Online Appendix

Proofs of the Results in Section 3

Proof of Lemma 1

1a. The CAR of firm *l* over δ time periods after announcing a leading recall is given by

$$CAR_l = \int_{\tau_l}^{\tau_l+\delta} \left(\frac{dS_t^l}{S_t^l}\right)_{recall} - \left(\frac{dS_t^l}{S_t^l}\right)_{no\ recall} = \int_{\tau_l}^{\tau_l+\delta} (\varphi_l(\tau_l) + \gamma_l(t-\tau_l))dt$$

In the above expression, the second equality follows from Equation (1) and the equation preceding that in Section 3, governing the stock market returns in the presence and absence of a recall, respectively. Similarly, the CAR of firm *f* over δ time periods after announcing a following recall is given by

$$CAR_f = \int_{\tau_f}^{\tau_f+\delta} \left(\frac{dS_t^l}{S_t^l}\right)_{recall} - \left(\frac{dS_t^l}{S_t^l}\right)_{no\ recall} = \int_{\tau_f}^{\tau_f+\delta} \left(\varphi_f(\tau_l,\tau_f) + \gamma_f(t-\tau_f)\right)dt$$

From the model assumptions, we have $|\varphi_l(\tau_l)| > \left|\varphi_f(\tau_l,\tau_f)\right|$ as long as $\tau_f \leq \tau_l + K$, where K is a constant as discussed in the paragraph leading up to Equation (2). Hence, as long as the market correction rate γ_l for the leader's returns is not higher than the correction rate γ_f for the follower, we have $|CAR_l| \geq \left|CAR_f\right|$. Hence the result.

1b. The magnitude of φ_f increases with τ_f for any given value of τ_l. Hence, the magnitude of CAR_f increases as the time difference between the leading and following recalls, i.e., $\tau_f - \tau_l$, increases.

Proof of Lemma 2

The magnitude of φ_l increases with τ_l. Thus, $|CAR_l|$ increases as more time elapses between the end of the previous cluster and the announcement of the leading recall of the next cluster.

Proof of Proposition 1

Suppose that firm 1 has already made the leading recall announcement at time τ_1. Then, in any given time period $t > \tau_1$, firm 2's decision regarding whether or not to issue a recall in that period is determined by the solution to the following problem.

$$V_t^2(R^1 = 1, e^1 = t - \tau_1) = min\begin{Bmatrix} P_t^2(f) \\ C_t^2 + \mathbb{E}V_{t+1}^2(R^1 = 1, e^1 = t + 1 - \tau_1) \end{Bmatrix}$$

We assume in our analysis that C_t^2 is increasing in *t*. Further, there exists a (large enough) *T* such that the cost associated with keeping the product on the market in period *T* exceeds the stock market penalty of recalling the product in *T*, i.e., $C_T^2 > P_T^2(f)$. Thus, $V_T^2(R^1 = 1, e^1 = T - \tau_1) = P_T^2(f)$. Then,

$$V_{T-1}^2(R^1 = 1, e^1 = T - 1 - \tau_1) = min\begin{Bmatrix} P_{T-1}^2(f) \\ C_{T-1}^2 + P_T^2(f) \end{Bmatrix}$$

Clearly, $C_{T-1}^2 > 0$ and from Lemma 1b, we have $P_T^2(f) > P_{T-1}^2(f)$. Therefore, $V_{T-1}^2(R^1 = 1, e^1 = T - 1 - \tau_1) = P_{T-1}^2(f)$. Following the same approach, we can show using backward induction that for any $t > \tau_1$, $V_t^2(R^1 = 1, e^1 = t - \tau_1) = P_t^2(f)$. Thus, in every time period *t* such that $\tau_1 < t < T$, it is optimal for firm 2 to recall the product than to keep it on the market. Consequently, it follows directly that it is optimal for firm 2 to issue a recall as soon as firm 1 makes the leading recall announcement.

Proof of Proposition 2

In the proof of Proposition 1, we mentioned that there exists a (large enough) T beyond which both firms might find it optimal to recall the product than to keep it in the market and incur the continuous market cost. Now, let us look at the optimal recall strategy of the firms in period T-1. For illustration purposes, we look at the recall decision from the perspective of firm 1 in this proof. However, the same logic also applies to firm 2.

