

# Promotion and Fast Food Demand

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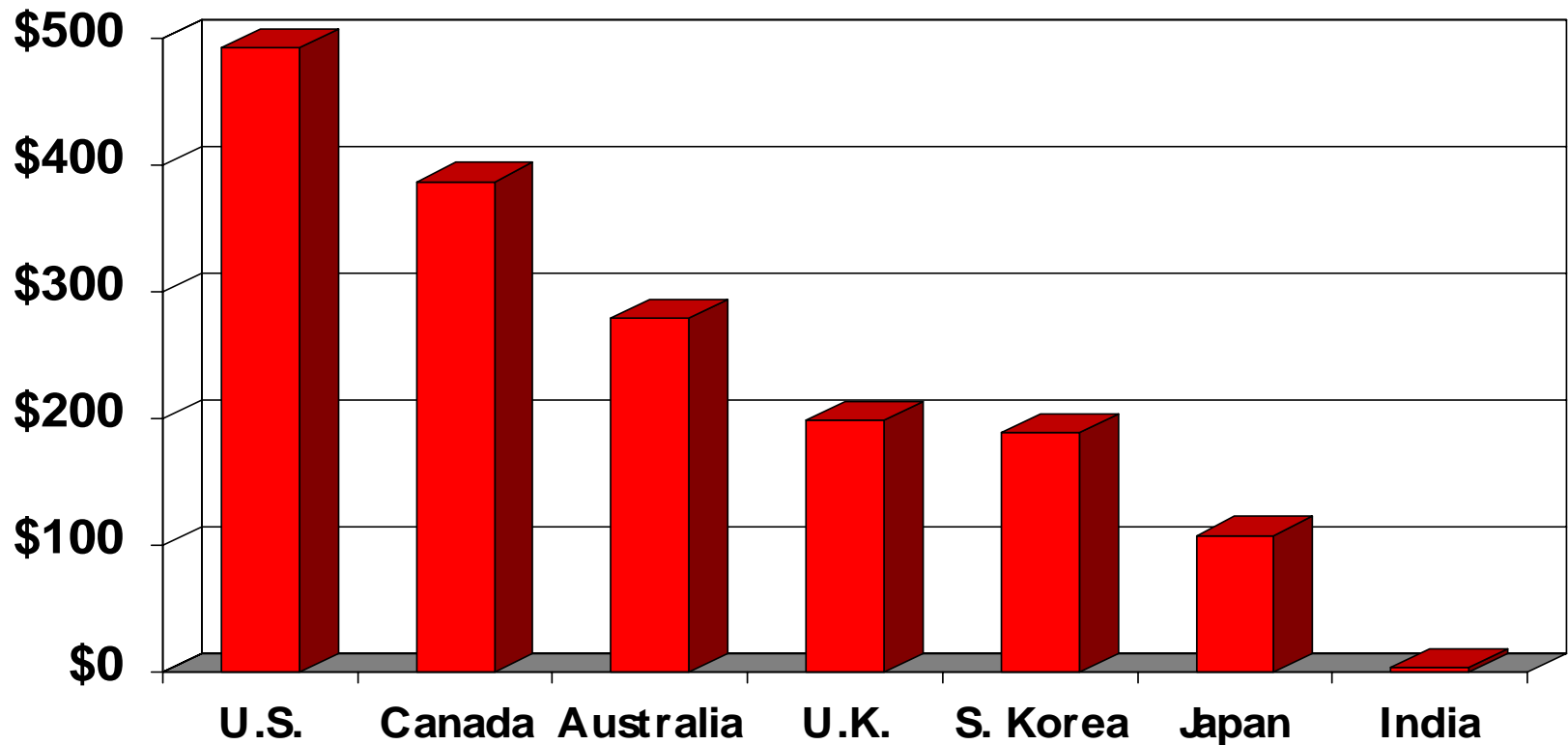
Paper presented at:

