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BEFORE THE
POSTAL REGULATORY COMMISSION
WASHINGTON, D.C. 20268–0001

PERIODIC REPORTING (PROPOSAL ONE)	Docket No. RM2022-3

RESPONSES OF THE UNITED STATES POSTAL SERVICE TO QUESTIONS 1-4 OF CHAIRMAN'S INFORMATION REQUEST NO. 2
(February 15, 2022)

The United States Postal Service hereby provides its responses to the above listed questions of Chairman's Information Request No. 2, issued February 1, 2022. Although these questions were initially posed under seal, upon further review and consultation, it was determined that both the questions and the responses are suitable for public treatment. The questions are stated verbatim and followed by the response.

Respectfully submitted,

UNITED STATES POSTAL SERVICE

By its attorney:

Eric P. Koetting

475 L'Enfant Plaza West, S.W.
Washington, D.C. 20260-1137
(202) 277-6333
eric.p.koetting@usps.gov
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RESPONSES OF THE UNITED STATES POSTAL SERVICE
TO CHAIRMAN'S INFORMATION REQUEST NO. 2

1. Please refer to the Postal Service's response to CHIR No. 1, question 3.c., where the Postal Service provided the formula to calculate the marginal time. *See* Response to CHIR No. 1 at 11-12. Please confirm that this formula does not include the derivative, with respect to volume, of the cluster averages appearing in the equation as additional explanatory variables. If confirmed, please explain why the cluster averages do not contribute to the calculation of the marginal times and, hence, the variabilities. If not confirmed, please explain how these averages are accounted for in the formula.

RESPONSE:

Confirmed. To understand why the cluster averages (and their estimated coefficients) do not contribute to the calculation of the marginal times and variabilities, one must first understand what the estimated coefficients on the cluster averages measure. That understanding begins with a recognition that cluster averages arise in two types of models, multilevel models and longitudinal models (which are sometimes called panel data models).

In multilevel models, the data are all cross-sectional, but the variables come in two or more different levels of aggregation. For example, in a study of educational attainment, observations on individual students may be clustered within the respective schools they attended. Variables relating to individual student characteristics are called level 1 variables, and variables relating to the school characteristics are called level 2 variables. In longitudinal (or panel data) models, observations are collected on the same set of individual units over time. Variables that vary both across individual units and through time are the level 1 variables and variables that vary only across individual units are the level 2 variables. In the top-down model of city carrier street time, which is longitudinal, the daily volumes at each ZIP Code are examples of level 1 variables and the ZIP code average volumes (the cluster averages) are examples of level 2 variables.

The interpretation of level 2 variables depends upon the type of model being estimated. In multilevel models, the impact of level 2 variable is known as the contextual effect.[1] The contextual effect measures the effect of a level on individual "moving" from one level 2 unit to another. In other words, it measures how much difference there is between two otherwise similar individual units arising from the fact that they are from different clusters. In the educational attainment example, the contextual effect would be the difference in attainment for similar students across different schools.

In contrast, the level 2 variables have no specific meaning in longitudinal or panel data models:[2]

> With longitudinal data, the contextual effect is fairly meaningless: it doesn't make sense for an observation (level 1) to move from one (level 2) individual to another, because they are by definition belonging to a specific individual. It therefore makes little sense to control for those observations in estimating the level 2 effect.

In longitudinal data, level 1 units are not clustered into higher level units, but are measured at repeated points through time. In this context, there is no corollary to the

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[1] *See*, Bell, Andrew, Fairbrother, Malcom and Kelvyn Jones, "Fixed and Random Effects Models: Making an Informed Choice," *Quality and Quantity*, Vol. 53, No.2, March 2019 at 1053.

[2] *Id*. at 1056.

effect of moving from one higher level cluster to another. In the top-down case, the contextual effect measures the difference in street hours for two ZIP Codes with the same amounts of volume. It thus does not contribute to the calculation of volume variability.

