VARIABILITY OF FOOD INTAKES: ANALYSIS OF DATA FOR 12 DAYS

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INTRODUCTION

There are important questions about the reliability of estimated mean daily intake levels of food energy and nutrients (1-15). One issue of concern is the number of days of intake data (sample size) required to estimate with a given reliability level mean daily intake per individual. Results from analyses of one and three day survey data have shown substantial day-to-day variation in intakes for a number of the nutrients (7-11, 13-15). Beaton et al. (11) and other researchers (8, 9) have estimated inter and intraindividual components of intake variance. One study (10) suggests the intraindividual standard deviation of food energy intake is about 25 percent of the mean.

The purpose of this study was to evaluate individual intake data for day to day patterns and relate these patterns to the reliability with which mean daily energy and nutrient intakes can be estimated. The study extends the results of Beaton and others utilizing a special survey data base that includes 12 daily records per individual.

DATA

The data for this investigation were obtained from the Exploratory Study of Longitudinal Measures of Individual Food Intake conducted in 1982 under the auspices of the Nutrition Monitoring Division of Human Nutrition Information Service, U.S. Department of Agriculture. This "methodology study" was designed to evaluate effects of different numbers of daily intake records and different methods of recording intake on estimated intake levels. To date, analyses of these data have evaluated only method effects for estimated mean individual daily intakes (16). The present analysis is restricted to data from the methodology study for the NFCS standard three day intake procedure replicated in four quarters. The data include 12 observations on daily intake per subject.

The subjects in the survey were female homemakers between the ages of 19 and 70 years. These female homemakers were thought to be those in the household who could provide the most accurate intake data. Thus, the study was not designed to evaluate intake levels of different household members. For the NFCS standard method, 100 of the potential 150 females completed the questionnaires in each of the quarters; thus, the sample size for the present analysis was 100.

Although the subjects for the study were all female household heads and meal planners, some information on differentiating characteristics was recorded. These characteristics were age, education level, employment status, and household size. Variables reflecting these characteristics are utilized in the subsequent analysis along with the recorded daily intakes to provide an evaluation of the influence of numbers of days on the reliability of the estimated mean intake.

MODELS FOR VARIABILITY ANALYSIS

Clearly if observations from the different days were independent, standard statistical methods could be used to relate numbers of days to the reliability of mean intake estimates. The standard deviation of the mean in this case would be calculated from the estimated variance of the underlying distribution and the sample size. There is, however, a question about the applicability of this simple statistic for estimating reliability of mean daily intakes. Specifically, a cursory examination of the available results from the methodology study (16) shows that the variances of estimated mean daily intakes did not decrease with increased numbers of observation days as rapidly as if the observations had been independent. Either the distributions of intakes were not constant and/or there were patterns in individual intakes across days.

The estimators for this investigation were modified to reflect the fact that individuals' daily intake records exhibited day-to-day correlations. Specifically, estimators were modified to reflect persistence in consumption behavior. Generally, this persistence means, other things equal, that a greater number of days are required to achieve a particular reliability level for the estimate of mean daily intake.

A regression analysis framework is convenient for generating expressions for the estimators incorporating persistence. Assume that $y_i = \mu + \varepsilon_i$ ($i = 1, 2, \ldots, 12$), i.e., that the reported intake for the i-th day (y_i) is equal to the mean intake (μ), plus an error ($\varepsilon_i = y_i - \mu$). The 12 observations per individual can be written as

$$\underline{y} = \underline{x}\mu + \underline{\varepsilon} \qquad (1)$$

where $\underline{y} = (y_1, y_2, \ldots, y_{12})'$, $\underline{\varepsilon} = (\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_{12})'$, and $\underline{x} = (1, 1, \ldots, 1)$. The day to day pattern in intakes or the relationship among the elements of $\underline{\varepsilon}$ can take different forms. For the present analysis, it is assumed that the elements of $\underline{\varepsilon}$ are related to each other by a first-order autoregressive process, i.e.,

$$\varepsilon_i = \rho\varepsilon_{i-1} + u_i \; ; \; i = 1, 2, \ldots, 12 \tag{2}$$

and that the u_i are independently and identically distributed with mean zero and variance σ^2. Under these assumptions the generalized least squares (GLS) estimators for the mean, standard deviation and standard error of the mean are,

$$\tilde{\mu} = (\underline{x}'\Omega^{-1}\underline{x})^{-1}\,\underline{x}'\Omega^{-1}\underline{y}$$

$$\tilde{\sigma}^2 = \frac{\tilde{\underline{\varepsilon}}'\Omega^{-1}\tilde{\underline{\varepsilon}}}{N - 1}$$

$$\tilde{\sigma}_\mu = \left|\tilde{\sigma}^2(\underline{x}'\Omega^{-1}\underline{x})^{-1}\right|^{1/2},$$

where $\tilde{\varepsilon}_i = y_i - \tilde{u}$ and Ω is the Prais-Winsten matrix (17) depending on the value of ρ. If ρ is unknown, it can be estimated by

$$\hat{\rho} = \left(\sum_{i=2}^{N} \hat{\varepsilon}_i\hat{\varepsilon}_{i-1}\right) / \sum_{i=2}^{N} \hat{\varepsilon}^2_{i-1} \; .$$

