative
Sex3**	-.426	-.052	.478	.477	Negative
Mtnest (married, have children no children in household)	-.353	.020	.373	.494	Positive
Sex4**	-.312	.048	.360	.434	Negative
Sex5**	-.309	-.039	.348	.359	Negative
Labor force3*	-.297	.098	.395	.525	Negative
HEALTH (self rated)	-.273	.062	.335	.246	Negative
MARITAL (widowed)	-.269	.074	.343	.486	Positive
BABIES (children under six)	-.268	-.020	.288	.390	Negative
Athome (children under 18)	-.257	-.067	.324	.447	Negative
Sex6**	-.253	-.025	.278	.287	Negative
SOCBAR(socializing at bars)	-.236	.014	.250	.316	Negative
HOMPOP (persons in household)	-.224	-.085	.309	.380	Negative

* In Labor force

1 Both husband and wife - if married
2 Neither husband nor five - if married
3 Respondent - all cases

**Sex frequency

1 Zero v. More - not married
2 Zero v. More - among married
3 Among all
4 Partners- none v. 1 or more - all cases
5 Among married
6 If greater than zero

Type V: Ambiguous - 15 largest values of R

Item*	C-A	C	A	R
CHILDS (number of children ever born)	.012	.217	.205	.387
MARITAL (single never married)	-.029	.180	.209	.362
UNEMP (ever unemployed last 10 years)	-.076	.114	.190	.303
PREMARSX (premarital sex - how wrong)	.082	.187	.105	.270
MOVIE (saw x-rated film this year)	-.008	.096	.104	.236
PORNLAW (legalize pornography)	-.034	.101	.135	.231
UpmobileEd (#)	.069	.157	.088	.220
SEXEDUC (favor sex education in schools)	.064	.147	.083	. 218
ADULTS (persons 18+ in household)	-.074	.037	.111	.218
MARITAL (currently married)	-.024	.086	.110	.200
Sex7*	-.081	.053	.134	.194
Sex8*	-.047	.070	.117	.188
Childs2 (children ever born among single)	.021	.129	.108	.179
MAPRES80 (prestige of mother's occupation)	.060	.118	.058	.169
MARITAL (married, ever divorced)	-.017	.083	.100	.168

* Sex7 number of sex partners 1 v. 2 or more

*Sex8 sex frequency if not currently married

schooling years minus mother's and father's mean school years