Additional insight into the contextual effect can be acquired by a more formal statement of its relationship between the level 1 and level 2 effects. In a panel data context, the level 1 relationship is sometimes called the "within" effect and the level 2 relationship is sometimes called the "between" effect. The contextual effect is the difference between those two effects; it is the measured within effect minus the measured between effect. In multilevel models, the between effect is often of interest because the research is focused on the impact of the level 2 variables on the dependent variable. The between effect can also be estimated in the panel data context, but it can often be biased, and has a questionable interpretation:[3]

> The between-cluster effect, β_B, assesses how a change in $\bar{x}_i$ is associated with a change in $\bar{x}_i$ It is estimated using only between-cluster variation. Different research traditions have different views as to whether these effects are informative. In multilevel research, the interest often lies on the level-two variables, and between-cluster effects of the level-one variables are level-two effects. The substantive interpretation of the cluster means of the level-one variables is different from the substantive interpretation of the level-one variables (Snijders and Berkhof 2008, 146). However, one should keep in mind that if the random-effects assumption is

[3] *See*, Schunk, Reinhard, and Francisco Perales, "Within- and Between-Cluster Effects in Generalized Linear Mixed Models: A Discussion of Approaches and the Xthybrid Command," *The Stata Journal*, Vol. 17, No. 1, at 95.

> violated (that is, there is unobserved heterogeneity at level two), the between-cluster effect is biased. In panel-data analysis, the interest lies chiefly on the within-cluster effects, so it is imperative to obtain estimates of these effects, that are robust to unobserved heterogeneity at level two (Allison 2009; Halaby 2004; Wooldridge 2010). From this perspective, it is questionable whether the between-cluster effects are of substantial interest at all.

In the top-down model, the contextual coefficients in the correlated random effects model are not part of the response in street hours to changes in volume. However, given this question, it may be of interest to estimate the between effects. The following table presents the marginal times and variabilities estimated with the between version of the top-down model.[4]

Results for the Between Panel Data Model

Volume	**Marginal Time**	**Variability**
DPS	5.37	28.0%
Cased	8.83	13.5%
Sequenced	4.67	2.8%
FSS	12.50	2.6%
In-Receptacle Parcels	-42.16	-6.2%
Deviation Parcels/ Accts.	97.01	10.6%
Collection	25.03	4.1%

Source: Between Panel Model.sas

[4] The between model was estimated by the SAS program entitled, Between Panel Model.sas, which is attached, along with its log and listing to this response.

The results of the between model present clear evidence of bias. For example, the in-receptacle marginal time and variability are negative and the marginal times for FSS mail and collection mail do not make operational sense. Neither the contextual coefficients from the CRE model. nor the between model coefficients. are applicable in calculating the variabilities of city carrier street time.

2. Please refer to the Postal Service's response to CHIR No. 1, question 3.b., which confirmed that the estimates of the coefficients of time-variant explanatory variables (including all volumes variables), are numerically the same as those that would be obtained using the fixed-effect estimation. *See id.* at 11. Please also refer to the following statement in the Bradley Study, "[h]owever, in previous cases, the Commission has expressed concern about the application of fixed effects to the estimation of attributable postal costs. The Commission has expressed two concerns. First the Commission argued that the fixed effects are not fixed, but actually 'endogenous,' meaning they are related to volume. In addition, the Commission expressed a concern that the fixed effects could change over time." Bradley Study at 86-87 (footnotes omitted). Finally, please refer to page 89 of the Bradley Study, where the errors ζ_i and ε_{it} are discussed. *See id.* at 89.

a. Please explain why, despite the fact that the estimates of the volumes' coefficients are numerically identical if calculated using fixed effects (FE) or Correlated Random Effects (CRE) methods, the estimates calculated using CRE are more statistically reliable than those calculated with FE.

b. Please confirm that in the CRE model, as in any alternative model, the statistical consistency of the estimators of the coefficients is critical for the statistical reliability of the calculated variabilities. If not confirmed, please explain.