Then the "feasible" GLS (with $\hat{\Omega}^{-1}$ instead of Ω^{-1}) can be applied to estimate the parameters of equation (1). Notice that if $\rho = 0$, $\tilde{\mu} = \hat{\mu} = \bar{y}$, $\tilde{\sigma}^2 = \hat{\sigma}^2$, and $\tilde{\sigma}_\mu = \hat{\sigma}_\mu = \sigma_{\bar{y}}$.

An important implication of assumed structure for the "persistence" in consumption patterns is for forecasting. The forecasting question is: given the sample to day i, what is the "best" estimate of the individual intake for the day i+1? Using models (1) and (2), the expected value of the individual intake for the day i+1 is

$$\tilde{y}_{i+1} = (1 - \hat{\rho})\tilde{\mu} + \hat{\rho}y_i \; . \tag{3}$$

Observe that the forecast estimator (3) incorporates "persistence" in consumption through both $\tilde{\mu}$ and $\hat{\rho}$. In the absence of intake persistence, $\rho = 0$, and $\hat{\mu} = \tilde{\mu}$, and $\hat{y}_{i+1} = \tilde{y}_{i+1}$, with the hats denoting the simple ordinary least squares estimators.

Estimated mean daily intakes for the diet components selected for the analysis can be evaluated individually or plotted as cumulative distributions for indicating impacts of added sample size for the set of individuals sampled. These cumulative distribution functions, when constructed using estimators of mean daily intakes for the subjects based on different numbers of days, provide for generalizing the results for individuals to the population. Specifically, comparisons between these cumulative distributions for different numbers of days utilized in estimating the individual daily mean intakes show how the set of individual estimates shifts as numbers of days used in estimation increases. These shifts in the cumulative distributions can be quantitifed easily. The shifts in the cumulative show the contribution to the accuracy of the set of estimated mean daily intakes from the increased numbers of days.

METHODS

Data for the 100 sampled subjects were used to estimate autocorrelation coefficients based on 12 intake records per person to quantify the persistence in daily intakes (ρ). These estimates were made for food energy, fat, iron and vitamin A. These four dietary components were selected for evaluation because it was believed that food energy intake levels would be relatively consistent across days, fat intake would be representative of macronutrient intake consistency and iron and vitamin A intakes would represent micronutrient intake for a widely distributed and a more food specific micronutrient, respectively.

First the autocorrelation coefficients for each of the 100 females were estimated. Then estimates of the expected next day intakes for each subject were calculated using three days' intake to predict the fourth day intake, six days' intake to predict the seventh day intake, eight days' intake to predict the ninth day intake and 11 days' intake to predict the twelfth day intake. All of these forecasts were calculated with and without ρ, the persistence factor. The difference between the actual (known) intake for each individual on days three, six, nine, and 12 and the forecasted intake based on the days in the sample up to these "test" days were used to estimate the absolute value of the "error". The forecasts were made assuming no autocorrelation and with autocorrelation. Finally, for each individual, the absolute error was determined for the difference between the GLS forecast and the GLS estimated mean intake including the added sample day.

After these calculations were made for each of the 100 sample subjects, absolute errors for estimated daily intakes were averaged across the sample to obtain a mean absolute error estimate for the total sample for each diet component. These estimates were made using both GLS and OLS forecasts. To further illustrate the importance of the persistence factor in forecasting intake levels and evaluating added days of intake data, the sample was partitioned into two subgroups based on values of the estimated autocorrelation coefficients for the individuals. That is, one subgroup contained individuals with estimated autocorrelation coefficients greater than 0.3 and the other subgroup was composed of individuals whose autocorrelation coefficients were less than 0.3.

Previous research (16) has shown that individuals who usually consume large amounts of food have larger standard deviations of mean daily intake than those who usually consume small quantities of food. It follows then physiologically that if the lower consumers of food energy are near maintenance levels, predicted intake levels should be more accurate than those for "large" eaters. To test this hypothesis, the 100 subjects were arrayed from highest to lowest in estimated average food energy intake. Then the top quartile and bottom quartile in this distribution were selected as subsamples. GLS estimates for mean daily intakes and mean absolute error values for GLS and OLS forecasts were calculated for these two subsamples.

