MIS Quarterly

RESEARCH ARTICLE

WHEN SOCIAL MEDIA DELIVERS CUSTOMER SERVICE: DIFFERENTIAL CUSTOMER TREATMENT IN THE AIRLINE INDUSTRY

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Appendix

Correlation Matrix

Table A1. Correlation Matrix

		1	2	3	4	5	6	7	8	9	10	11	12
1	Log of Followers												
2	Collaborating Organization Mentioned	0.0183											
3	Log of Complaints Within the Previous Hour	0.0024	-0.0095										
4	Log of Retweets	0.1899	0.002	0.0258									
5	Competing Airline Mentioned	0.0279	0.0028	-0.0212	0.0195								
6	Only Users Mentioned	0.0977	-0.041	0.0847	0.0581	-0.1443							
7	Log of Updates	0.7931	0.0179	0.0141	0.0936	0.0225	0.1427						
8	@Order	0.0729	0.0848	-0.0307	0.03	0.3807	0.4597	0.1028					
9	Profile	0.4901	0.0163	0.0027	0.0472	0.0277	0.0682	0.5112	0.049				
10	Hashtag	0.0003	0.0091	-0.0099	0.0546	0.0039	-0.027	-0.0289	-0.0279	0.0263			
11	Offensive	0.0386	-0.0078	0.0442	0.0082	-0.0041	0.0793	0.0794	0.0324	0.0285	-0.0319		
12	URL	0.0825	0.0136	0.023	0.0991	-0.0135	0.0367	0.0619	-0.0166	0.0503	0.0876	-0.0128	

Clustering Complaining Tweets

We follow a bag-of-words approach to group similar tweets into clusters using the K-Means algorithm. Considering the inherently noisy nature of text in tweets, first, we preprocess and clean the data set. For example, we process hashtags, Internet slang words, user names, and repetitive characters before any transformation. We also remove stop words and use stemming techniques to structure the data further. Next, we implement the term frequency-inverse document frequency (TF-IDF) approach to map the most frequent words to feature indices and to reweight them over the entire corpus. As the dimensionality of text data can be very high, we employ latent semantic analysis (LSA) techniques to reduce the high dimensionality of the data.

One limitation of the K-Means algorithm is that it may converge to a local minimum, which is highly dependent on the initialization of the centroids. To overcome this problem, we run the computation several times with different initializations of the centroids distant from each other in general rather than random initialization, as recommended by previous researchers (Han et al. 2012). Another limitation is that K-Means requires the number of clusters to be specified at the beginning. As there are no pre-identified absolute class labels available for our tweets to match against the clustering outcome, we use the silhouette coefficient (Rousseeuw 1987) to assess the appropriate number of clusters suitable for our data. However, since this measure is known to suffer from the "curse of dimensionality" for high dimensional datasets such as text data, we use it as a baseline measure to make a reasonable choice for the number of clusters. The best silhouette coefficient score was obtained for 40 clusters. Therefore, 40 clusters were obtained. Accordingly, we introduce cluster fixed effects into our benchmark model and the results are presented in Table A2.