c. Please confirm that, for the estimators of the coefficients appearing in the CRE model to be statistically consistent, Proposal One implicitly makes the assumption of strict exogeneity as defined by Wooldridge.[5]

i. Please confirm that strict exogeneity implies that the idiosyncratic errors (ε_{it}) are uncorrelated with the entire stream, from time period 1 to the last time period, of time varying explanatory variables.

ii. If 2.c.i. is confirmed, then please confirm that this assumption implies, for example, that unobserved changes in ZIP Code level management over time are uncorrelated with all volumes, past, present, and future.

iii. If any of the above are not confirmed, please state the technical assumptions made about the time varying explanatory variables,

[5] *See* Jeffrey M. Wooldridge, *Econometrics: Panel Data Methods*, January 2009, *https://ifs.org.uk/uploads/cemmap/programmes/Background%20reading%20May%202016.pdf*, at 12 (Wooldridge).

and the idiosyncratic errors, ε_{it}, to assure the statistical consistency of the estimators.

d. Please perform, within the CRE estimation, the pairwise tests of equality between the coefficient of each volume explanatory variable and the coefficient of the cluster volume average corresponding to that variable, and report, in detail, the results of each test.

e. Please perform the joint test of equality between the vector of coefficients of the volume explanatory variables and the vector of coefficients of their corresponding cluster averages, and report, in detail, the results of the test.

RESPONSE:

a. Correlated random effects models have several advantages over traditional fixed effects model and those advantages go to addressing concerns that the Commission has raised about the application of the fixed effects model to measuring the variability of mail processing costs.

First, the CRE model allows the inclusion of cross-sectional (or "cluster") explanatory variables, which cannot be included in a fixed effects model. Thus, the CRE model can address the concern that there may be other explanatory variables, beyond the fixed effects, that can cause non-volume variations in street time across ZIP codes.

Second, the CRE model explicitly allows for, and in fact specifies, that cross ZIP Code differences may be correlated with volume. This directly address the Commission's concern that unobserved effects may be correlated with volume. In fact, the empirical results for the top-down model indicate that there are significant correlations between the unobserved heterogeneity and volume. Moreover, because of the construction of the CRE model, any remaining unobserved heterogeneity across ZIP codes is necessarily not correlated with volume.

Third, as a random effects model, the CRE model allows estimation of the effects of time-varying non-volume variables (such as the proportion of deliveries that are curbline in a ZIP Code), in addition to traditional time-related fixed effects. This allows controlling for time-varying changes in the delivery environment not captured by time-specific effects. However, the data supporting Proposal One indicated that there is very little change in the delivery environment over the period of analysis. Variables that describe the delivery environment such as the number of delivery points, the proportions of different types of delivery points, or the distribution of walking and driving routes have *de minimis* variation over the course of the year, indicating that time-varying changes in the delivery environment are not confounding the estimated variabilities.[6]

These advantages make the CRE model a more reliable and informative estimator for calculating the variability of city carrier street time than the traditional fixed effect model.

b. An estimator of a parameter, β, is consistent if the estimator's probability limit is equal to β. This is generally considered to be a useful characteristic of an estimator:[7]

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[6] *See*, Bradley Report at 91-92.

[7] *See*, Pindyck, Robert S., and Daniel L. Rubinfeld, *Econometric Models and Economic Forecasts*, 2nd edition, McGraw-Hill Book Company, New York, 1981 at 30.