If firm 2 has already issued a recall, then the optimal strategy for firm 1 in period T-1 is straightforward from Proposition 1: issue a recall. Hence, we only focus on the case where firm 2 has not issued a recall as of the beginning of period T-1. Then, firm 1's decision regarding whether or not to issue a recall in period T-1 is determined by the solution to the following problem.

$$V_{T-1}^1(R^2 = 0, e^2 = 0) = min \begin{Bmatrix} P_{T-1}^1(l) \\ C_{T-1}^1 + r_{T-1}^2 P_T^1(f) + (1 - r_{T-1}^2) P_T^1(l) \end{Bmatrix}$$

From the above expression, we see that if $C_{T-1}^1 < P_{T-1}^1(l) - r_{T-1}^2 P_T^1(f) - (1 - r_{T-1}^2) P_T^1(l)$, then the optimal strategy in period T-1 is to keep the product on the market. Otherwise, firm 1 should issue a recall in period T-1. If we define the threshold $TC_{T-1}^1 = P_{T-1}^1(l) - r_{T-1}^2 P_T^1(f) - (1 - r_{T-1}^2) P_T^1(l)$, then we see that the above discussed recall strategy is consistent with the optimal strategy laid out in the statement of Proposition 2. Furthermore, the above structure of the optimal recall strategy leads to the following expressions.

$$r_{T-1}^1 = Probability\, \{C_{T-1}^1 \geq P_{T-1}^1(l) - r_{T-1}^2 P_T^1(f) - (1 - r_{T-1}^2) P_T^1(l)\}$$

and

$$r_{T-1}^2 = Probability\, \{C_{T-1}^2 \geq P_{T-1}^2(l) - r_{T-1}^1 P_T^2(f) - (1 - r_{T-1}^1) P_T^2(l)\}$$

Thus, we have 2 equations involving 2 unknowns (r_{T-1}^1 and r_{T-1}^2). By solving these two simultaneous equations, we obtain the equilibrium recall probabilities in period T-1. Furthermore, we see that the equilibrium recall probabilities in period T-1 depend only on the cost and stock market penalties incurred in the future periods, i.e., T-1 and T.

Now, suppose that the structure of the optimal recall strategy laid out above holds for period t+1. In what follows, we will use induction to show that the same structure also holds for period t. Consistent with our above argument, we focus on the case where firm 2 has not issued a recall as of the beginning of period t. Then, firm 1's decision regarding whether or not to issue a recall in period t is determined by the solution to the following problem.

$$V_t^1(R^2 = 0, e^2 = 0) = min \begin{Bmatrix} P_t^1(l) \\ C_t^1 + r_t^2 \mathbb{E} V_{t+1}^1(R^2 = 1, e^2 = 1) + (1 - r_t^2) \mathbb{E} V_{t+1}^1(R^2 = 0, e^2 = 0) \end{Bmatrix}$$

From the above expression, we see that if $C_t^1 < P_t^1(l) - r_t^2 \mathbb{E} V_{t+1}^1(R^2 = 1, e^2 = 1) - (1 - r_t^2) \mathbb{E} V_{t+1}^1(R^2 = 0, e^2 = 0)$, then it is optimal for firm 1 to keep the product on the market, and recall otherwise. Furthermore, the threshold $TC_t^1 = P_t^1(l) - r_t^2 \mathbb{E} V_{t+1}^1(R^2 = 1, e^2 = 1) - (1 - r_t^2) \mathbb{E} V_{t+1}^1(R^2 = 0, e^2 = 0)$ depends only on the cost and stock market penalties incurred in periods t and beyond. Thus, the equilibrium recall probabilities r_t^1 and r_t^2 can be obtained by solving two simultaneous equations, similar to our discussion above. Hence the result.

Estimation of Parameters Using Expectation-Maximization (EM) Algorithm

The parameters of the model in Equation (4) are estimated using an expectation-maximization (EM) algorithm (Veen and Schoenberg 2008). The classification of recalls as leading, following, or neither, is the branching structure of the self-excited Hawkes process (Hawkes 1971a) and is an unobserved latent variable. The EM algorithm works iteratively by first estimating the branching structure from the data at the expectation (E) stage and then estimating model parameters ($\boldsymbol{\beta}, \theta, \omega$) at the maximization (M) stage where the background $\exp(X'_{m,t}\beta)$ is observed after the inclusion of the year-quarter and firm fixed effects as well as model variety, model volume, model age, and model age[2]. Letting t_i be the time of the i-th recall, we define the branching structure for the recalls using the following variables:

$$\lambda_{m,t_i} = \exp(X'_{m,t_i}\beta) + \sum_{\substack{t_i-\ell\leq t' \leq t_i \\ m':f(m')\neq f(m)}} \theta \times e^{-\omega\times(t_i-t')}\mathbb{I}_{[RecallSize_{m',t'}>0]}$$

$$\Phi_i = \begin{cases} 1, if\ i\ is\ a\ leading\ recall. \\ 0, otherwise. \end{cases}$$

$$\Upsilon_i = \begin{cases} 1, if\ i\ is\ a\ following\ recall. \\ 0, otherwise \end{cases}$$

