Creating Retail Decision Support Systems using Consumer Transaction Data

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Outline

- Introduction
- Quantitative Approaches to Pricing
- Pricing Decision Support Systems
- The Determinants of Price Elasticity
- Micro-Marketing Pricing Strategies
- Experimental Results
- Conclusions

Introduction

Retail Pricing using Transaction Data

Retail Pricing and Promotion

Collecting Transaction Data

Why do companies collect this information?

Category Management

The Next Generation of Transaction Systems

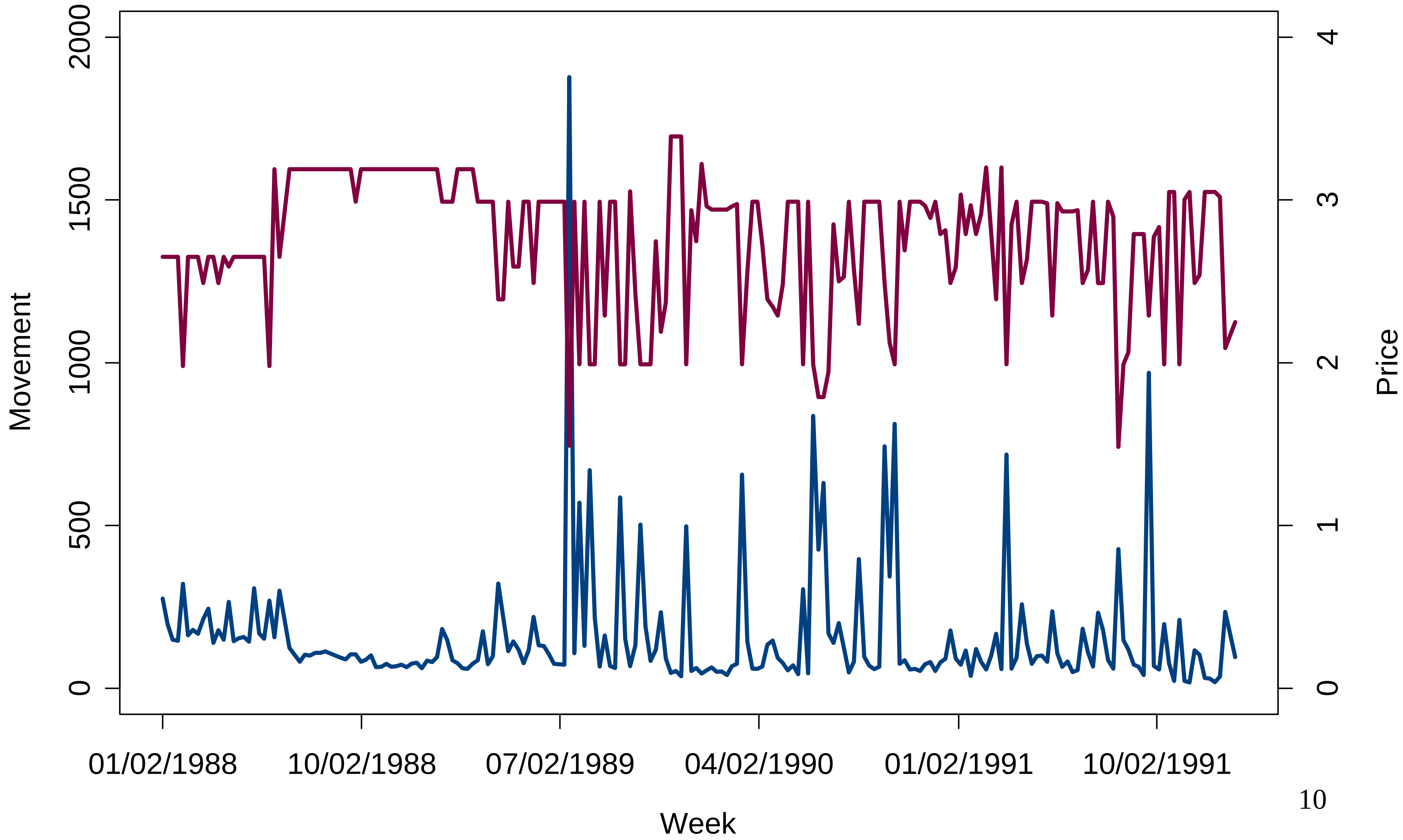
- RFID has the potential to "revolutionize" the marketplace
- Examples:
  - Electronic pricing environments (e.g., e-commerce sites and electronic shelf labels) enable price experimentation in real-time
- What happens to price, product, promotion, and placement?

