Measuring Contagion in the Diffusion of Consumer Package Goods

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Our main goal

- Despite what is shown in the literature and what managers and researchers believe, we want to prove that information about new package goods diffuses through word of mouth.
- Why is this important?
  - If adopters of a new packaged-good influence other consumers, retailers can target new-product promotions to consumers who are both innovative and influential.
  - Some innovative consumers are valuable to the retailer because they:
    - Buy the new product **AND**
    - Influence others to also buy it

Agenda

- The Bass Model
  - How innovations diffuse through word of mouth or contagion
- Common wisdom regarding the diffusion of new package goods
- Main requirements for detecting WOM or contagion
- Our proposed consumer-level diffusion model
- Results and Implications

The Bass Diffusion Model

- There is a pool of **M** potential adopters
- Some of them adopt the new product on their own (innovators) with probability **p**
- Others are imitators, and their adoption probability depends on
  - the imitation rate **q** multiplied by
  - how many people already use the product **N**.

$$\underbrace{n_t}_{\text{New adopters}} = (\underbrace{p}_{\text{Proportion who will adopt on their own}} + \underbrace{qN_t}_{\text{Proportion who will immitate}})(\underbrace{M - N_t}_{\text{Cummulative adopters}})$$

Current common wisdom

- There is no WOM or contagion in the diffusion of new packaged goods
- Why Not?
  - Consumers only talk to each other about products that are more relevant to their lives
    - Ipad, Iphone, Cars, etc.
    - Laundry detergent, chewing gum, Shampoo
  - The pattern of new adoptions shows exponential decay, which is not consistent with diffusion through WOM

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WOM can exist without words

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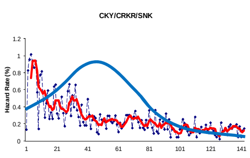
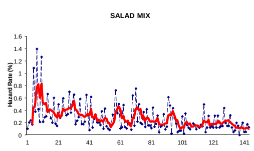
Contagion co-exists with Exponential Decay

- As long as there is heterogeneity in innovativeness
  - If some people are more innovative than others, they will adopt early, on their own.
  - If the distribution of innovativeness is skewed (more innovators than laggards), observed adoptions will decay exponentially even though laggards imitate from innovators
- Or there is more marketing activity earlier in the product life cycle





Basic assumptions of traditional diffusion models

- All consumers are equally innovative (same probability of adopting on their own) – Homogeneity in innovativeness
- Once a consumer adopts the new product, she will forever produce WOM - Temporal homogeneity
- A potential adopter is influenced by every consumer who already owns the product – Spatial homogeneity

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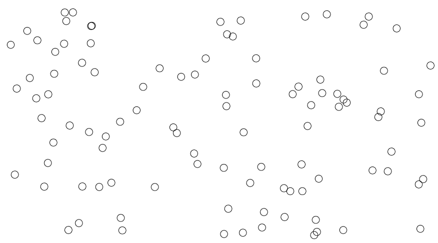
Basic assumptions of traditional diffusion models T=0



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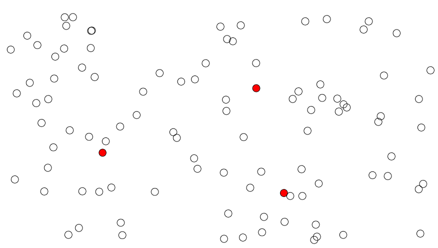
Basic assumptions of traditional diffusion models T=1



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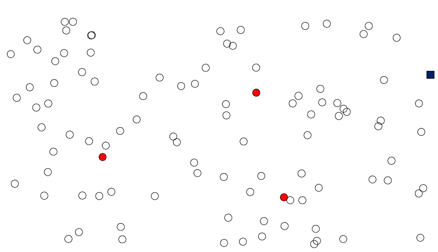
Basic assumptions of traditional diffusion models T=2



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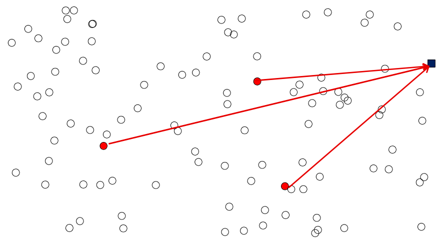
Basic assumptions of traditional diffusion models T=2