Several studies (e.g., 18, 19, 20) have suggested that characteristics of individuals such as age, sex, education, employment, household income, location of residence and other factors, influence estimated intake levels. An analysis for effects of selected socioeconomic characteristics in forecasting intake levels were conducted. Recall that the sample was rather homogeneous. That is, all subjects were adult females with moderate household income levels and residing in one region of the U.S. Therefore, the analysis for socioeconomic characteristic impacts was somewhat limited. This analysis was restricted to food energy intake.

The socioeconomic characteristics examined were age, household size, employment status and education level. The sample partitions were specified as follows:

Age
- 19 to 28 years
- 29 to 38 years
- 39 to 48 years
- 49 to 58 years
- 59 to 70 years

Household Size
- 1 or 2 members
- 3 members
- 4 members
- 5 or more members

Employment Status
- unemployed
- employed part-time (< 39 hours/week)
- employed full-time (> 40 hours/week)

Education Level
- < high school
- high school graduate
- > high school

RESULTS FOR INDIVIDUALS

Estimates of autocorrelation showed that 27 of the 100 subjects had coefficients for food energy intake greater than 0.3, indicating these individuals exhibited considerable persistence in caloric intake (Table 1). Interestingly, similar numbers of subjects had relatively high estimated autocorrelation coefficients for fat (26), iron (28) and vitamin A (29). Forty-five of the subjects had negative autocorrelation coefficients for food energy. These negative values indicated that eating patterns alternate, from high to low consumption levels, while the 55 positive values showed consistency in levels of food energy intake. The numbers of positive values for fat, iron and vitamin A were somewhat less indicating intake levels of these three nutrients were somewhat less consistent than food energy intake levels.

Mean absolute error values for estimated daily individual intakes for the sample are summarized in Table 2. Observe that these results indicate that the major gains in accuracy of mean daily intake estimates occurred prior to day seven. That is, subsequent to day six, added observations generally contributed relatively less to the accuracy of the estimates. Accuracy in this case is measured in an operational way--the forecast based on previous days contrasted with the actual intake value in the comparable day. From Table 2 note that from the root mean square errors the differences in the estimates when no autocorrelation was included (which assumes days are independent) were larger. Thus, the patterns in consumption are valuable in estimating next day intakes and, in general, detract from estimates of the additional accuracy that can be obtained by adding another day to the sampling design.

Since the larger the autocorrelation coefficient, the greater is the persistence in consumption, it follows that forecasts for individuals with larger autocorrelation coefficients should require fewer days for accurate estimates of next day intake than estimates for subjects with small autocorrelation coefficients. Results for the empirical testing of this proposition are in Tables 3 and 4. The values in Table 3 for the absolute errors between GLS forecast and GLS mean intake show a limited decrease in accuracy between day three and day six. Similar conclusions can not be drawn from results provided in Table 4 until days nine and 12.

Tables 5 and 6 provide the forecast evaluation results for "small eaters" and "large eaters," respectively. These results show clearly that small eaters have much more predictable consumption patterns than "large eaters". In fact, very little additional information is gained after day six for "small eaters," i.e., the average root mean square error estimates are nearly the same for days six, nine and 12. The "large eaters" also showed greatest gains in accuracy of estimated mean daily intake prior to day seven. However, added observations after day six did improve, albeit in a limited way, the accuracy of the forecasts relative to observed intake levels.

Results for the sample partitioned into five age groups are provided in Table 7. Comparisons of these mean square error values with the ones in Table 2 for the total sample showed that the accuracy of predicted intake is not respondent age dependent. That is, the mean absolute errors for the age partitioned sample are not increased or decreased with increasing/decreasing age. The possible exception is for females ages 59 to 70 years. Results in Table 7 show improved accuracy of predicted intake compared to actual intake for the oldest age group; however, this result may be confounded with the lesser quantities of food consumed by the older individuals.

As indicated in Table 8, household size was not found to be an important characteristic for influencing the accuracy of predicted food intake levels. That is, comparisons of results provided in Table 2 with results in Table 8 show that accuracy of predictions, whether for days three, six, nine or 12 were not improved significantly for households of different sizes.

Table 9 provides evidence that food intake patterns of subjects employed full time are more variable, and thus more difficult to predict accurately, than the food intake patterns of subjects unemployed or employed part-time. This conclusion is based on the mean absolute errors for individuals employed full time being consistently greater than similar estimates for the total sample (Table 1). Eighty-three percent of the mean absolute errors for subjects employed part-time or unemployed were smaller than comparable estimates for the total sample.

Education level of the respondent was also an important factor for predicting accurately food energy intake levels. For both the GLS and OLS forecasts, the mean absolute errors for subjects having less than a high school education were significantly less than similar results for the total sample. Less educated individuals likely had less variety in their diets than more educated respondents. There were no differences observed in the accuracy of predictability of food energy intakes between respondents with a high school education and those with an education beyond high school.

