Marketing Mix Model Assignment

I. Results Table

Coefficient Estimates for Advertising Metrics

	Model 2		Model 3		Model 4		Model 5	
	Est.	Std. Err.	Est.	Std. Err.	Est.	Std. Err.	Est.	Std. Err.
nat	0.0000346126	-0.0000222597	0.0000357074	-0.0000221933	0.0000235455	-0.0000228521	0.0000144039	-0.0000219891
lag1nat	0.0001097211***	-0.0000233585	0.0001168139***	-0.00002331	0.0001253849***	-0.0000232007	0.0000791903***	-0.0000223388
lag2nat	-0.0000225366	-0.000023314	-0.0000232438	-0.0000232841	0.0000132947	-0.0000230859	0.0000263583	-0.0000222443
lag3nat	0.000025224	-0.0000233174	0.0000225496	-0.0000232597	0.0000509639**	-0.0000230291	0.000028694	-0.0000221966
lag4nat	0.0000485100**	-0.0000233644	0.0000446924*	-0.0000233189	0.0000834846***	-0.0000231323	0.0000714342***	-0.0000222819
lag5nat	-0.0000306305	-0.0000222447	-0.0000341619	-0.0000221897	0.0000379352*	-0.0000228019	0.0000470185**	-0.0000219493
loc	0.0000462991*	-0.0000246759	0.0000475195*	-0.0000244943	0.000023336	-0.0000251873	0.0000358784	-0.0000246247
lag1loc	0.0000438940*	-0.0000254214	0.0000465950*	-0.0000252493	0.0000394286	-0.0000253529	0.0000553359**	-0.0000247996
lag2loc	0.0000345414	-0.0000249924	0.0000335976	-0.0000248278	0.0000382567	-0.0000251458	-0.0000047698	-0.0000246316
lag3loc	0.0000097825	-0.0000249807	0.0000131952	-0.0000248075	0.0000218644	-0.0000250986	0.00003869	-0.0000245972
lag4loc	0.0000162259	-0.0000253813	0.0000150736	-0.0000252128	0.0000323283	-0.0000252026	0.000027399	-0.0000246503
lag5loc	-0.0000017714	-0.000024655	-0.000002734	-0.0000244887	0.0000260233	-0.0000250973	0.0000345677	-0.000024538
dig	0.000047883	-0.0000398762	0.0000465109	-0.0000393966	0.0000232355	-0.0000408526	0.0000263078	-0.0000396832
lag1dig	0.0000086131	-0.0000478461	0.0000182048	-0.0000472651	0.0000303375	-0.0000455722	0.000061109	-0.0000440907
lag2dig	-0.0000179097	-0.0000479139	-0.0000274385	-0.0000473408	-0.0000222502	-0.0000454748	-0.0000336166	-0.0000440039
lag3dig	0.0000448931	-0.0000478997	0.0000384267	-0.0000473537	0.0000503609	-0.0000455014	0.0000422325	-0.0000440273
lag4dig	-0.0000178597	-0.0000477845	-0.0000036273	-0.0000472403	0.0000170665	-0.0000455389	-0.0000044618	-0.0000440675
lag5dig	-0.0000444347	-0.0000396999	-0.0000583822	-0.0000392677	-0.0000033172	-0.0000405596	0.0000120009	-0.0000393215
compnat	0.0001226882	-0.0001053506	0.0001131894	-0.0001038527	-0.0000274054	-0.0001048869	-0.0002993202	-0.0002273891
lag1compnat	0.0002188353*	-0.0001124157	0.0002396194**	-0.0001111884	0.0002210239**	-0.0001088776	-0.0004598257**	-0.0002288984
lag2compnat	-0.0000280021	-0.0001108987	-0.0000478568	-0.0001093729	0.0000009256	-0.0001082125	-0.0002934	-0.0002265807
lag3compnat	-0.0001587902	-0.0001105884	-0.0001842241*	-0.0001092369	-0.0001473524	-0.0001074433	-0.0004816012**	-0.0002249202
lag4compnat	0.0001124192	-0.0001113792	0.0001358507	-0.0001101433	0.0001466452	-0.0001076806	-0.0003219661	-0.0002247693
lag5compnat	-0.0000121349	-0.0001041706	-0.0000539839	-0.0001031375	0.0000052328	-0.0001064316	0.0001239732	-0.0002253043
comploc	0.0000120833	-0.0000900749	0.0000404967	-0.0000900821	0.0000275803	-0.0000921089	0.0000634181	-0.0002267537
lag1comploc	-0.0000335643	-0.0000925634	-0.0000596111	-0.0000925743	-0.0000560073	-0.0000925294	0.0001218615	-0.0002293606
lag2comploc	0.0002312182**	-0.0000907834	0.0002340424***	-0.0000907315	0.0002197776**	-0.0000916974	-0.0006132065***	-0.0002307193
lag3comploc	0.0000458124	-0.0000907444	0.0000552578	-0.0000907787	0.0000769529	-0.0000915044	0.0001954899	-0.0002297131
lag4comploc	0.0001052288	-0.0000922771	0.0000546399	-0.0000923967	0.0000697168	-0.0000923735	-0.0000548095	-0.0002286151
lag5comploc	-0.0000973987	-0.0000900453	-0.0000746969	-0.0000902802	-0.0000528706	-0.0000928827	-0.0003954841*	-0.00022901
compdig	0.0000075423	-0.0001275835	0.0000187663	-0.0001252715	-0.0001005241	-0.000129981	0.0001577682	-0.0003234949
lag1compdig	0.000127336	-0.0001464108	0.0002174741	-0.0001438634	0.0001484839	-0.0001400555	0.00047091	-0.0003405418
lag2compdig	-0.0002259185	-0.0001464345	-0.0002977520**	-0.0001437883	-0.0003708136***	-0.0001389586	-0.0004156668	-0.0003390709
lag3compdig	0.0000757785	-0.0001459493	0.0001115093	-0.0001433806	0.0000375348	-0.0001387254	0.000171177	-0.0003395961
lag4compdig	0.0003478856**	-0.0001450304	0.0003413534**	-0.0001427802	0.0003431199**	-0.0001382653	-0.0000114346	-0.0003392488
lag5compdig	-0.0003648660***	-0.0001250791	-0.0004109660***	-0.0001231592	-0.0003718981***	-0.0001280479	-0.0008358409***	-0.0003211488
Observations	142,600		142,600		142,600		142,600	
R2	0.9569		0.9577		0.9647		0.9731	
Adjusted R2	0.9566		0.9574		0.9616		0.9686	
Residual Std. Error	0.0260172800 (df = 141703)		0.2390954000 (df = 141703)		0.2271203000 (df = 130778)		0.2053525000 (df = 121850)	