Table A2. Benchmark Model: Content Fixed Effects

Cluster ID	Response-Time	Response-Choice	Cluster ID	Response-Time	Response-Choice
1	-0.0388	-0.1337***	21	0.0355	0.0506*
	(0.0471)	(0.0334)		(0.0410)	(0.0302)
2	-0.0259	-0.0619*	22	-0.0361	0.0569
	(0.0474)	(0.0341)		(0.0473)	(0.0359)
3	0.0032	0.0749**	23	-0.1000**	-0.1164***
	(0.0450)	(0.0334)		(0.0446)	(0.0321)
4	0.0750	-0.1375***	24	0.0179	-0.1085***
	(0.0478)	(0.0333)		(0.0517)	(0.0366)
5	-0.0381	-0.0242	25	0.0555	-0.0341
	(0.0428)	(0.0313)		(0.0447)	(0.0326)
6	-0.0379	0.1323***	26	0.0084	-0.0622*
	(0.0363)	(0.0268)		(0.0461)	(0.0333)
7	-0.0899**	0.0290	27	0.0305	-0.3690***
	(0.0389)	(0.0285)		(0.0759)	(0.0464)
8	0.0691	-0.4064***	28	0.0233	-0.0302
	(0.0528)	(0.0344)		(0.0463)	(0.0340)
9	0.1707**	-0.5960***	29	0.1233***	-0.0295
	(0.0688)	(0.0410)		(0.0416)	(0.0299)
10	-0.0295	-0.0742**	30	0.0109	0.0202
	(0.0403)	(0.0289)		(0.0436)	(0.0324)
11	-0.0152	-0.2016***	31	-0.0773**	0.0272
	(0.0473)	(0.0325)		(0.0391)	(0.0287)
12	-0.0120	-0.0338	32	0.0316	0.1039***
	(0.0428)	(0.0312)		(0.0382)	(0.0282)
13	-0.0262	0.0995***	33	0.0440	0.0166
	(0.0448)	(0.0335)		(0.0451)	(0.0332)
14	0.0070	-0.1397***	34	-0.0467	-0.0184
	(0.0411)	(0.0294)		(0.0424)	(0.0309)
15	-0.0422	-0.6096***	35	0.0242	-0.1386***
	(0.0719)	(0.0423)		(0.0557)	(0.0389)
16	-0.0209	-0.1825***	36	-0.0305	0.0390
	(0.0364)	(0.0259)		(0.0459)	(0.0341)
17	0.0778*	0.0555*	37	-0.0257	0.0091
	(0.0416)	(0.0308)		(0.0427)	(0.0316)
18	-0.0193	-0.0035	38	-0.0626	-0.3381***
	(0.0478)	(0.0353)		(0.0590)	(0.0383)
19	-0.0039	0.0079	39	-0.0168	-0.1718***
	(0.0444)	(0.0322)		(0.0474)	(0.0329)
20	0.0586	-0.1636***			
	(0.0430)	(0.0301)			

Individual Airlines

To investigate whether our results are driven by a single airline, we estimate the joint model of response-choice and response-time with the same set of independent variables for each airline. The results, presented in Table A3, suggest that the *follower-based preferential treatment effect* (H1) is evident for all seven airlines. For American Airlines, United Airlines, Delta Airlines, and Southwest Airlines, a higher number of followers is associated with a faster response. Surprisingly, for Alaska Airlines and Virgin America, having more followers seems to result in a slower response. One possible explanation is that both airlines share a similar strategy of intentionally trading off response speed with more deliberation time while preparing their responses. It is interesting to note that the two airlines have become sister airlines following the 2016 acquisition of Virgin America by Alaska Air Group.[1]

The estimates of error correlation between the response-choice model and the response-time model are negative and significant for United Airlines and American Airlines, and are insignificant for Delta Airlines, JetBlue Airways, and Southwest Airlines. The positive and significant estimates of the error correlations of Alaska Airlines and Virgin America are consistent with the fact that, for these two airlines, having more followers leads to higher probability of being responded to but longer delay in receiving the responses. Overall, the pattern of the size of error correlations seems to suggest that the workflow of managing customer complaints on Twitter at Delta Airlines, JetBlue Airways, and Southwest Airlines, might be different from that of the other four airlines in our sample. For example, for the three airlines with negligible error correlations between the response-choice model and the response-time model, the two decisions might have been made by two different groups of agents (including possibly machine algorithm), while for the other four airlines, the two decisions might have been made by the same group of agents.

The coefficients of the bystander effect remain negative for six out of the seven airlines in our sample, although some coefficients are statistically insignificant. The one with a positive sign is not statistically significant.

Overall, we find the results of individual airline analysis largely consistent with the results from the main analysis.

Table A3. Robustness: Individual Airlines

	Log of Followers		Collaborating Organization Mentioned	
Airline	**Response-Choice**	**Response-Time**	**Response-Choice**	**Response-Time**
American Airlines	0.0560***	-0.0645***	0.0956	-0.0788
	(0.0047)	(0.0058)	(0.0867)	(0.1110)
United Airlines	0.0458***	-0.0326***	-0.3203***	0.2617*
	(0.0051)	(0.0069)	(0.0869)	(0.1390)
Delta Airlines	0.0463***	-0.0212*	-0.0091	0.3471
	(0.0082)	(0.0114)	(0.1662)	(0.3163)
Southwest Airlines	0.0335***	-0.0783***	-0.2057	0.0140
	(0.0076)	(0.0189)	(0.1676)	(0.5238)
JetBlue Airways	0.0640***	0.0082	-0.4022***	0.0672
	(0.0089)	(0.0091)	(0.1409)	(0.1766)
Alaska Airlines	0.0597***	0.0976***	-0.2515*	-0.7050*
	(0.0131)	(0.0345)	(0.1495)	(0.4090)
Virgin America	0.0723***	0.1684***	-0.2198	-0.8535
	(0.0112)	(0.0331)	(0.1734)	(0.5198)

***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors in parentheses. Refer to Tables A4 and A5 for detailed estimation results.