> As a rule, econometricians tend to be more concerned with consistency than with a lack of bias as an estimation criterion. A biased yet consistent estimator may not equal the true parameter on average, but will approximate the true parameter as the sample information grow larger.

c. Partially confirmed. The summary article cited does not provide a full explanation of the strict exogeneity assumption in correlated random effects model, which is necessary to gain an understanding of the nature and implications of the assumption. In fact, there are different forms of the strict exogeneity assumption and more generally, there are variety of exogeneity assumptions applicable for panel data models.[8] For example, there is sequential exogeneity in which the expected value of current stochastic shocks, conditioned on historical values of the explanatory variables, is zero:

$$E(\mu_{it}|x_t, x_{t-1}, ... , x_1) = 0, \qquad \mathrm{t} = 1,2, \ldots . \mathrm{T}$$

This can be contrasted with strict exogeneity, in which the expected value of current stochastic shocks, conditioned on past, current, and future values of the explanatory variables, is zero:

$$E(\mu_{it}|x_{i1}, x_{i2}, ... , x_{iT},) = 0, \qquad \mathrm{t} = 1,2, \ldots . \mathrm{T}.$$

[8] For a full discussion of exogeneity assumptions in panel data models *see*, Wooldridge, Jeffrey M., *Econometric Analysis of Cross Section and Panel Data*, 2nd Edition, The MIT Press, Cambridge, MA, 2010, at 164.

Stating the assumption in this form may make it seem like a new, or additional, condition on the linear regression analysis, but in fact it is just a different version of the well-known assumption that the explanatory variables in the regression are non-stochastic or fixed in repeated samples:[9]

> Classical treatments of ordinary least squares and generalized least squares with panel data tend to treat the $x_{it,}$ as fixed in repeated samples; in practice, this is the same as the strict exogeneity assumption.

However, this is not the assumption being made for the correlated random effects model. In the correlated random effects model, the explanatory variables are not assumed to be non-stochastic as in traditional models:[10]

> Traditional unobserved components panel data models take the x_{it} as nonrandom. We will never assume the x_{it} are nonrandom because potential feedback from y_{it} to x_{is} for s > t needs to be addressed explicitly.

Specifically, in the correlated random effects model, the explanatory variables are assumed to be strictly exogenous conditioned on the unobserved effect:[11]

> For inference and efficiency discussions, it is more convenient to state the strict exogeneity assumption in terms of conditional expectations. With an unobserved effect, the most

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[9] *Id.* at 166.

[10] *Id*. at 287.

[11] *Id*.

> revealing form of the strict exogeneity assumption is $E(y_{it}|x_{i1}, x_{i2}, \ldots, x_{iT}, c_i) = E(y_{it}|x_{it,}c_i) = x_{it,}\beta + c_i$ (10.12) for t=1,2, ... T. The second equality is the functional form assumption on $E(y_{it}|x_{it,}c_i)$. It is the first equality that give the strict exogeneity its interpretation. It means that, once x_{it} <u>and</u> <u>c_i</u> are controlled for, x_{is} has no partial effect on y_{it} for $s \neq t$. [Emphasis in original.}

In other words, once the impact of the unobserved effect and the current explanatory variables on the dependent variable are accounted for, then values for the explanatory variables in other periods do not affect the dependent variable. For the top-down model, this means assuming that the time to collect and deliver mail in a ZIP Code on a given day depends upon that day's mail volume and not volumes on past and future days. Professor Wooldridge goes on to explain that this conditional strict exogeneity is more likely to hold than the traditional strict exogeneity described above, through the following example:[12]

> Suppose that y_{it} is the output for soybeans for farm i during year t, and x_{it} contains capital, labor, materials (such as fertilizer), rainfall, and other observable inputs. The unobserved effect, c_i, can capture the average quality of land, managerial ability of the family running the farm, and other unobserved, time-constant factors. A natural assumption is that, once current inputs have been controlled for, *along with* c_i,inputs used in other years have no effect on output during the current year. However, since the optimal choice of inputs in every year generally depends upon c_i, it is likely that some partial correlation between output in year *t* and inputs in other years will exist if c_i is not controlled for. [Emphasis in original.]

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[12] *Id.* at 288.