RESULTS FOR TOTAL SAMPLE

Cumulative distributions for the four selected dietary components plotted for three, six, nine and 12 day GLS estimated means are exhibited in Figures 1 through 4. From the figures, it is clear that the big contribution to the accuracy of the set of estimated mean daily intakes is achieved by the increase in numbers of days from three to six days. Alternatively, the increase in numbers of days from nine to 12 days produced a relatively smaller improvement. The big gains occurred at lesser numbers of days for food energy than for the other three dietary components but, in general, do not differ appreciably. This analysis could be extended to partitions of the sample for age, household size, employment status and education level. Comparisons between the cumulative distributions for these partitions would demonstrate how, for specific subgroups, the estimated mean daily intakes for the sample improve with added numbers of days or sample.

CONCLUSIONS

Results of this analysis demonstrate: 1) the importance of reflecting appropriately patterns in day-to-day food consumption in the estimation of mean daily intake levels, 2) the importance of these consumption patterns in evaluating incremental contributions of added days of intake information to the accuracy of estimated mean daily intakes, 3) the potential for conditioning sample sizes for observable characteristics of survey subjects for reliability of mean intake estimates and 4) the estimated improvement of results for the sample subjects as a group that can be obtained by comparisons of cumulative distributions.

The general results on contributions of numbers of days or sample size to the accuracy of mean intake estimates suggest that for the four diet components examined, the benefits fall off importantly after six days. This conclusion holds across the nutrients and for different patterns of food consumption indicated by the estimates of the coefficient of autocorrelation. In addition, the plots of the cumulative functions for estimates of mean daily intakes for the total sample show that the larger changes in accuracy occur between the three and six days of sample sizes. These results are altered appreciably if eating patterns which make the assumption of independence between days inappropriate are not incorporated in the estimation and evaluation processes.

The exact nature of the patterns in intakes between days of individuals warrants more careful investigation. In the present analysis, this pattern assumed a first-order autoregressive form. It is clear from the results, however, that this assumption on the pattern in day to day intakes was only a gross approximation, more appropriate for some individuals than others. With larger samples, permitting analyses of day to day effects in more detail, alternative models of persistence should be investigated as well as perhaps physiological and institutional reasons for this persistence or patterning of daily individual intakes.

The evidence of patterns in day to day individual intakes for all diet components raises many questions about previous estimates of reliability of estimated mean daily intake and numbers of recorded days intakes. Most of the previous analyses have been conducted using estimators for means and variances of daily intake that presume independence of daily intakes. They may have substantially underestimated the true variances of estimators of mean daily intakes. In statistical terms, the estimated means are unbiased but not efficient and the variance estimators biased. Clearly, the reduced efficiency for the estimator of mean daily intake and bias in the variance estimator depend upon as yet not well known day to day eating patterns.

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Table 1. Summary of estimated coefficients of autocorrelation for food energy, fat, iron and vitamin A.

Dietary Component	Absolute Value		Sign	
	<0.3	>0.3	-	+
Food energy	27*	73	45	55
Fat	26	74	58	42
Iron	28	72	59	41
Vitamin A	29	71	56	41

*Number of subjects with autocorrelation coefficient estimators for food energy greater than 0.3.

Table 2. Mean absolute errors for estimated daily individual intakes of food energy, fat, iron and vitamin A.

Dietary Component	Day and Mean Absolute Error Estimator			
	Day 3	Day 6	Day 9	Day 12
	GLS Forecast and Actual Intake			
Food Energy (kcal)	458	456	361	315
Fat (gm)	30	26	21	18
Iron (mg)	3.8	3.0	2.8	3.3
Vitamin A (IU)	3155	3163	3080	3021
	OLS Forecast and Actual Intake			
Food Energy (kcal)	450	493	386	333
Fat (gm)	30	27	23	20
Iron (mg)	3.8	3.3	3.2	3.4
Vitamin A (IU)	3185	3278	3219	3277
	GLS Forecast and GLS Mean Intake			
Food Energy (kcal)	173	117	74	86
Fat (gm)	11	7	5	5
Iron (mg)	1.4	1.0	1.0	1.0
Vitamin A (IU)	1093	823	703	784

Table 3. Mean absolute errors for estimated daily individual intakes of individuals with autocorrelation coefficients of greater than 0.3.

Dietary Component	Day and Mean Absolute Error Estimator			
	Day 3	Day 6	Day 9	Day 12
	GLS Forecast and Actual Intake			
Food Energy (kcal)	394	326	370	289
Fat (gm)	26	18	21	16
Iron (mg)	3.3	2.1	2.3	2.3
Vitamin A (IU)	3108	2755	2146	4001
	OLS Forecast and Actual Intake			
Food Energy (kcal)	387	456	395	323
Fat (gm)	26	24	28	20
Iron (mg)	3.4	3.2	3.4	2.9
Vitamin A (IU)	3068	3247	2899	4426
	GLS Forecast and GLS Mean Intake			
Food Energy (kcal)	157	164	110	152
Fat (gm)	12	10	9	9
Iron (mg)	1.4	1.1	1.2	1.1
Vitamin A (IU)	1231	1047	1042	937

Table 4. Mean absolute errors for estimated daily individual intakes of individuals with autocorrelation coefficients of less than 0.3.