The log-likelihood function considering a Poisson distribution of the Hawkes process model is given by:

$$l(\boldsymbol{\beta},\theta,\omega) = \sum_{i=1}^{N}\Phi_i\left\{\log(\exp(X'_{m,t_i}\beta)) - \int_0^T (\exp(X'_{m,t}\beta))\,dt\right\}$$
$$+\sum_{i=1}^{N}\Upsilon_i\left\{\log\left(\exp(X'_{m,t_i}\beta) + \sum_{\substack{t_i-\ell\leq t' \leq t_i \\ m':f(m')\neq f(m)}} \theta \times e^{-\omega\times(t_i-t')}\mathbb{I}_{[RecallSize_{m',t'}>0]}\right)\right\}$$
$$-\Upsilon_i\int_0^T\left[\exp(X'_{m,t}\beta) + \sum_{\substack{t-\ell\leq t' \leq t \\ m':f(m')\neq f(m)}} \theta \times e^{-\omega\times(t-t')}\mathbb{I}_{[RecallSize_{m',t'}>0]}\right]dt$$

Since the true branching structure is latent (unobserved), we replace the branching probabilities by the estimated branching probabilities:

$$\widehat{\Phi_i} = \frac{\exp(X'_{m,t_i}\beta)}{\hat{\lambda}_{m,t_i}} \qquad \widehat{\Upsilon_i} = \frac{\hat{\theta}e^{-\omega(t_i-t')}}{\hat{\lambda}_{m,t_i}}$$

<u>Steps of the Hawkes Process Model Parameter Estimation</u>

1. Initialize the background recall rate for each recall event $i \in \{1,\cdots,N\}$ using randomly drawn probability weights P_i from an uniform distribution. Normalize the weights to sum to one, i.e., $\sum_{i=1}^{N} P_i = 1$.
2. Initialize the number of days of excitation ℓ (see Equation (4)) to 0.
   a. Set iteration counter p=0.
   b. Compute the initial log-likelihood and the value of $(\boldsymbol{\beta^0},\theta^0,\omega^0)$ that maximizes the log-likelihood. Increment p to p+1.
   c. For every iteration $p \geq 1$: Compute $\widehat{\Phi}_i^p$ and $\widehat{\Upsilon}_i^p$ using the parameter estimates $(\boldsymbol{\beta^{p-1}},\theta^{p-1},\omega^{p-1})$ from iteration $p-1$.
   d. Compute the revised log-likelihood value $l^p(\cdot)$ using the estimated $\widehat{\Phi}_i^p$ and $\widehat{\Upsilon}_i^p$.
   e. Determine $(\boldsymbol{\beta^p},\theta^p,\omega^p)$ by maximizing the log-likelihood in iteration p.
   f. Increment p to p+1 and repeat steps (c) to (e) until model convergence, i.e., when $|l^{p+1}(\cdot) - l^p(\cdot)| \leq \epsilon \approx 10^{-1}$.
3. Increment ℓ to $\ell + 1$ and repeat steps 2(a)-2(f).
4. Repeat steps 1 to 3 using $B = 1000$ bootstrap samples. Compute the robust standard errors of the estimated parameters using the 1000 bootstrap estimates.

We did bootstrapping at the quarterly level for the following reasons: 1) it is the finest temporal level needed for bootstrapping that does not destroy the time-series structure; and 2) it allows for precision of estimates without creating artificial clusters due to the repeated observations selected during bootstrapping.

We also used multiple random starts for the EM chains, which increases the likelihood of reaching the global optimum since the local optima are discarded by comparing the final log-likelihood values from the different starts. We performed 1000 random starts of the Hawkes model. The best (maximum) log-likelihood value reached was -1533.78. However, each of the 1000 runs was quite similar to this best value. Specifically, 23.1% of the runs were within 0.1% of the best value, and 96.7% of the runs were within 5% of the best value. Overall, the output from the Hawkes process model is fairly consistent and the possibility of the algorithm getting stuck at local optima appears to be low given that the multiple random starts all converge around the best likelihood value specified above.