AIC Meetings, Edmonton, AB

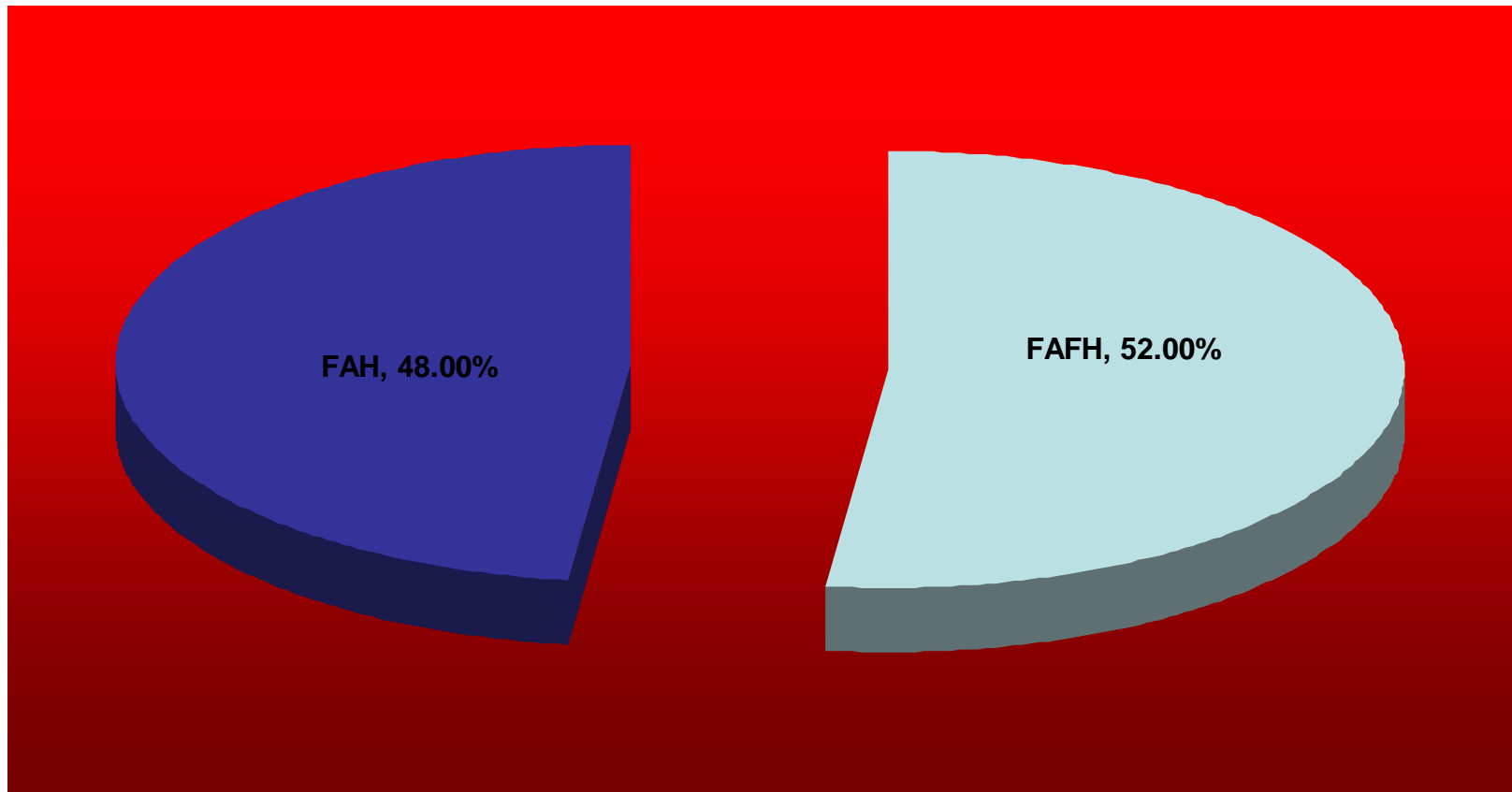
Nov. 5, 2007