Dietary Component	Day and Mean Absolute Error Estimator			
	Day 3	Day 6	Day 9	Day 12
	GLS Forecast and Actual Intake			
Food Energy (kcal)	482	504	357	324
Fat (gm)	31	28	21	19
Iron (mg)	3.9	3.3	2.9	3.6
Vitamin A (IU)	3175	3330	3461	2621
	OLS Forecast and Actual Intake			
Food Energy (kcal)	473	506	383	336
Fat (gm)	31	28	22	20
Iron (mg)	3.9	3.4	3.1	3.7
Vitamin A (IU)	3233	3290	3350	2808
	GLS Forecast and GLS Mean Intake			
Food Energy (kcal)	179	100	60	51
Fat (gm)	11	6	4	4
Iron (mg)	1.4	0.7	0.5	0.5
Vitamin A (IU)	1037	731	565	721

Table 5. Mean absolute errors for estimated daily individual intakes of small eaters.

Dietary Component	Day and Mean Absolute Error Estimator			
	Day 3	Day 6	Day 9	Day 12
	GLS Forecast and Actual Intake			
Food Energy (kcal)	350	213	311	258
Fat (gm)	26	14	17	16
Iron (mg)	3.0	2.5	2.3	3.1
Vitamin A (IU)	1800	1781	2535	2272
	OLS Forecast and Actual Intake			
Food Energy (kcal)	355	241	327	245
Fat (gm)	26	14	19	15
Iron (mg)	3.1	2.9	2.4	3.2
Vitamin A (IU)	1862	1925	2533	2185
	GLS Forecast and GLS Mean Intake			
Food Energy (kcal)	113	60	56	69
Fat (gm)	8	4	4	4
Iron (mg)	1.0	0.7	0.5	0.7
Vitamin A (IU)	702	610	586	508

Table 6. Mean absolute errors for estimated daily individual intakes of large eaters.

Dietary Component	Day and Mean Absolute Error Estimator			
	Day 3	Day 6	Day 9	Day 12
	GLS Forecast and Actual Intake			
Food Energy (kcal)	488	558	390	358
Fat (gm)	36	33	23	23
Iron (mg)	3.1	3.4	3.0	3.5
Vitamin A (IU)	4663	3013	3057	2471
	OLS Forecast and Actual Intake			
Food Energy (kcal)	472	645	401	416
Fat (gm)	35	35	25	27
Iron (mg)	3.1	3.8	3.8	3.8
Vitamin A (IU)	4401	3057	3046	3274
	GLS Forecast and GLS Mean Intake			
Food Energy (kcal)	198	163	93	111
Fat (gm)	14	9	5	6
Iron (mg)	1.3	0.9	0.8	0.6
Vitamin A (IU)	1843	649	578	1461

Table 7. Mean absolute errors for estimated daily individual food energy intakes for individuals partitioned by age classifications.

Age (Years) Group	Day and Mean Absolute Error Estimator			
	Day 3	Day 6	Day 9	Day 12
	GLS Forecast and Actual Intake			
19 to 28	481	407	327	316
29 to 38	390	461	331	318
39 to 48	481	554	368	343
49 to 58	577	409	448	334
59 to 70	407	420	336	249
	OLS Forecast and Actual Intake			
19 to 28	508	505	335	381
29 to 38	385	498	367	321
39 to 48	451	579	415	377
49 to 58	553	419	442	312
59 to 70	408	450	361	286
	GLS Forecast and GLS Mean Intake			
19 to 28	161	183	90	111
29 to 38	140	101	67	76
39 to 48	212	124	65	95
49 to 58	225	89	84	94
59 to 70	138	121	72	64

Table 8. Mean absolute errors for estimated daily individual food energy intakes for individuals partitioned by household size classifications.

Household Size Groups	Day and Mean Absolute Error Estimator			
	Day 3	Day 6	Day 9	Day 12
	GLS Forecast and Actual Intake			
1 and 2	488	351	461	236
3	501	468	347	283
4	370	594	344	362
5 or more	449	447	262	414
	OLS Forecast and Actual Intake			
1 and 2	486	352	465	247
3	494	524	368	332
4	351	646	406	357
5 or more	442	493	285	423
	GLS Forecast and GLS Mean Intake			
1 and 2	175	114	78	80
3	188	135	68	88
4	146	99	71	108
5 or more	177	116	77	72

Table 9. Mean absolute errors for estimated daily individual food energy intakes for individuals partitioned by employment status classifications.