Table A1. Clustering Robustness Check #3. Logistic Regression: Likelihood of a Recall

Day Dummies	Parameter Estimate (Std. Error)	Average Marginal Effect (Std. Error)	Average Marginal Effect (%)[a]
(1)	(2)	(3)	(4)
Day(-1)	0.03 (0.01)***	0.06 (0.02)	3.5%
Day(-2)	0.02 (0.01)**	0.04 (0.02)	2.6%
Day(-3)	0.03 (0.01)***	0.07 (0.02)	3.7%
Day(-4)	0.03 (0.01)***	0.07 (0.02)	3.7%
Day(-5)	0.07 (0.01)***	0.14 (0.02)	7.7%
Day(-6)	0.06 (0.01)***	0.12 (0.02)	6.5%
Day(-7)	0.04 (0.01)**	0.08 (0.02)	4.5%
Day(-8)	0.03 (0.01)**	0.06 (0.02)	3.2%
Day(-9)	0.02 (0.01)*	0.04 (0.02)	2.3%
Day(-10)	0.04 (0.01)**	0.08 (0.03)	4.5%
Day(-11)	0.02 (0.01)*	0.04 (0.02)	2.5%
Day(-12)	0.03 (0.01)*	0.06 (0.02)	3.5%
Day(-13)	0.02 (0.01)+	0.04 (0.02)	2.3%
Day(-14)	0.04 (0.02)*	0.08 (0.03)	4.3%
Day(-15)	0.02 (0.01)+	0.04 (0.02)	2.3%
Day(-16)	0.01 (0.01)	0.02 (0.02)	1.1%
Day(-17)	0.01 (0.01)	0.02 (0.02)	1.1%
Day(-18)	0.02 (0.02)	0.04 (0,04)	1.4%
Day(-19)	0.01 (0.02)	0.02 (0.04)	0.9%
Day(-20)	0.01 (0.02)	0.02 (0.04)	0.9%

[a] Average marginal effect percentage is calculated relative to the base recall probability. All covariates and fixed effects used in Table 5 included, but not shown. Number of observations = 6,188,300, which is based on the total number of models (645 per Table 1) and the total number of days across the 48 years (17,520 per Table 2), reduced by the fact that not every model is on the market every day in our 48-year study. Significance levels, + p<0.01, * p<0.05, ** p<0.01, *** p<0.001

Table A2. Clustering Robustness Check #4. Hawkes Process Model Output Summary Statistics at the Component Level

Component	Total # of Recalls	# of Recalls in Clusters	# of Leading Recalls[a]	# of Following Recalls[b]	Avg. # of Following Recalls in Cluster	Avg. # of Days with no Recall Before a Cluster	Avg. # of Days Cluster Lasts	# of Clusters That Had At Least One Following Recall Involving the Same Component as the Leading Recall[c]
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Brakes	451	352 (78%)	71 (16%)	281 (62%)	8.6	16	41	23 (32%)
Fuel Sys.	351	274 (78%)	27 (8%)	247 (70%)	7.8	15	34	5 (19%)
Body	281	215 (77%)	17 (6%)	198 (70%)	7.6	16	28	7 (41%)
Steering	268	217 (81%)	30 (11%)	187 (70%)	7.8	15	36	12 (40%)
Gear Box	215	168 (78%)	24 (11%)	144 (67%)	7.4	16	32	9 (38%)
Seat Belt	230	178 (77%)	12 (5%)	166 (72%)	6.6	17	30	4 (33%)
Suspension	185	132 (71%)	20 (11%)	112 (61%)	7.6	16	33	8 (40%)
Electricals	253	177 (70%)	7 (3%)	170 (67%)	4.6	17	24	2 (29%)
Speed	159	115 (72%)	20 (13%)	95 (60%)	7.8	16	36	4 (20%)
Lighting	138	86 (62%)	2 (1%)	84 (61%)	5.8	15	22	0 (0%)
Engine	147	93 (63%)	17 (12%)	76 (52%)	7.4	15	30	5 (29%)
Visibility	123	70 (57%)	4 (3%)	66 (54%)	6.4	16	24	0 (0%)
Wheels	97	64 (66%)	8 (8%)	56 (58%)	3.2	17	16	2 (25%)
Seats	107	63 (59%)	2 (2%)	61 (57%)	4.4	16	18	0 (0%)
Air Bags	112	69 (62%)	5 (4%)	64 (57%)	7.3	16	24	0 (0%)

[a] Number of leading recalls is the same as the number of clusters. [b] Columns 4 and 5 add up to column 3 since each recall in a cluster must either be a leading or a following recall. [c] Column 9 is a count of the number of clusters led by the respective component in each row that has at least one following recall involving the same component. The percentage is calculated as column 9 divided by column 4.