Please note that the conditional strict exogeneity assumption is even more likely to hold for the top-down model because the explanatory variables are the volumes tendered by customers to be delivered and collected in a specific ZIP Code, on a given day, and are not inputs to be chosen by the Postal Service

i. Partially confirmed. As explained above, in the correlated random effects model, the assumption on the expected value of the idiosyncratic errors is conditioned on c_i, the unobserved effect.

ii. Not confirmed. Any differences in management across ZIP codes will be captured by the cluster variables in the correlated random effects model. Any changes in management through time will be captured through the model's time-specific variables. The strict exogeneity assumption relates to one-time idiosyncratic shocks like bad weather or a major traffic accident that causes delivery delays. The correlated random effects model assumes that these types of shocks were not caused by historical volume and do not affect future volumes. In the context of the top-down model, it is important to recall that the period of estimation is just one year.

iii. The technical assumptions made about the time varying explanatory variables, and the idiosyncratic errors, ε_{it}, to assure the statistical consistency of the estimators are presented within the answers provided to the preceding subpart of this question, above.

d. To perform the requested tests of equality of certain coefficients, one tests a set of linear restrictions on the model of the form $\boldsymbol{R}\beta - \boldsymbol{r}$. **R** is a J x K matrix of restrictions to be tested, with J being the number of restrictions and K being the number of estimated coefficients included in the restrictions, β is the K x 1 vector of coefficients being tested and **r** is the K x1 vector of test outcomes.[13] Each row of **R** is one restriction on the estimated coefficients. In most cases, each row of **R** will contain zeros for the coefficients not included in the restriction. For example, suppose there are four coefficients being tested, β_1 through β_4. Further suppose that two hypothesis tests are being made: $\beta_1 = \beta_3$; $\beta_2 = \beta_4$. Then, the restrictions being tested would take the following $\boldsymbol{R}\beta - \boldsymbol{r}$ form:

$$\begin{bmatrix} 1 & 0 & -1 & 0 \\ 0 & 1 & 0 & -1 \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}.$$

The equality of coefficients is tested with the following Wald statistic, which has a Chi-Square distribution:

$$W = (\boldsymbol{R}\beta - \boldsymbol{r})'\left[R\hat{V}R'\right]^{-1}(\boldsymbol{R}\beta - \boldsymbol{r}).$$

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[13] For a discussion of the testing procedure, see, Greene, William, H., *Econometric Analysis,* 2nd ed., Macmillan Publishing, New York, 1993, at 187.

Note that the test makes use of the heteroscedasticity corrected covariance matrix. The following table presents the Wald statistics requested tests:[14]

Test	Test Statistic	Pr > Chi Sq
dps = zdps	17.10	<.0001
dps2 = zdps2	2.49	0.1143
cm = zcm	10.60	0.0011
cm2 = zcm2	12.66	0.0004
seq = zseq	0.10	0.756
seq2 = zseq2	1.05	0.3051
fss = zfss	0.00	0.9624
fss2 = zfss2	0.82	0.3646
irp = zirp	6.87	0.0088
irp2 = zirp2	6.59	0.0103
devpa = zdevpa	0.51	0.4763
devpa2 = zdevpa2	3.17	0.0749
cv = zcv	1.30	0.2548
cv2 = zcv2	2.92	0.0873

e. The Wald statistic for the joint test of equality between the vector of coefficients of the volume explanatory variables and the vector of coefficients of their corresponding cluster averages is 109.47 with a probability value of <.0001. This indicates rejection of the null hypothesis of equality of the two sets of coefficients.

[14] The Wald statistics are calculated in the SAS program entitled, CRE Model.Requested Coefficient Tests.sas. The program and its log and listing are attached to this response.

3. For the sake of measuring the impact of the top-down model on multicollinearity and for purposes of comparison, please use the "approach to estimating variabilities for city carrier street time that relied upon three separate econometric equations, one for letters and flats, one for in-receptacle parcels, and one for deviation parcels and accountables"[15] to re-estimate the three separate econometric equations with the data employed to estimate the CRE model. Please report the estimation results along with all relevant analyses or comments. If this three-part estimation cannot be performed, please explain why.