Employment Status Groups	Day and Mean Absolute Error Estimator			
	Day 3	Day 6	Day 9	Day 12
	GLS Forecast and Actual Intake			
Unemployed	456	453	354	290
Employed Part-Time	399	462	320	320
Employed Full-Time	498	454	393	332
	OLS Forecast and Actual Intake			
Unemployed	448	468	365	300
Employed Part-Time	377	486	349	295
Employed Full-Time	499	518	427	384
	GLS Forecast and GLS Mean Intake			
Unemployed	174	104	85	82
Employed Part-Time	161	94	71	76
Employed Full-Time	181	143	65	96

Table 10. Mean absolute errors for estimated daily individual food energy intakes for individuals partitioned by educational status classifications.

Educational Status Groups	Day and Mean Absolute Error Estimator			
	Day 3	Day 6	Day 9	Day 12
	GLS Forecast and Actual Intake			
< High School	408	246	343	210
High School Graduate	473	502	350	352
> High School	446	454	404	270
	OLS Forecast and Actual Intake			
< High School	411	339	380	218
High School Graduate	464	529	369	371
> High School	434	481	442	291
	GLS Forecast and GLS Mean Intake			
< High School	140	85	68	79
High School Graduate	177	121	71	95
> High School	183	126	85	64

FIGURE 1: CUMULATIVE FREQUENCY DISTRIBUTIONS OF THE 3-DAY, 6-DAY, 9-DAY, AND 12-DAY "ADJUSTED" MEANS OF FOOD ENERGY (KCAL) INTAKE FOR ALL INDIVIDUALS.