Table A3. Test of Significance of Abnormal Returns and Difference between Leading and Following Recalls

	Mean CAR (%) Leading	Adjusted Patell t-Statistic	Mean CAR (%) Following	Adjusted Patell t-Statistic	Leading and Following CAR Difference (%)[a]	Adjusted Patell t-Statistic
(1)	(2)	(3)	(4)	(5)	(6)	(7)
(-1, 0)	-0.11	-1.98*	-0.07	-1.29	-0.04	-0.52
(-1, 1)	-0.28	-2.58*	-0.09	-2.35*	-0.19	-1.65+
(-1, 5)	-0.89	-6.48***	-0.22	-3.17**	-0.67	-4.35***
(-5, 5)	-0.67	-5.49***	-0.16	-2.75**	-0.51	-4.01***
(-5, 10)	-0.44	-4.78***	-0.17	-2.96**	-0.27	-2.08*
(-5, 15)	-0.39	-4.23***	-0.16	-2.91**	-0.23	-2.14*
(-5, 20)	-0.23	-1.90+	-0.11	-1.73+	-0.12	-0.93
(-5, 25)	-0.07	-0.89	-0.04	-0.76	-0.03	-0.31
(-5, 30)	-0.05	-0.94	-0.03	-0.59	-0.02	-0.29

[a] Leading and Following CAR Difference = Mean CAR Leading – Mean CAR Following. Significance levels, + p<0.10, *p<0.05, **p<0.01, ***p<0.001

Table A4. Descriptive Statistics for the Event Study

Variables	Mean	Min	Max	Sdev
CAR [-1, 0]	-0.09	-0.17	0.14	0.05
CAR [-1, 1]	-0.17	-0.39	0.19	0.08
CAR [-1, 5]	-0.45	-1.21	0.25	0.10
CAR [-5, 5]	-0.33	-0.81	0.28	0.09
CAR [-5, 10]	-0.28	-0.83	0.33	0.09
CAR [-5, 15]	-0.26	-0.65	0.27	0.07
CAR [-5, 20]	-0.16	-0.48	0.16	0.06
CAR [-5, 25]	-0.05	-0.26	0.18	0.06
CAR [-5, 30]	-0.04	-0.16	0.09	0.04
Leading Recall	0.09	0.00	1.00	0.00
Revenue[a]	23154.60	279.10	85845.10	15782.40
Past Recalls	31.00	4.00	84.00	9.45
Recall Size	139952	20	7900000	378170
Market Share	15.70	7.30	72.90	6.43
Market Cap[b]	30.00	20.00	148.90	30.10
Model Variety	26.34	11.00	204.00	6.80
Model Volume	112928	40	3421173	131680
Model Age	746	30	7260	896
Model Age^2	1368000	900	52707600	3296000