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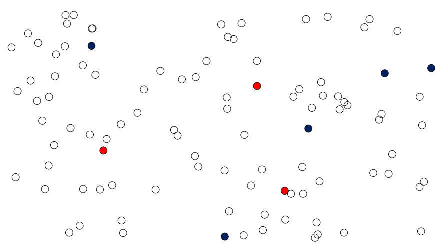
Basic assumptions of traditional diffusion models T=2



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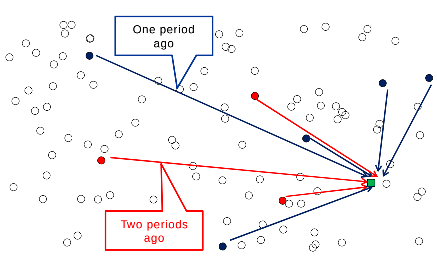
Basic assumptions of traditional diffusion models T=3



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Potential biases in diffusion models

- Temporal heterogeneity
  - Influence from past adopters diminishes over time
- Spatial heterogeneity
  - Nearest neighbors have more influence than distant ones
- Unobserved heterogeneity in innovativeness
  - Consumers differ on their willingness to try new products and on how soon they do it.
- Correlated unobservables
  - All unobservable factors that might affect adoption
    - Advertising, Price, Sales Promotions, Distribution

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Main requirements for detecting contagion in diffusion models

- Must account for unobservable factors
  - Time-Invariant, Cross-section variant
    - Stable consumer characteristics, such as innovativeness, product involvement
  - Time-variant, Cross-section invariant
    - Temporal trends, such as seasonality or economic conditions
  - Time-variant, Cross-section variant
    - Local or targeted promotions
    - Product availability

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Our proposed model

- Consumer *i*
- New Product *j*
- Week *t*
- λ_{ijt} = hazard rate = probability that consumer *i* will try product *j* exactly *t*-weeks after introduction, given that she did not try yet.

Consumer and product specific baseline

Consumers response to MKTG for prod. j

Contagion coefficient for prod. j

Indirect effect of all unobservables

$$\ln(\lambda_{ijt}) = \alpha_{ij} + \beta_j X_{ijt} + \underbrace{\delta_{1j} t + \delta_{2j} \ln t}_{} + \gamma_j N_{ijt}^{RK} + \theta_j M_{ijt}^{RK}$$

Marketing effort

Time trend

Number of adopters among the K nearest neighbors who bought the product within R periods before t

Number of adopters who are not neighbors and bought the product within R periods before t

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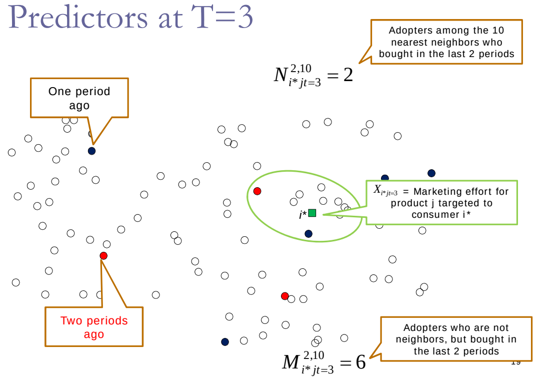
Predictors at T=3



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Consumer and product specific baseline

Consumers response to MKTG for prod. j

Contagion coefficient for prod. j

Adjustment for all unobservables

$$\ln(\lambda_{ijt}) = \alpha_{ij} + \beta_j X_{ijt} + \delta_{1j} t + \delta_{2j} \ln t + \gamma_j N^{RK}_{ijt} + \theta_j M^{RK}_{ijt}$$

Trend

$$\boxed{\alpha_{ij} = \alpha_j + \Lambda_j Z_i}$$

Factor decomposition to account for individual differences in baseline hazard

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Empirical application

- Our data
  - 5,912 members of a retailer's loyalty program
    - One metropolitan area
    - Geocodes
  - Weekly trial and repeat purchases
    - 124 weeks of data
  - 67 new packaged-goods launched in the first 50 weeks
    - Bakery, Baking mixes, Candy, Charcoal, Cookies, Condiments, Tissues/Napkins, Frozen grocery, Packaged meats, Refrigerated groceries, Salad mixes, Shelf-stable vegetables, Soft drinks, Teas, Yogurt
  - Weekly prices and sales-promotions for each new product