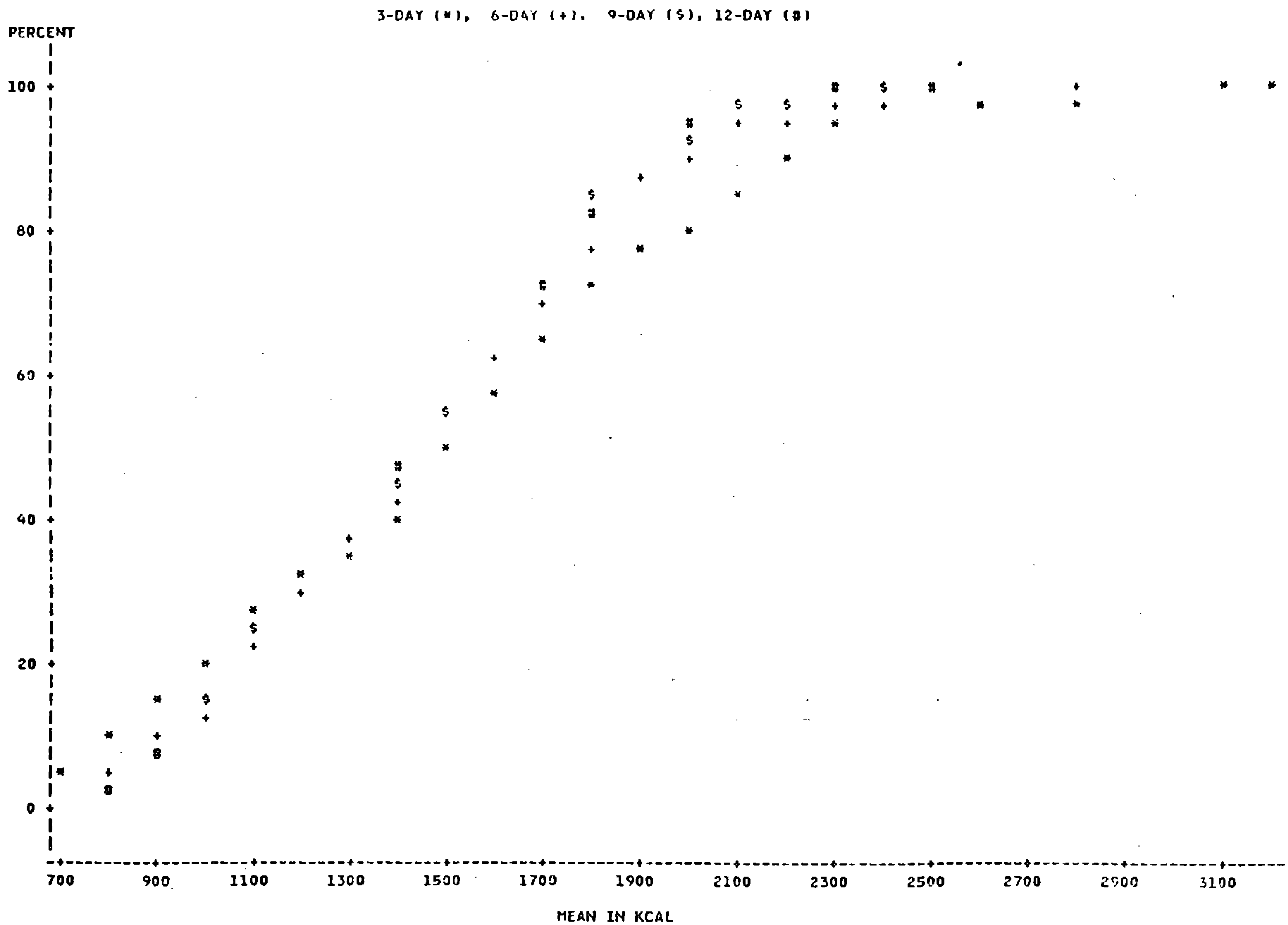

FIGURE 2: CUMULATIVE FREQUENCY DISTRIBUTIONS OF THE 3-DAY, 6-DAY, 9-DAY, AND 12-DAY "ADJUSTED" MEANS OF FAT (GM) INTAKE FOR ALL INDIVIDUALS.

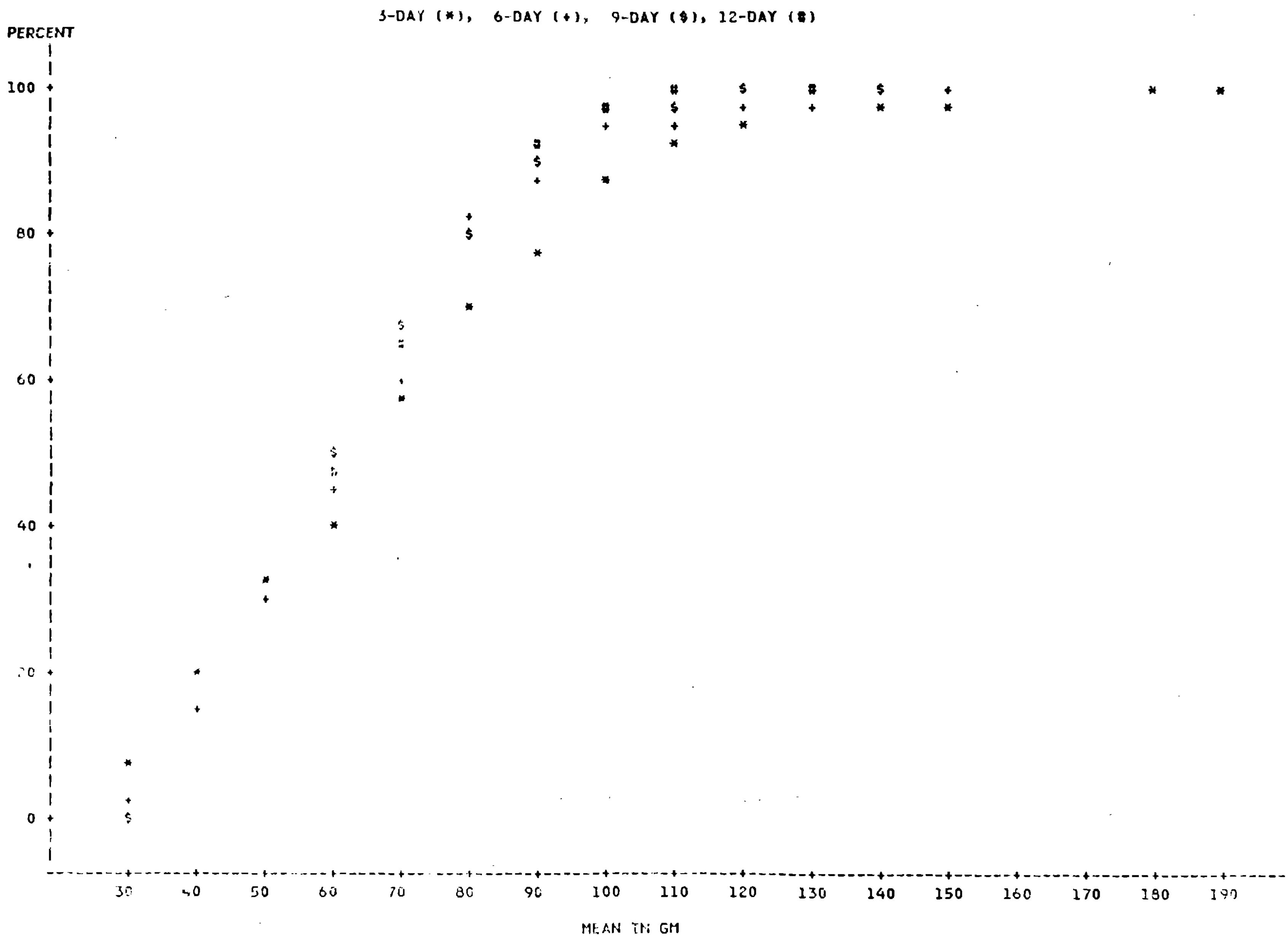

FIGURE 3: CUMULATIVE FREQUENCY DISTRIBUTIONS OF THE 3-DAY, 6-DAY, 9-DAY, AND 12-DAY "ADJUSTED" MEANS OF IRON (MG) INTAKE FOR ALL INDIVIDUALS.