RESPONSE:

The requested three-part estimation cannot be performed because the Postal Service delivery operations data systems do not record separate times for separate activities, like the delivery of in-receptacle parcels or the delivery of deviation parcels and accountables. Thus, the data used to estimate the top-down model include only total street time and do not include separate street time quantities for letter delivery, in-receptacle parcel delivery, and deviation parcel and accountable delivery. In the previous research that presented the three-part analysis, a special field study was performed to identify separate times for in-receptacle parcel delivery and deviation parcel and accountable delivery.

[15] Bradley Study at 1 (footnote omitted); *see also* Petition at 2 (footnote omitted).

4. To measure the statistical importance of Collected Volumes and the potential omitted-variable bias induced by their non-inclusion as explanatory variables, please estimate both the pooled regression model and the CRE model with, and without, Collected Volumes, and calculate the corresponding variabilities. Please report the estimation results and the variabilities along with all relevant analyses or comments.

RESPONSE:

The following table provides the marginal times and variabilities for the pooled model for both the case in which all volume variables are included and the case in which the collection volume term is dropped. The full volume variable results are from the SAS program entitled Pooled CCE Model Combined Acct Restricted Quad.Time Effects.sas which was previously submitted. The results for the case with the collection volumes dropped are from the SAS program entitled Pooled CCE Model Combined Acct Restricted Quad.Time Effects.Without CV.sas which is attached, along with its log and listing, to this response. The marginal times and variabilities for the delivered volumes are very similar across the two versions.

Results for the Pooled Model with All Volume Variables

Volume	Marginal Time	Variability
DPS	1.43	7.7%
Cased	0.87	1.4%
Sequenced	1.93	1.2%
FSS	2.98	0.6%
In-Receptacle Parcels	19.57	3.0%
Deviation Parcels/ Accts.	64.05	7.3%
Collection	7.13	1.2%

Source: Pooled CCE Model Combined Acct Restricted Quad.Time Effects.sas

Results for the Pooled Model Dropping Collection Volume

DPS	1.44	7.8%
Cased	0.89	1.4%
Sequenced	1.95	1.2%
FSS	2.98	0.6%
In-Receptacle Parcels	19.68	3.0%
Deviation Parcels/ Accts.	64.69	7.3%

Source: Pooled CCE Model Combined Acct Restricted Quad.Time Effects.Without CV.sas

The following table provides the marginal times and variabilities for the CRE model for both the case in which all volume variables are included and the case in which the collection volume term is dropped. The full volume variable results are from the SAS program entitled CRE Model Combined Restricted Quad With Time Effects.sas which was previously submitted. The results for the case with the collection volumes dropped are from the SAS program entitled CRE Model Combined Restricted Quad With Time Effects.Without CV.sas which is attached, along with its log and listing, to this response.

The marginal times and variabilities for the delivered volumes are very similar across the two versions.

Results for the CRE Model with All Volume Variables

Volume	**Marginal Time**	**Variability**
DPS	1.43	7.7%
Cased	0.86	1.4%
Sequenced	1.93	1.2%
FSS	2.98	0.6%
In-Receptacle Parcels	19.51	3.0%
Deviation Parcels/ Accts.	64.26	7.3%
Collection	7.12	1.2%

Source: CRE Model Combined Restricted Quad With Time Effects.sas

Results for the Pooled Model Dropping Collection Volume

Volume	**Marginal Time**	**Variability**
DPS	1.44	7.8%
Cased	0.88	1.4%
Sequenced	1.95	1.2%
FSS	2.98	0.6%
In-Receptacle Parcels	19.62	3.0%
Deviation Parcels/ Accts.	64.90	7.3%

Source: CRE Model Combined Restricted Quad With Time Effects.Wtihout CV.sas

Omitting collection volume In both the pooled model and the CRE model leads to slightly higher marginal times and variabilities, as expected. These changes reflect the slight omitted variables bias caused by the omission, as the positive impact of collection volume on street time is picked up by other variables. However, the small size of the bias suggests it may be possible to update the street time variability equation in the future without having to field a special collection volume study.