# Fast Food Spending per Capita

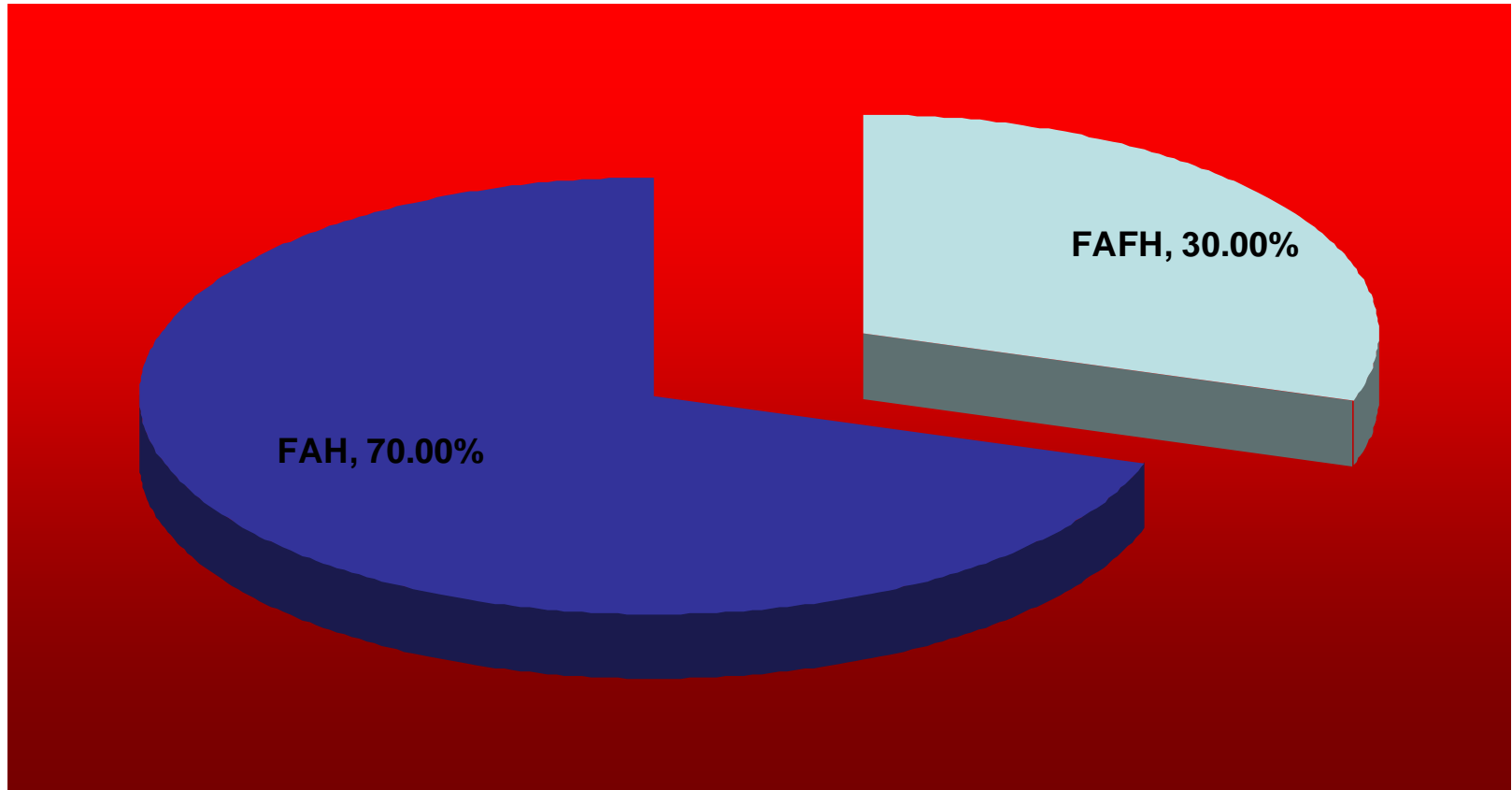
(US \$, Euromonitor, 2004)