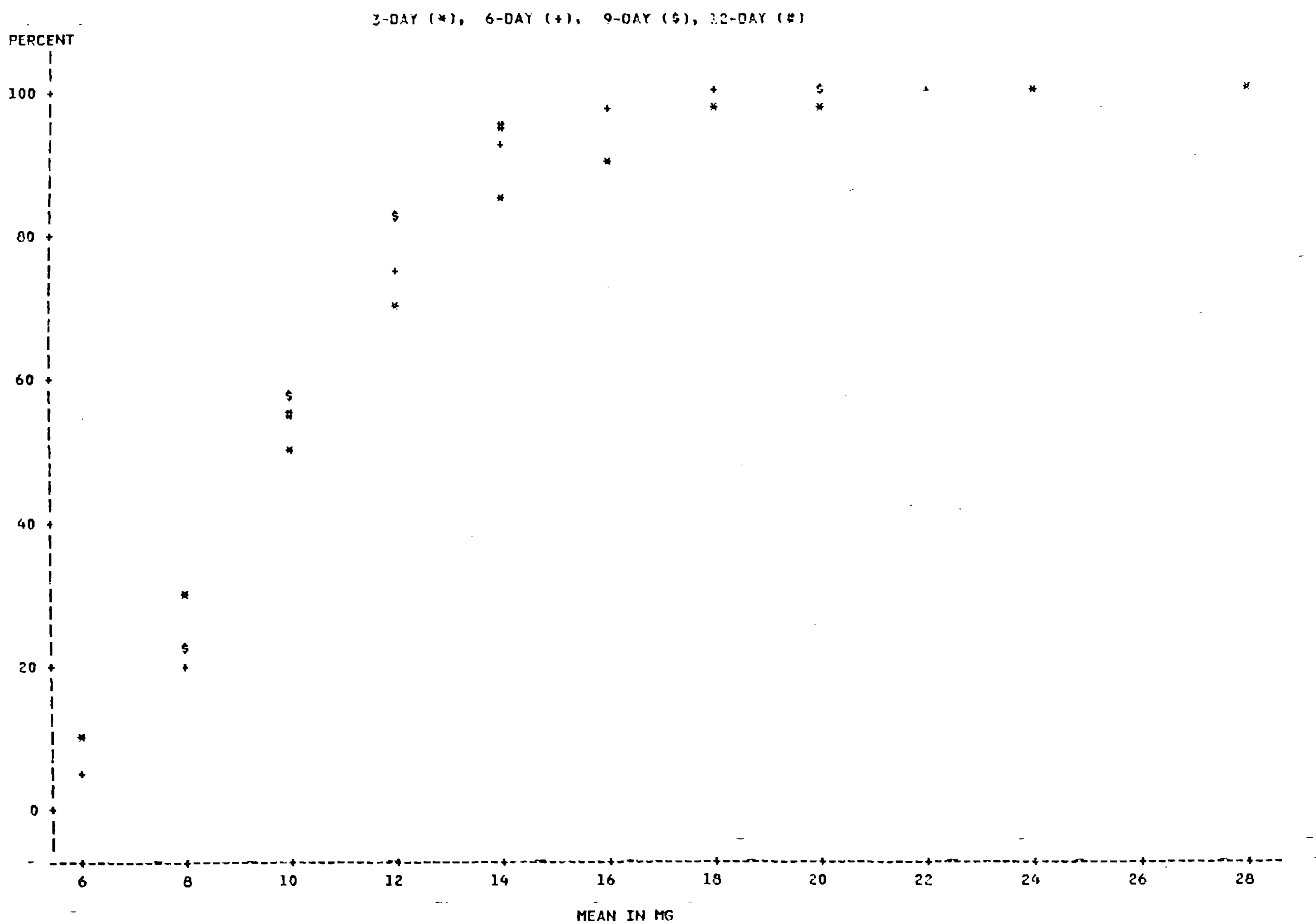

FIGURE 4: CUMULATIVE FREQUENCY DISTRIBUTIONS OF THE 3-DAY, 6-DAY, 9-DAY, AND 12-DAY "ADJUSTED" MEANS OF VITAMIN A (IU) INTAKE FOR ALL INDIVIDUALS.