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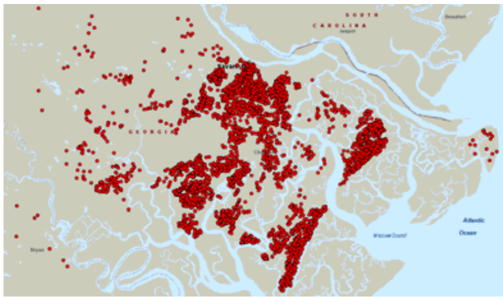
Empirical application



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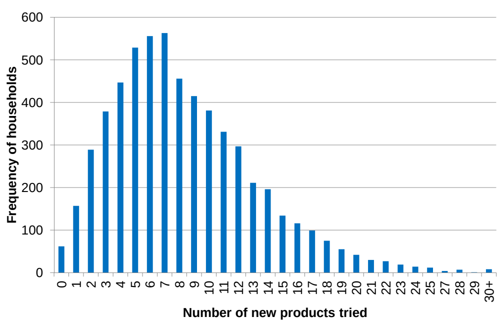
Number of products tried out of 67



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Diffusion Maps

PRODUCT # 11

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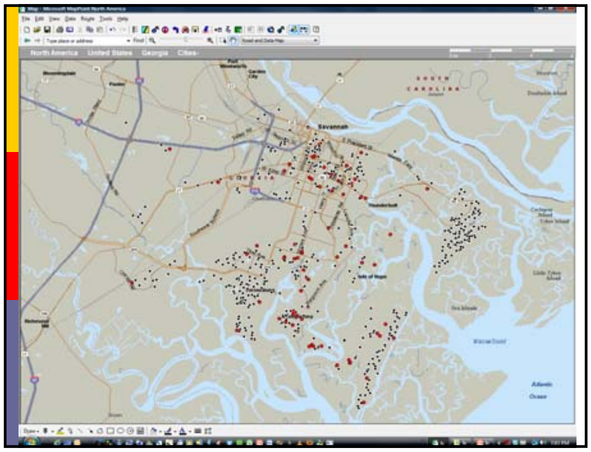
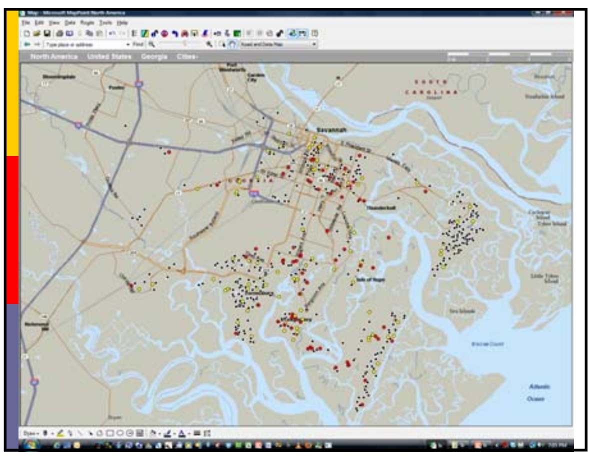

North America
United States
Georgia
Savannah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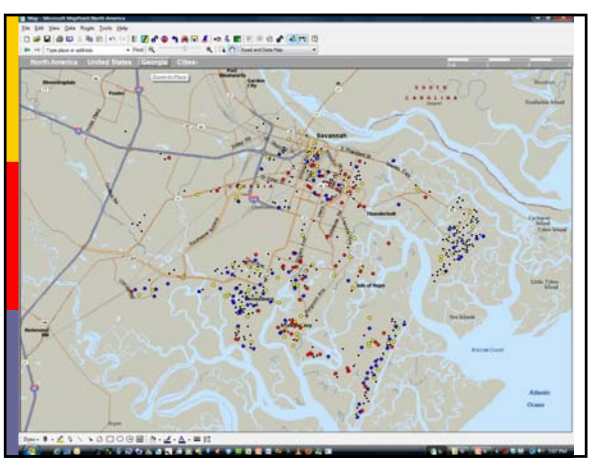
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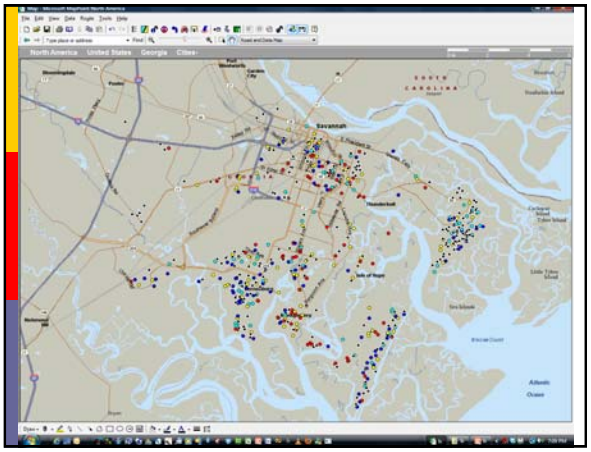