[1]https://blog.alaskaair.com/alaska-airlines/news/asplusvx-customer-questions/

Table A4. Joint Model of Choice and Response-Time – Estimation Results for Individual Airlines								
	AmericanAir		United		Delta		SouthWest	
Variable	Response-Choice (Probit)	Response-Time (Log-Normal)	Response-Choice (Probit)	Response-Time (Log-Normal)	Response-Choice (Probit)	Response-Time (Log-Normal)	Response-Choice (Probit)	Response-Time (Log-Normal)
Log of Followers	0.0560***	-0.0645***	0.0458***	-0.0326***	0.0463***	-0.0212*	0.0335***	-0.0783***
	(0.0047)	(0.0058)	(0.0051)	(0.0069)	(0.0082)	(0.0114)	(0.0076)	(0.0189)
Collaborating Organization Mentioned	0.0956	-0.0788	-0.3203***	0.2617*	-0.0091	0.3471	-0.2057	0.0140
	(0.0867)	(0.1110)	(0.0869)	(0.1390)	(0.1662)	(0.3163)	(0.1676)	(0.5238)
Competing Airline Mentioned	0.0983***	-0.1703***	-0.0609*	0.1182**	-0.0004	0.2724	-0.9663***	0.1623
	(0.0330)	(0.0449)	(0.0338)	(0.0477)	(0.0979)	(0.1859)	(0.0718)	(0.3155)
Only Individual Users Mentioned	-0.6445***	0.4995***	-0.5228***	0.1186***	0.1067*	0.1042	-0.6247***	0.4102**
	(0.0271)	(0.0408)	(0.0221)	(0.0389)	(0.0564)	(0.1086)	(0.0517)	(0.2067)
Log of Complaints within the Previous Hour	-0.0143***	0.0419***	-0.0183***	0.0228***	-0.0255***	0.0699***	-0.0116***	0.0104***
	(0.0003)	(0.0004)	(0.0005)	(0.0011)	(0.0013)	(0.0027)	(0.0011)	(0.0036)
Log of Retweets	-0.3029***	0.4965***	-0.2913***	0.2505***	-0.7557***	0.7582***	-0.3256***	0.7641***
	(0.0274)	(0.0373)	(0.0268)	(0.0418)	(0.0860)	(0.1706)	(0.0465)	(0.1465)
Hashtag	0.0440***	-0.0368***	-0.0134	0.0262**	-0.1228***	0.0336	0.0051	0.0178
	(0.0075)	(0.0095)	(0.0082)	(0.0107)	(0.0170)	(0.0275)	(0.0114)	(0.0274)
Offensive	-0.1303***	0.1143**	-0.2005***	-0.0277	-0.5237***	0.2381	-0.2383***	0.2942
	(0.0435)	(0.0579)	(0.0465)	(0.0674)	(0.1418)	(0.2879)	(0.0721)	(0.2046)
URL	-0.1653***	0.1408***	-0.4569***	0.2155***	-0.2395***	0.0762	-0.4965***	0.1654
	(0.0237)	(0.0307)	(0.0231)	(0.0400)	(0.0492)	(0.0768)	(0.0366)	(0.1417)
@Order	-0.3637***	0.3358***	-0.7378***	0.1491***	-0.5437***	-0.0070	-0.2330***	-0.2154
	(0.0187)	(0.0285)	(0.0226)	(0.0531)	(0.0439)	(0.1042)	(0.0380)	(0.1446)
Log of Updates	-0.0493***	0.0325***	-0.0494***	0.0114*	-0.0322***	0.0144	-0.0414***	0.0048
	(0.0041)	(0.0051)	(0.0045)	(0.0061)	(0.0069)	(0.0095)	(0.0062)	(0.0165)
Profile	0.0046	0.0338	0.0390*	0.0445*	-0.0221	0.0269	0.0019	0.0496
	(0.0181)	(0.0222)	(0.0203)	(0.0254)	(0.0290)	(0.0387)	(0.0284)	(0.0654)
Error Correlation	-0.8891***		-0.2165***		-0.0757		0.0010	
	(0.0043)		(0.0584)		(0.0866)		(0.1435)	
Observations	50,963	50,963	49,254	49,254	18,478	18,478	24,889	24,889
Log - Likelihood	-71168.67	-71168.67	-57141.77	-57141.77	-25314.76	-25314.76	-32852.23	-32852.23