II. Interpretation of advertising coefficient estimates

We learned four different models that were developed to estimate causal ad effects on brand quality:

- Model #2 is a descriptive regression of brand quality on multiple lags of brand advertising and competitor advertising, brand effects and time effects, but without weighted standard errors.
- Model #3 is based on model #2 with the standard errors weighed by the number of respondents of the brand quality survey.
- Model #4 is descriptive regression with brand-quarter fixed effects, which means that the model controls the unobserved effects of brand-level variables such as budgetary changes that tend to happen quarterly.
- Model #5 is an all controls model. The industry-week fixed effects are added to the Model #4 to control for unobserved effects of industry-level variables such as seasonal fluctuations in industry demand.

We observed that adjusted R-square statistics increases as we add control variables to the model. For example, in Model #2 the adjusted R-square statistics is 0.9566, and the statistics increases to 0.9686. Although the difference may not be substantial, an increase implies that added variables, i.e. weighted standard errors, brand-quarter effects, and industry-week effects reduce the proportion of unexplained variance.

We also observed that the estimates of advertising parameters become more consistent with more control variables in the model. For example, in the set of "own national traditional ad spend" of Models #2 and #3, there are 2 negative estimates and 3 positive estimates out of 6 estimates in total. However, in Models #4 and #5, all estimates become positive. Similarly, in the set of "competitors' national traditional ad spend", the estimates have a mixed pattern of positive and negative effects in Models #2 and #3 but become mainly negative in the fourth and fifth models. These changes in estimate patterns suggest that estimates of advertising parameters become more precise and the model becomes more reliable in explaining causal ad effects as we add control variables.

Based on the regression output of Model #5, we observed that "own national and local traditional ad spend" and "competitors' national and local traditional ad spend" have significant effects on the perceived brand quality as their p-values suggest ($p < 0.05$ or 0.01). From this we can conclude that such findings:

- Perceived quality tends to increase with the brand's own traditional advertising in national and local media; however, digital advertising doesn't seem to have significant effects on the brand quality.

Perceived quality tends to decrease with competitors' traditional advertising in national and local media, and with competitors' digital advertising.

These are the findings that could not have been clearly observed in a descriptive model, where there are no controls for unobserved factors that might affect both a brand's advertising expenditure and perceived quality.

I.Takeaway

We learned how endogeneity problems arise in estimating casual advertising effects and how we can use control variables to handle such problems. It was interesting to see how brand-quarter and industry-week fixed effects in the model change the estimates of advertising coefficients, making the estimates more precise and reasonable. In regard to using R to run regression, using the f*elm* function to fit models with multiple group fixed effects and multiplying factor variables to create an interaction variable were useful commands we learned from the exercise. We expect to use our understanding of endogeneity and R commands frequently as a business analyst, not just in marketing analytics but in all other fields of business analytics.