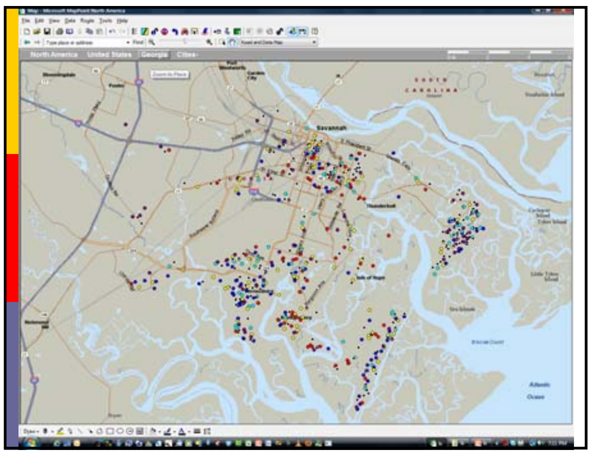

Diffusion Maps

PRODUCT # 19

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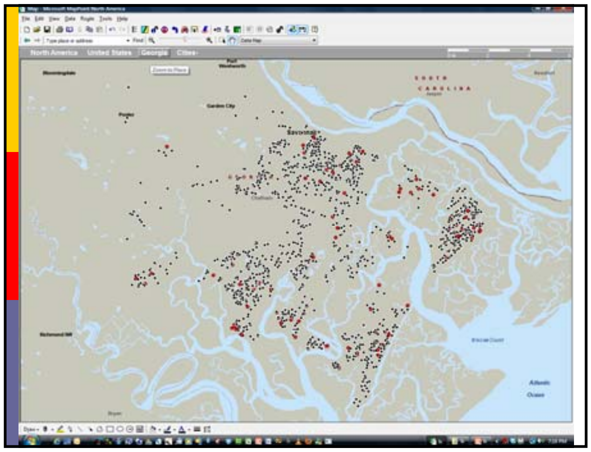
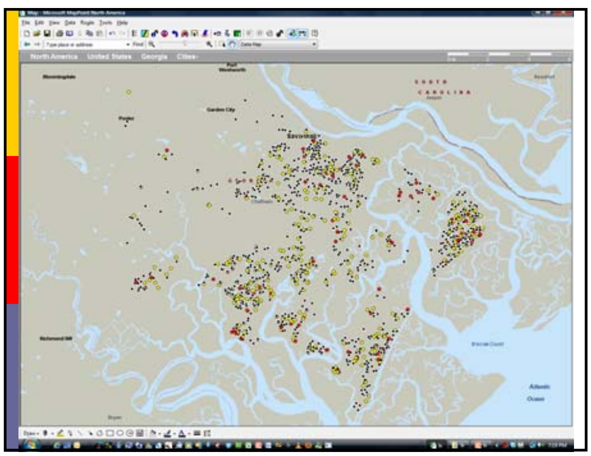
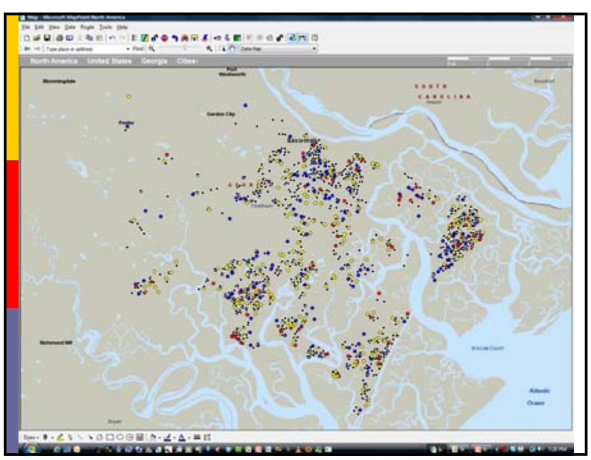
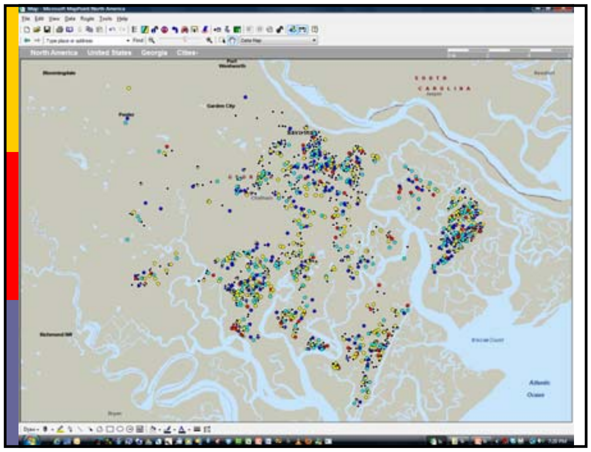
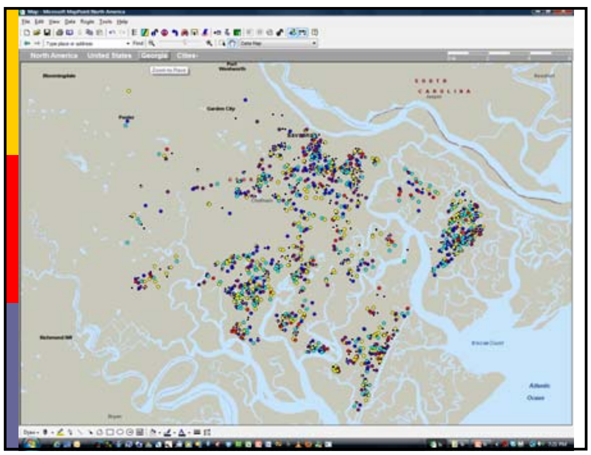
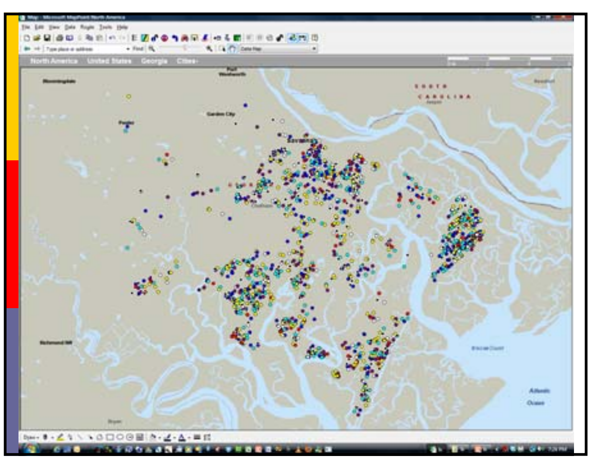












Model selection

K = nearest neighbors

R = relevant past periods

Out of 67 tested products

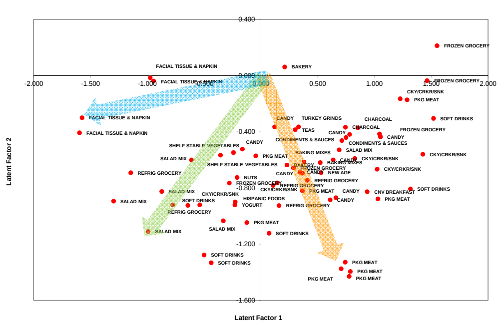
K \ R	Bayesian Information Criterion (BIC)			# of Positive & Significant Contagion Coefficients (p < 0.05)		
	4 weeks	8 weeks	full window (i.e., temporal homogeneity)	4 weeks	8 weeks	full window (i.e., temporal homogeneity)
0		677,800			0 (i.e., no contagion)	
200	675,871	675,948	676,151	36	34	29
500	675,672	675,832	676,080	35	36	25
1000	675,578	675,711	675,963	40	36	17
1500	675,605	675,764	675,981	36	38	13
full sample (i.e., spatial homogeneity)	676,725	676,894	677,081	14	10	5