For brevity, the constant and coefficients for Day of Week dummies, Airline dummies, and Cluster dummies are not reported.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Robust standard errors in parentheses.

Table A5. Joint Model of Choice and Response-Time – Estimation Results for Individual Airlines						
	JetBlue		AlaskaAir		VirginAmerica	
Variable	Response-Choice(Probit)	Response-Time (Log-Normal)	Response-Choice(Probit)	Response-Time (Log-Normal)	Response-Choice (Probit)	Response-Time (Log-Normal)
Log of Followers	0.0640***	0.0082	0.0597***	0.0976***	0.0723***	0.1684***
	(0.0089)	(0.0091)	(0.0131)	(0.0345)	(0.0112)	(0.0331)
Collaborating Organization Mentioned	-0.4022***	0.0672	-0.2515*	-0.7050*	-0.2198	-0.8535
	(0.1409)	(0.1766)	(0.1495)	(0.4090)	(0.1734)	(0.5198)
Competing Airline Mentioned	-0.8322***	-0.0986	-0.5463***	-1.3717***	-0.8138***	-2.4338***
	(0.0739)	(0.1155)	(0.0952)	(0.2682)	(0.1086)	(0.3467)
Only Individual Users Mentioned	-0.6634***	0.0702	-0.6908***	-1.7170***	-0.4846***	-1.2500***
	(0.0532)	(0.0829)	(0.0733)	(0.2091)	(0.0825)	(0.2557)
Log of Complaints within the Previous Hour	-0.0146***	0.0279***	-0.0401***	-0.1148***	-0.0254***	-0.0445***
	(0.0008)	(0.0013)	(0.0050)	(0.0145)	(0.0034)	(0.0104)
Log of Retweets	-0.9134***	0.6906***	-0.5548***	-0.4112	-0.1908***	-0.2006
	(0.0694)	(0.1104)	(0.0953)	(0.2773)	(0.0619)	(0.1869)
Hashtag	-0.0096	-0.0012	0.0293	0.0659	0.0000	0.0251
	(0.0129)	(0.0123)	(0.0202)	(0.0528)	(0.0202)	(0.0591)
Offensive	-0.4948***	-0.0442	-0.4899***	-0.9366**	-0.6434***	-1.3318***
	(0.0914)	(0.1154)	(0.1506)	(0.4320)	(0.1474)	(0.4571)
URL	-0.5034***	-0.0154	-0.4046***	-0.8325***	-0.3241***	-0.8085***
	(0.0361)	(0.0499)	(0.0559)	(0.1532)	(0.0541)	(0.1608)
@Order	-0.3363***	0.0409	-0.2477***	-0.4711***	-0.3665***	-0.8811***
	(0.0375)	(0.0623)	(0.0473)	(0.1372)	(0.0594)	(0.1888)
Log of Updates	-0.0577***	-0.0059	-0.0820***	-0.1847***	-0.0712***	-0.1577***
	(0.0076)	(0.0079)	(0.0117)	(0.0306)	(0.0106)	(0.0311)
Profile	-0.0062	-0.0766**	0.1030*	0.3463**	-0.0116	-0.1752
	(0.0366)	(0.0337)	(0.0552)	(0.1432)	(0.0605)	(0.1752)
Error Correlation	-0.0627		0.9879***		0.9960***	
	(0.1011)		(0.0019)		(0.0008)	
Observations	16,827	16,827	6,082	6,082	7,169	7,169
Log -Likelihood	-19556.26	-19556.26	-9643.521	-9643.521	-9008.531	-9008.531

For brevity, the constant and coefficients for Day of Week dummies, Airline dummies, and Cluster dummies are not reported.
***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors in parentheses.

