

Analysis Report

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SAMPLE REPORT - Rafael Data Analysis Portfolio

Descriptive Statistics

The analysis commenced by assessing the mean degradation rates of three biological parameters (X, Y, and Z) under the influence of two drugs, A and B. The results indicated that Drug A generally leads to a decrease in all three parameters, with mean rates of -0.237, -0.090, and -0.132, respectively. In contrast, Drug B increased parameters X and Y with mean rates of 0.291 and 0.111, respectively, while slightly decreasing parameter Z with a mean rate of -0.099.

Drug	Mean Rate X	Mean Rate Y	Mean Rate Z
A	-0.237	-0.090	-0.132
B	0.291	0.111	-0.099

Linear Mixed Models

Linear mixed models (LMMs) were applied to further investigate these effects, allowing for the consideration of random effects due to individual variability and other unobserved heterogeneities.

Parameter X: The model for X revealed that Drug B significantly increased the rate of X compared to Drug A, as evidenced by an estimate of 0.529 ($p = 0.014$).

Parameter Y: For Y, both the intercept and the effect of Drug B were significant, with Drug B increasing Y more substantially than Drug A (estimate = 0.201, $p < 0.001$).

Parameter Z: The analysis for Z showed that Drug A significantly decreased Z (estimate = -0.132, $p = 0.016$), whereas Drug B's effect was not significant ($p = 0.749$).

Parameter	term	estimate	std.error	statistic	df	p.value
X	(Intercept)	-0.237	0.114	-2.090	820	0.037
	DrugB	0.529	0.215	2.457	820	0.014
Y	(Intercept)	-0.090	0.030	-3.015	819	0.003
	DrugB	0.201	0.056	3.570	819	0.000
Z	(Intercept)	-0.132	0.054	-2.425	815	0.016
	DrugB	0.033	0.103	0.320	815	0.749

Estimated Means Comparison

Estimated marginal means were calculated to corroborate these findings:

- **Parameter X:** Drug A's mean effect on X was significantly negative at -0.237 ($p = 0.040$), whereas Drug B's effect, although positive, was not statistically significant ($p = 0.112$).
- **Parameter Y and Z:** Similar patterns were observed, with Drug A showing significant decreases in Y and Z, and Drug B showing either insignificant or marginally significant effects.

Parameter	Drug	Em mean	SE	df	lower.CL	upper.CL	t	p
X	A	-0.237	0.114	88.117	-0.463	-0.011	-2.088	0.040
	B	0.291	0.183	433.382	-0.068	0.651	1.592	0.112
Y	A	-0.090	0.030	88.015	-0.149	-0.030	-3.012	0.003
	B	0.111	0.048	432.726	0.017	0.205	2.328	0.020
Z	A	-0.132	0.054	87.903	-0.240	-0.024	-2.423	0.017
	B	-0.099	0.088	430.245	-0.271	0.074	-1.123	0.262

The influence of the degradation of parameters Z on X

The analysis of the influence of the degradation of parameters Z on X was conducted by examining the effects of lagged changes in Z across three different lag periods. The statistical model employed fixed effects for the intercept and lagged changes in Z, while accounting for random effects related to Patient_Id and Drug, and including the residual variability.

For Lag 1, the fixed effect of the intercept was significant with an estimate of -0.197 ($SE = 0.038$, $t(376) = -5.139$, $p < 0.001$). The lagged change in Z1 had a substantial and significant negative impact on X, with an estimate of -1.077 ($SE = 0.328$, $t(376) = -3.281$, $p = 0.001$). The random effects for both Patient_Id and Drug were estimated as zero, indicating no significant variability attributable to these factors. The residual standard deviation for the observation level was 0.686.

Lag 1

effect	group	term	estimate	std.error	statistic	df	p.value
fixed		(Intercept)	-0.197	0.038	-5.139	376.000	0.000
fixed		Lagged_Change_Z1	-1.077	0.328	-3.281	376.000	0.001
ran_pars	Patient_Id	sd__(Intercept)	0.000				
ran_pars	Drug	sd__(Intercept)	0.000				
ran_pars	Residual	sd__Observation	0.686				

For Lag 2, the intercept remained significant, with an estimate of -0.170 (SE = 0.041, $t(376) = -4.196$, $p < 0.001$). However, the effect of the lagged change in Z2 on X was not significant, with an estimate of -0.329 (SE = 0.279, $t(376) = -1.180$, $p = 0.239$). Similar to Lag 1, the random effects for Patient_Id and Drug were negligible, with the residual standard deviation slightly increasing to 0.695.