# U.S. Food Budget

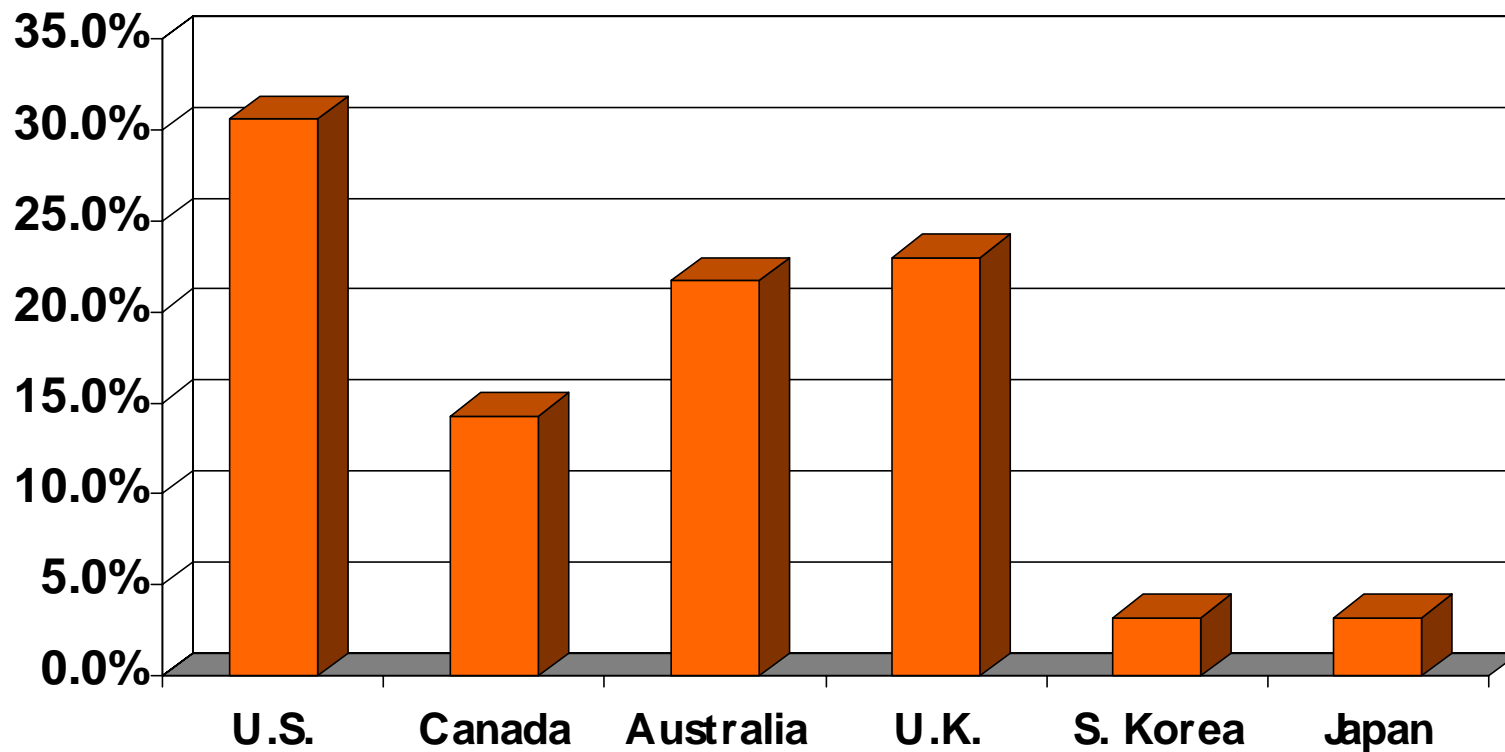


# Canada Food Budget



# Obesity Rates

(% BMI > 30, OECD, 2005)



# Overview

- What is the problem?
- Objectives
- Contribution
- Data
- Empirical Model
- Results
- Conclusions

# Problem

- Fast food firms face marketing restrictions
  - Fast food the “new cigarettes”
  - Advertising bans to children
  - Price promotion more common
- Fast food firms’ argument
  - Industry competitive
  - Promotion changes market share
  - Aggregate demand does not change

# Problem...

- Previous research in cigarettes and alcohol:
  - Duffy (1995) – no aggregate impact
  - Dikempe, et al. (1999) – little aggregate impact
- Problems with these studies
  - Used aggregate data – big measurement issues
  - Models do not account for unit-sales effects

# Objectives

- To determine the impact of fast food price promotion on: (1) overall fast food sales, and (2) restaurant share
- To develop a new discrete / continuous model of differentiated product demand

# Features of Empirical Model

- Utility-based Discrete / Continuous Choice
- Explicit Spatial Representation of Distance
  - Nutritional attribute distance among meals
  - Demographic distance among households
  - Temporal distance among purchase occasions
- Compact way to incorporate:
  - Differentiation
  - Segmentation
  - Dynamics (habit, learning, addiction...)

# Data

- NPD CREST household level data
- 6 years, 139 households, 5,257 obs
- Top 20 fast food restaurants, plus other
- Outside option is all other spending
- 260 unique food items
- Impute prices with hedonic approach

# Empirical Model

- Discrete / Continuous Choice:

$$\max U = U\left(\sum_j q_{ijn} \phi_{ijn}, q_{ion} \phi_{ion} \mid y_i = \sum_j p_{ijn} q_{ijn} + q_{ion}\right)$$

- Quality index:

$$\phi_{ijn} = \exp\left(\begin{array}{l} (1/\eta)(\gamma_{ijn} + \beta d_{jn} + \pi D_i + \lambda_1 f(\mathbf{M}) + \lambda_2 g(\mathbf{S}) + \\ \lambda_3 h(\mathbf{T}) + \lambda_4 e(\mathbf{M}, \mathbf{S}, \mathbf{T}) + \xi_{ijn} + \mu_{ijn} \end{array}\right)$$