[a] Revenue is in $ millions. [b] Market Cap is in $ billions

Table A5. Correlation Matrix for the Event Study

		1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	CAR [-1, 0]	1.00													
2	CAR [-1, 1]	0.21*	1.00												
3	CAR [-1, 5]	0.19*	0.32*	1.00											
4	CAR [-5, 5]	0.11*	0.27*	0.41*	1.00										
5	CAR [-5, 10]	0.09	0.29*	0.35*	0.49*	1.00									
6	CAR [-5, 15]	0.12	0.18*	0.38*	0.37*	0.55*	1.00								
7	CAR [-5, 20]	0.06	0.11*	0.24*	0.33*	0.51*	0.54*	1.00							
8	CAR [-5, 25]	0.07	0.08	0.15*	0.35*	0.46*	0.36*	0.53*	1.00						
9	CAR [-5, 30]	0.05	0.06	0.08	0.28*	0.32*	0.27*	0.31*	0.57*	1.00					
10	Leading Recall	-0.05	-0.13*	-0.16*	-0.17*	-0.14*	-0.11*	-0.10*	-0.09	-0.06	1.00				
11	Revenue	-0.06	-0.08	-0.09	-0.13*	-0.17*	-0.12*	-0.08*	-0.06	-0.05	-0.04	1.00			
12	Past Recalls	0.01	0.03	0.07	0.06	0.09	0.06	0.04	0.05	0.03	0.02	0.04	1.00		
13	Recall Size	-0.02	-0.04*	-0.09*	-0.11*	-0.10*	-0.09*	-0.09*	-0.06*	-0.03	0.14*	0.19*	0.04	1.00	
14	Market Share	-0.03	-0.04	-0.09*	-0.10*	-0.12*	-0.09*	-0.06*	-0.05	-0.02	0.17*	0.28*	0.15*	0.19*	1.00
15	Market Cap	-0.01	-0.04	-0.06*	-0.07*	-0.07*	-0.04*	-0.04*	-0.03	-0.01	0.25*	0.31*	0.23*	0.11*	0.22*
16	Model Variety	-0.01	-0.03	-0.02	-0.03	-0.06*	-0.04*	-0.03	-0.02	-0.01	-0.05	0.09*	0.06*	-0.07*	0.04
17	Model Volume	-0.02	-0.04	-0.06*	-0.05*	-0.07*	-0.03	-0.02	-0.03	-0.01	0.09*	0.13*	0.08*	0.27*	0.14*
18	Model Age	0.01	0.03	0.02	0.04	0.03	0.02	0.02	0.02	0.01	0.05	0.09*	0.16*	0.18*	0.09*
19	Model Age^2	0.01	0.01	0.01	0.02	0.02	0.01	0.01	0.01	0.01	0.03	0.07*	0.08*	0.11*	0.06*

		15	16	17	18	19
15	Market Cap	1.00				
16	Model Variety	0.05*	1.00			
17	Model Volume	0.13*	-0.08*	1.00		
18	Model Age	0.11*	-0.05*	-0.06*	1.00	
19	Model Age^2	0.07*	-0.03	-0.02	0.61*	1.00

*p<0.05

Table A6. Event Study Robustness Check #3. GEE Estimates of the Leading Recall CARs as a Function of the Number of Following Recalls within a Cluster

Event Window	(-1, 0)	(-1, 1)	(-1, 5)	(-5, 5)	(-5, 10)	(-5, 15)	(-5, 20)	(-5, 25)	(-5, 30)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Number of Following Recalls	0.00	0.01	0.05+	0.05+	0.07*	0.08*	0.07+	0.05	0.02
	(0.00)	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
Observations	266	266	266	266	266	266	266	266	266
Wald Chi^2	65.14***	76.22***	84.84***	85.89***	92.29***	86.29***	82.29***	76.77***	71.29***

All covariates and fixed effects used in Table 5 included, but not shown. 266 recalls as per number of leading recalls from Table 3. Bootstrapped robust standard error estimates and exchangeable dependence structure used. Standard errors in parentheses, + p<0.10, *p<0.05, **p<0.01, ***p<0.001

Table A7. Event Study Robustness Check #4. GEE Estimates of the CARs for Same Component Following and Different Component Following with Leading Recalls as the Reference Category

Event Window	(-1, 0)	(-1, 1)	(-1, 5)	(-5, 5)	(-5, 10)	(-5, 15)	(-5, 20)	(-5, 25)	(-5, 30)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Same Component Following	0.05	0.10*	0.15***	0.17***	0.17*	0.15*	0.14+	0.06	0.02
	(0.03)	(0.04)	(0.04)	(0.05)	(0.07)	(0.06)	(0.07)	(0.05)	(0.03)
Different Component Following	0.05	0.08*	0.11**	0.14**	0.15*	0.15*	0.13+	0.06	0.02
	(0.03)	(0.04)	(0.04)	(0.05)	(0.06)	(0.06)	(0.06)	(0.05)	(0.03)
Observations	2273	2273	2273	2273	2273	2273	2273	2273	2273
Wald Chi^2	267.91***	257.66***	250.04***	235.11***	216.84***	202.76***	188.28***	174.83***	164.22***

All covariates and fixed effects used in Table 5 included, but not shown. 2273 recalls = 266 leading recalls from Table 3 + 2007 following recalls from Table 3. Bootstrapped robust standard error estimates and exchangeable dependence structure were used. Standard errors in parentheses, + p<0.10, *p<0.05, **p<0.01, ***p<0.001