Lag 2

effect	group	term	estimate	std.error	statistic	df	p.value
fixed		(Intercept)	-0.170	0.041	-4.196	376.000	0.000
fixed		Lagged_Change_Z2	-0.329	0.279	-1.180	376.000	0.239
ran_pars	Patient_Id	sd__(Intercept)	0.000				
ran_pars	Drug	sd__(Intercept)	0.000				
ran_pars	Residual	sd__Observation	0.695				

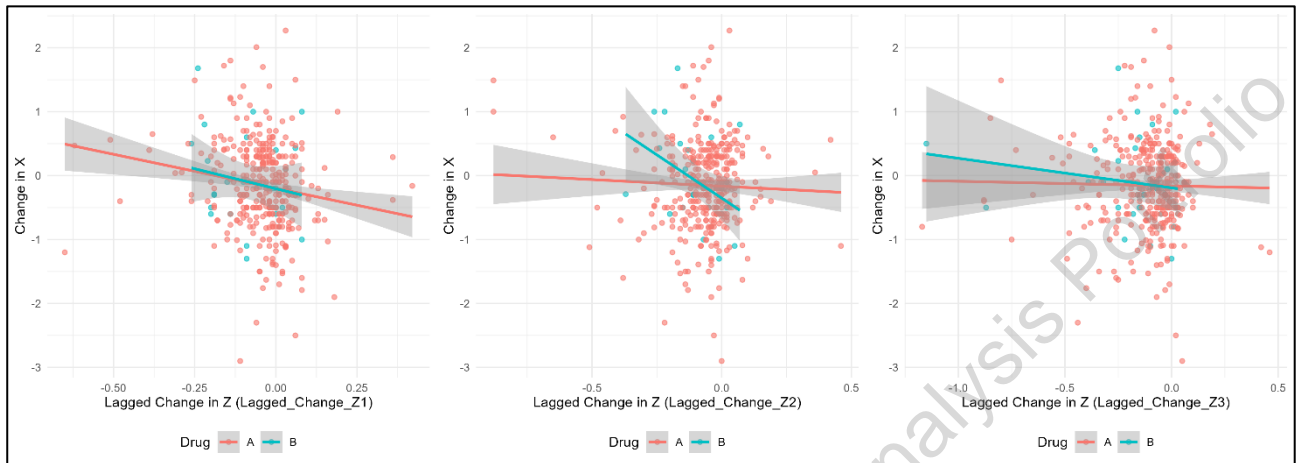
For Lag 3, the intercept continued to be significant with an estimate of -0.165 (SE = 0.043, $t(376) = -3.797$, $p < 0.001$). The effect of the lagged change in Z3 on X was non-significant, with an estimate of -0.135 (SE = 0.195, $t(376) = -0.693$, $p = 0.489$). As with the previous models, the random effects for Patient_Id and Drug were estimated at zero, with the residual standard deviation remaining stable at 0.696.

Lag 3

effect	group	term	estimate	std.error	statistic	df	p.value
fixed		(Intercept)	-0.165	0.043	-3.797	376.000	0.000
fixed		Lagged_Change_Z3	-0.135	0.195	-0.693	376.000	0.489
ran_pars	Patient_Id	sd__(Intercept)	0.000				
ran_pars	Drug	sd__(Intercept)	0.000				
ran_pars	Residual	sd__Observation	0.696				

Overall, these results suggest that the influence of the degradation of parameter Z on X is most pronounced at Lag 1, where a significant negative effect is observed. As the lag increases, the impact diminishes and becomes non-significant, indicating that the immediate prior changes in Z are more influential on X than those from earlier time points. The negligible random effects imply that the variability in X is primarily captured by the fixed effects and residual error, rather than by differences among patients or drugs.

The provided visualizations showcase the relationship between changes in parameter Z at different lags (Lag 1, Lag 2, and Lag 3) and the subsequent changes in parameter X for two drugs, Drug A and Drug B. Each plot represents a different time lag, providing insight into how historical changes in Z influence the current changes in X.



Lag models for each Drug

Drug A is it happens

Drug B nao sabe

He wants to predict the time from

If Z falls below 0.45 can I predict when X is going to drop below 5.

Graph of the degradations – 3 graphs with both drugs on it.