Deriving Big Five Personality Traits

For each customer, we derive the "big five" personality traits (i.e., openness, conscientiousness, extraversion, agreeableness, neuroticism), which have long been shown to affect various human behaviors (Goldberg 1993). Traditionally, these personality traits have been measured with the use of personality questionnaires. However, on social media, most people are not willing to spend the extra effort in responding to such questionnaires, making the measurement of personality difficult (Chen et al. 2015). Therefore, deriving personality from people's writings on social media has become an attractive option for the researchers.

Several previous studies successfully derived personality traits from people's writings based on the already established relationship between word use and personality (Fast and Funder 2008; Hirsh and Peterson 2009). Yarkoni (2010) examined web blogs and showed that people's word use reliably correlates with their personality. Several recent research studies focused on people's writings on Twitter and/or Facebook to predict their personality (Golbeck et al. 2011; Golbeck, Robles, and Turner 2011; Gou et al. 2014; Sumner et al. 2012). Almost all of these previous studies used lexicons such as the Linguistic Inquiry and Word Count (LIWC) dictionary to extract word features from text. Although the findings on the accuracy of such lexicon-based personality predictions are mixed, the predicted personality values from some studies have shown moderate correlations with the personality measurements from the questionnaires (Golbeck, Robles, and Turner 2011).

We derived all five traits for each customer in a lexicon-based approach, using the customer's past tweets as input to the LIWC dictionary (Pennebaker et al. 2015). Each trait is computed using the number of words that correspond to the words in a LIWC word category that is known to correlate with the trait. Given a vector containing the correlation coefficients, and a vector containing word counts of corresponding word categories, the trait is computed as the dot product of the two vectors (i.e., a linear combination of the word counts weighted by the correlation coefficients; Chen et al. 2015). For this study, we adopt the significant correlations from Yarkoni, as the correlations are based on a substantially larger corpus in comparison to other similar work (Golbeck et al. 2011; Golbeck, Robles, and Turner 2011; Sumner et al. 2012), and also because their effectiveness of deriving personality traits has been independently validated and used by other researchers (Chen et al. 2015; Gou et al. 2014). We augment our empirical model with the derived big five personality traits, accounting for the likely omitted variable bias due to differences in customer personality.

Training Protocol for Identifying Complaint Tweets

The Merriam Webster dictionary defines a *complaint* as an expression of grief, pain, or dissatisfaction. Accordingly, in this study, any user tweet that expresses a user's grief, pain, or dissatisfaction toward the airline under consideration is categorized as a complaint. In other words, we consider a user tweet as a complaint if it carries negative sentiment toward the airline. This is in line with prior research (Ma et al. 2015) that treated negative messages from customers on Twitter as complaints.

Customer complaints to an airline come in a variety of forms such as expressions of dissatisfaction regarding the following issues:

- **Operational issues**: mishandled baggage, flights delays, flight cancellations, long queues in airports, over-sold flights, in-flight entertainment issues, unsatisfactory meals in-flight, broken seats in-flight, computer system delays, seat change without notification, unfair service charges
- **Employee-related issues**: rude flight attendants, unprofessional gate agents, incompetent workers
- **Issues related to airline's dedicated customer service**: longer than usual on-hold times, calls hung-up by customer care agents, complaints unresolved for a long time, unsatisfactory compensation
- **Disgust toward the airline**: tweets with extreme language, tweets with warnings of potential brand switching

Some sample complaint tweets are listed in Table A6.