Some parameter estimates

Correction for unobservables

Product	Intercept	Price	Promotion	Linear Trend	Log Linear Trend	**Spatial Contagion	**Non-Neighbors	Latent Factor 1	Latent Factor 2
BAKERY	-6.495	0.262	0.634	-0.007	-0.221	3.024	0.107	0.209	0.062
BAKERY	-3.618	-0.810	-0.312	0.003	-0.453	6.782	0.209	0.229	-0.636
BAKING MIXES	-7.640	0.852	0.694	-0.012	0.150	0.485	-0.273	0.522	-0.619
BAKING MIXES	-5.937	-1.447	0.386	-0.007	0.008	2.047	*1.162*	0.379	-0.614
CANDY	-3.087	-2.937	0.841	-0.014	-0.041	0.644	-0.099	0.780	-0.418
CANDY	-3.615	-3.071	0.739	-0.016	0.189	1.198	-0.214	0.364	-0.694
CANDY	-3.861	-1.017	0.746	0.005	-0.279	2.287	0.405	0.120	-0.364
CANDY	-3.952	-2.285	0.718	-0.013	0.029	1.277	-0.531	-0.164	-0.523
CANDY	-4.465	-2.134	0.905	-0.017	0.024	1.766	-0.332	0.636	-0.599
CANDY	-4.576	-2.426	1.086	-0.010	-0.048	1.961	-0.422	1.052	-0.436
CANDY	-4.045	-1.714	0.372	0.003	-0.801	2.078	-0.667	0.609	-0.884
CANDY	-4.391	-3.125	0.543	0.004	-0.590	1.520	-0.154	0.660	-0.869
CANDY	-4.447	-2.300	0.924	-0.002	-0.273	*2.392*	-0.292	0.343	-0.687
CHARCOAL	-2.122	-0.602	0.232	-0.011	0.036	0.336	-0.052	0.853	-0.371
CHARCOAL	-15.341	1.553	0.498	-0.022	0.236	2.074	-0.726	0.744	-0.367
CKY/CRKR/SNK	-2.340	-0.508	0.228	-0.002	-0.286	0.526	0.004	1.425	-0.560
CKY/CRKR/SNK	-2.819	-1.681	0.678	-0.006	-0.069	0.761	-0.377	0.142	-0.763
CKY/CRKR/SNK	-4.604	-0.809	0.527	0.016	-0.437	0.317	0.485	1.023	-0.666

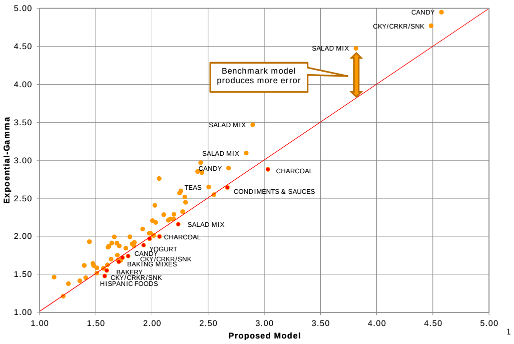
Factor loadings for innovativeness



How well does the model work?

- Predictive validity test
  - Calibrate the model using the first 84 weeks
  - Predict trials for the remaining 40 weeks
- Compare with benchmark model
  - Highly flexible Exponential-Gamma hazard model
  - Root-mean-square error (RMSE) comparing actual and predicted trial rate in each week for 40 weeks and each of the 67 new products

RMSE predicting weekly trial rates for the last 40 weeks



Contagion in the adoption of packaged goods

MANAGERIAL IMPLICATIONS

Frozen Foods and Soft Drinks

- Two measures for each consumer:
  - Innovativeness scores for consumer *A* and category *j* $\alpha_{Aj} = \alpha_j + \Lambda_j Z_A$
  - Influence by consumer A on consumer B

$$W_{AB} = \sum_{j \in O_B} \left\{ \exp\left[R_{jAB} \left(\gamma_j K_{AB} \right) \right] - 1 \right\}$$