- Indirect Utility:

$$\begin{aligned} V(p/\phi, y) = & \alpha_1 \ln(p_j / \phi_{ij}) + \alpha_2 \ln(1 / \phi_{i0}) + \alpha_3 \ln(p_j / \phi_{ij})^2 \\ & + \alpha_4 \ln(1 / \phi_{i0})^2 + \alpha_5 \ln(p_j / \phi_{ij}) \ln(1 / \phi_{i0}) \end{aligned}$$

# Empirical Model...

- Quality is a function of:
  - Promotional activity
  - Demographics
  - Spatial distance among meals – **M**
  - Spatial distance among households – **S**
  - Temporal distance among events – **T**
  - Random error term

# Distance Metrics

- Approach is synthesis of:
  - Continuous / discrete choice method
  - Distance Metric approach
- Distance Metrics:
  - **M** = Inverse Euclidean distance in nutrients
  - **S** = Inverse Euclidean distance in HH attributes
  - **T** = Inverse Euclidean distance in time

# Empirical Model...

- Solving for expected expenditure (continuous):

$$E[q_{ij}p_j] = \left( \frac{y_i}{\eta / \alpha_3} \right) \left( \frac{\exp\{\delta_{ij}\}}{1 + \exp\{\delta_{ij}\}} \right) (\ln(1 + \sum_j \exp\{\delta_{ij}\}))$$

- Where mean utility is given by:

$$\begin{aligned} \delta_{ij} = & (1/\nu)(\gamma_{ijn} + \beta d_{jn} + \pi D_i + \lambda_1 f(\mathbf{M}) + \lambda_2 g(\mathbf{S}) \\ & + \lambda_3 h(\mathbf{T}) + \lambda_4 e(\mathbf{M}, \mathbf{S}, \mathbf{T}) + \xi_{ijn} ) \end{aligned}$$

- Estimate mean utility function
- Problems: (1) endogeneity of fast food prices and (2) unobserved heterogeneity

# Endogeneity

- Use IV estimator – GMM
- Need to linearize estimating equation:
  - Contraction mapping algorithm (BLP, 1995)

$$m(\delta_{ij}) = \delta_{ij} + \ln(q) - \ln[\tilde{q}(\delta_{ij}, \theta)]$$

- Iterate on  $m$  until convergence
- Estimate using GMM with spatially-weighted prices and exogenous variables as IV

# Unobserved Heterogeneity

- State dependence often confused with unobserved heterogeneity in panel data
  - Factors not observed, but constant within HH
  - Will explain inertia, but left to error term
- Control for unobserved heterogeneity with error-components model:

$$\gamma_{ijn} = \gamma_j + \varepsilon_{in}$$

# Primary and Secondary Impacts

- Need to disaggregate price effects into:
  - Primary impact (category choice, quantity)
  - Secondary impact (brand choice)
- Two ways to disaggregate:
  - Elasticity-based decomposition
  - Unit-sales based decomposition
- Use unit sales to estimate true P/S effect

# Results

- Specification Tests
- Spatio-temporal Model Results
- Elasticity Decomposition
  - By restaurant
  - Overall average

# Specification Tests

Model Comparison	Test Statistic (chi-square)
1. Spatial vs Non-Spatial	89.709
2. HH Spatial vs Spatial	61.715
3. Temporal vs Spatial	4.715
4. Full Model	12.210

# Spatio-Temporal Parameters

Variable	Estimate	T-ratio
ln(price)	-1.713	-79.899
M	-0.033	-3.798
S	0.328	4.493
T	0.799	2.278
MT	-0.022	-3.314
ST	0.188	1.376

# S-T Parameters...

- Price response not -1.0 like others
- Menu differentiation
- Demographic clustering
- State-dependent demand
  - Habitual consumption
  - Learning effects
  - Addiction?
- Menu differentiation attenuated with time

# Elasticity Decomposition

Firm	Elasticity		Unit Sales	
	Primary	Secondar	Primary	Secondar
1. MCD	0.422	0.578	0.845	0.155
2. A&W	0.327	0.673	0.823	0.177
3. SBY	0.315	0.685	0.797	0.203
4. BK	0.360	0.639	0.869	0.131
5. KFC	0.340	0.659	0.842	0.158
6. DQ	0.282	0.718	0.732	0.268
Ave.	0.279	0.721	0.673	0.327

# Conclusion

- Primary effect dominates
  - Promotion not about market share
  - Promotion “grows the pie”
- Fast food firms compete on differentiation
- Fast food firms target similar demographics
- Demand is dynamic
  - Firms can exploit habitual consumption
  - Pricing below marginal cost is rational