Table A6. Sample Complaint Tweets

- @airline Trapped in San Juan trying to get home to Seattle on thrice cancelled flight 1393. No help, no compensation, no apologies!
- @airline I'm so mad! 1st u delay my bags and then you deliver my new brand Perry Ellis bag w/ one wheel torn off!
- The joys of flying @airline! Leave the gate, back to the gate, get off the plane, back on the plane. I'll only be 7.5hrs late...
- @airline told me yesterday they knew where my baggage was and I should have it by noon. Now they are saying they can't locate it. #awful
- @airline been ON the plane for over an hour here in Dallas just wait to fix a light.. Pilot said it would be 20 minutes. Still waiting
- I shoulda taken @Amtrak. @airline y'all playing games today! I shoulda been in NYC by now. #fail
- @airline fail again!! FL1678 BOS-SFO on old 757-300 with NO power, personal ent sys or wifi. Gonna be a long 6 hours. You can do better!
- My arrival into LA gets delayed by 12+ hrs but yet my bags still don't fucking make it here?! Never again @airline, never again.
- Frustration @airline: I was early yet you would charge $75 to grab early flight even with open seats...now my flight delayed #fail cust svc
- Why would you change my seat @airline? Now I'm going to get very airsick stuck by the window. Certainly not the seat I had at check-in.
- disheartened by @airline Cancelled our reservation not once but twice, never informing us...and now it's our problem not theirs...
- Was just hung up on by reservations for @airline who claims my reservation never existed. Astounded at the poor customer service.
- NEVER flying @airline again. Booked window & aisle seats in the same row, was given two middle seats 10 rows apart. Lots more. Avoid – awful
- @airline LAS-EWR First class is a joke. Better get a refund ASAP. Awful!!!
- At this point I have to assume that @airline just loves keeping us waiting on runways until we reach past our boiling point.
- @airline computers go down twice while boarding flight 310 and we aren't even done with the B group. Waiting to reboot
- @airline too disappointed in your service. Left LAX on our honeymoon last Thursday on first class, was treated disgustingly horrible.
- @AmericanAir How is it that you refuse to refund the change fee for moving to a flight that YOU subsequently CANCELLED? #smh #poorservice
- It's not irony that a trip using a voucher from a cancelled @airline flight results in a cancelled flight. That's @airline!
- @airline1 have tried since June to get a refund, still no response. Will start flying @airline2 due very poor customer service from @airline1.
- Hate @airline it's been over a month no response from their "customer service" department as promised. Never fly them!
- Just had the worst customer service call with "Lu" from @airline - borderline aggressive to SkyMiles members - is it time to switch?
- Very disappointed by the lack of professionalism displayed by the @airline gate agent today. His condescension made a bad situation worse
- @airline very unpleasant flight (#2580). Disrespectful flight attendant because my 2y boy not wanting to sit alone but me to hold him.

Using Heckman's Method to Estimate the Joint Model

The response-time model, the response-choice model, and the error correlation structure are summarized below.

$$\ln z = \begin{cases} X\gamma + \eta, & if\ \ y = 1 \\ \text{Unobserved}, & if\ \ y = 0 \end{cases}$$

$$y = \begin{cases} 1\text{ (responded)}, & if\ \ y^* = X\beta + \varepsilon > 0 \\ 0\text{ (did not respond)}, & if\ \ y^* = X\beta + \varepsilon \leq 0 \end{cases}$$

$$\begin{pmatrix} \eta \\ \varepsilon \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma^2 & \rho\sigma \\ \rho\sigma & 1 \end{pmatrix} \right)$$

From the above model specification, we have

$$E\left[\ln z \mid y = 1\right] = X\gamma + E\left[\eta \mid \varepsilon > -X\beta\right]$$

Using standard results on truncated bivariate normal distribution (e.g., Johnson and Kotz 1972), we know

$$E\left[\eta \mid \varepsilon > -X\beta\right] = \rho\sigma \frac{\phi\left(X\beta\right)}{\Phi\left(X\beta\right)} = \rho\sigma\lambda\left(X\beta\right)$$

where $\lambda(\cdot)$ is the inverse Mills ratio for the Normal distribution. Hence,

$$E\left[\ln z \mid y = 1\right] = X\gamma + \rho\sigma\lambda\left(X\beta\right)$$

To estimate the response-time model, we can use the following procedure which was suggested by Heckman (1979):

1. Estimate β consistently using a Probit model where the dependent variable is the response decision (i.e., y). The estimate of β from the Probit model, $\hat{\beta}$, would be the coefficients of the response-choice model.

2. Compute the estimated inverse Mills ratio for each observation as $\hat{\lambda}_i = \lambda\left(X_i\hat{\beta}\right)$ using $\hat{\beta}$.

3. Include $\hat{\lambda}_i$ in a regression of ln z on X_i to obtain the coefficients of the response-time model. The coefficients of $\hat{\lambda}_i$ will be a measure of $\rho\sigma$, from which we can derive the estimated error correlation ρ using additionally the estimated standard deviation, σ, of the disturbance η.

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