    - R_{jAB} = 1 if consumer A purchased product *j* before consumer B, 0 otherwise
    - K_{AB} = 1 if consumer A is a K-nearest neighbor of consumer B, 0 otherwise
  - Out-degree centrality $OC_i = \sum_{i'=1}^{N} W_{ii'}$
  - Eigenvector centrality $\lambda x_i = \sum_{i'=1}^{N} w_{ii'} x_{i'}$

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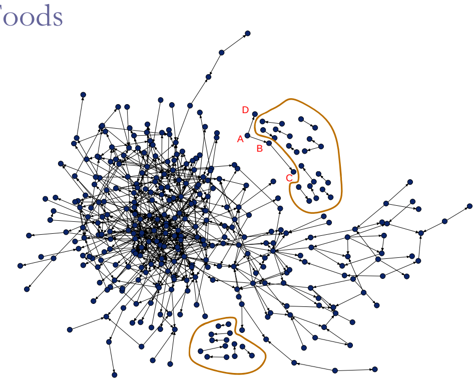
Subset of network influences for Frozen Foods



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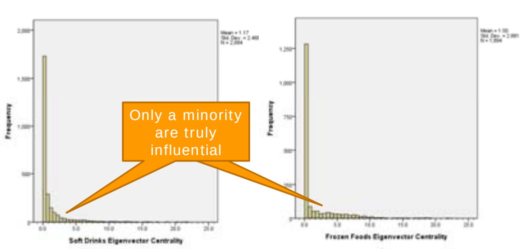
Distribution of influence



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Innovativeness and Influence for Soft Drinks and Frozen Foods

Convergent Validity

		Soft Drinks			Frozen Foods		
		Innovativeness	Outer-degree Centrality	Eigenvector Centrality	Innovativeness	Outer-degree Centrality	Eigenvector Centrality
Soft Drinks	Innovativeness	**1.00**					
	Outer-degree Centrality	**0.50**	**1.00**				
	Eigenvector Centrality	**0.35**	**0.65**	**1.00**			
Frozen Foods	Innovativeness	**0.16**	0.09	0.09	**1.00**		
	Outer-degree Centrality	0.03	0.08	**-0.13**	**0.58**	**1.00**	
	Eigenvector Centrality	0.03	0.08	**-0.32**	**0.55**	**0.65**	**1.00**

Discriminant validity

Convergent Validity

Correlations in **bold** are statistically significant at the 0.01 level.

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Number of trials by tercile of Innovativeness and Influence

Frozen Foods

Trials by the segment

			INFLUENCE			
			Top tercile	Middle tercile	Bottom tercile	Total
INNOVATIVENESS	Top tercile	Customers	425	205	59	689
		Direct trials	42	20	5	67
		Influenced trials	51	11	2	64
	Middle tercile	Customers	215	290	184	689
		Direct trials	19	27	16	62
		Influenced trials	16	9	2	27
	Bottom tercile	Customers	49	194	447	690
		Direct trials	4	16	28	48
		Influenced trials	10	8	6	24
	Total	Customers	689	689	690	2068
		Direct trials	65	63	49	177
		Influenced trials	77	28	10	115

Trials influenced by the segment

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Number of trials by tercile of Innovativeness and Influence

Soft Drinks

			INFLUENCE			
			Top tercile	Middle tercile	Bottom tercile	Total
INNOVATIVENESS	Top tercile	Customers	514	266	81	861
		Direct trials	66	14	8	88
		Influenced trials	65	15	3	83
	Middle tercile	Customers	183	350	328	861
		Direct trials	15	28	21	64
		Influenced trials	19	15	5	39
	Bottom tercile	Customers	164	245	453	862
		Direct trials	15	23	33	71 ?
		Influenced trials	13	10	4	27
	Total	Customers	861	861	862	2584
		Direct trials	96	65	62	223
		Influenced trials	97	40	12	149

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Implications for the retailer

- Something useful to do with the data from the loyalty program
- First, use the data on adoptions of all new products in the past to measure each customer on the major product categories
  - Innovativeness
  - Influence
- If a manufacturer is introducing a new product:
  - Who is likely to adopt it, and do it sooner?
  - Who is likely to influence others?
- The value of a customer comes not only from his/her purchases, but from the purchases by influenced customers

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