Quantitative Approaches to Pricing

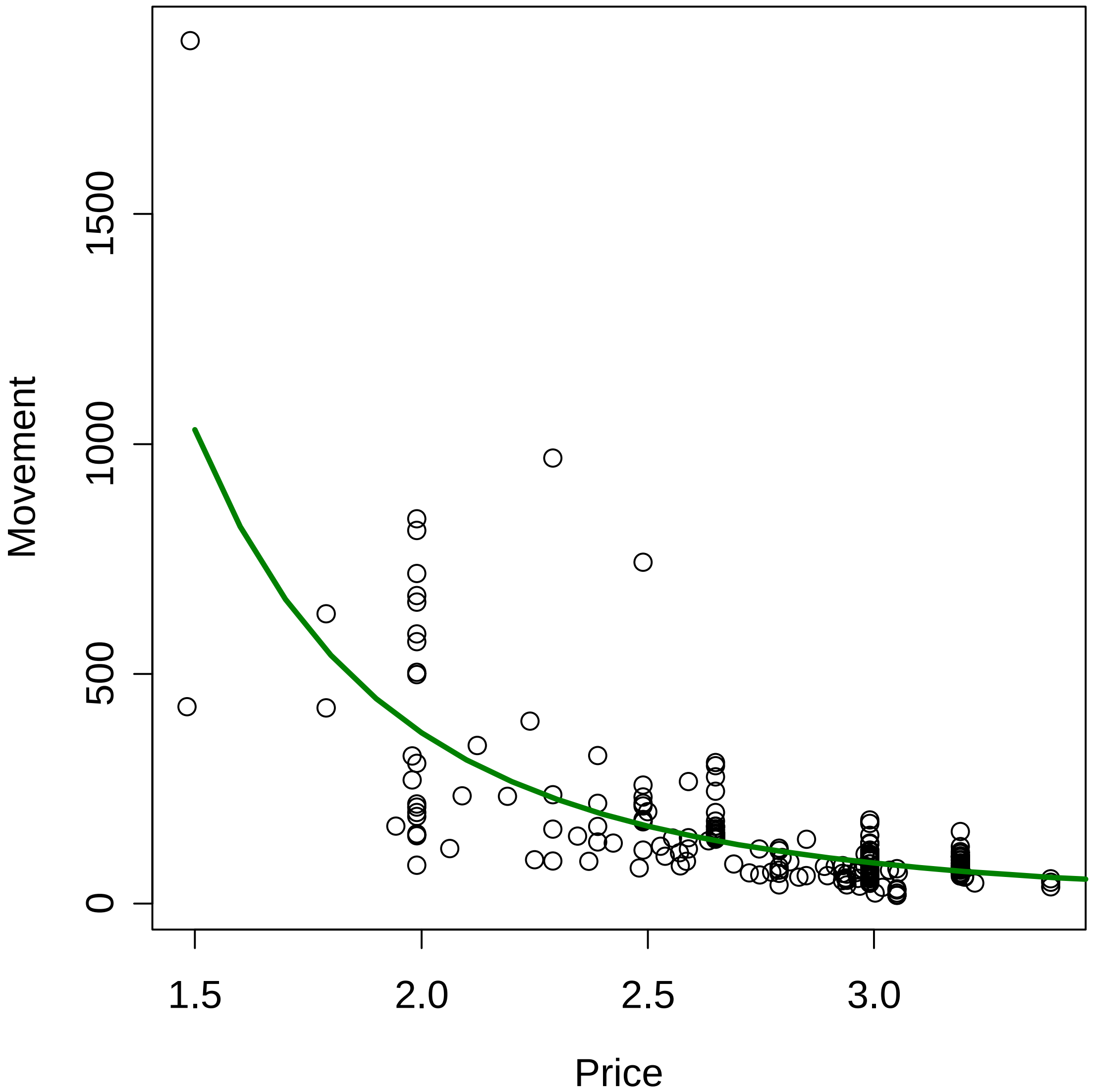
Goal

- How can we better exploit the *installed base* of data:
  - Store level scanner data
- To make these types of decisions at *low cost*:
  - Everyday pricing
  - Zone/store pricing decisions
  - Planning the promotional calendar
  - Trade promotions

Weekly Movement and Price of TropPrem64



Movement vs Price of TropPrem64



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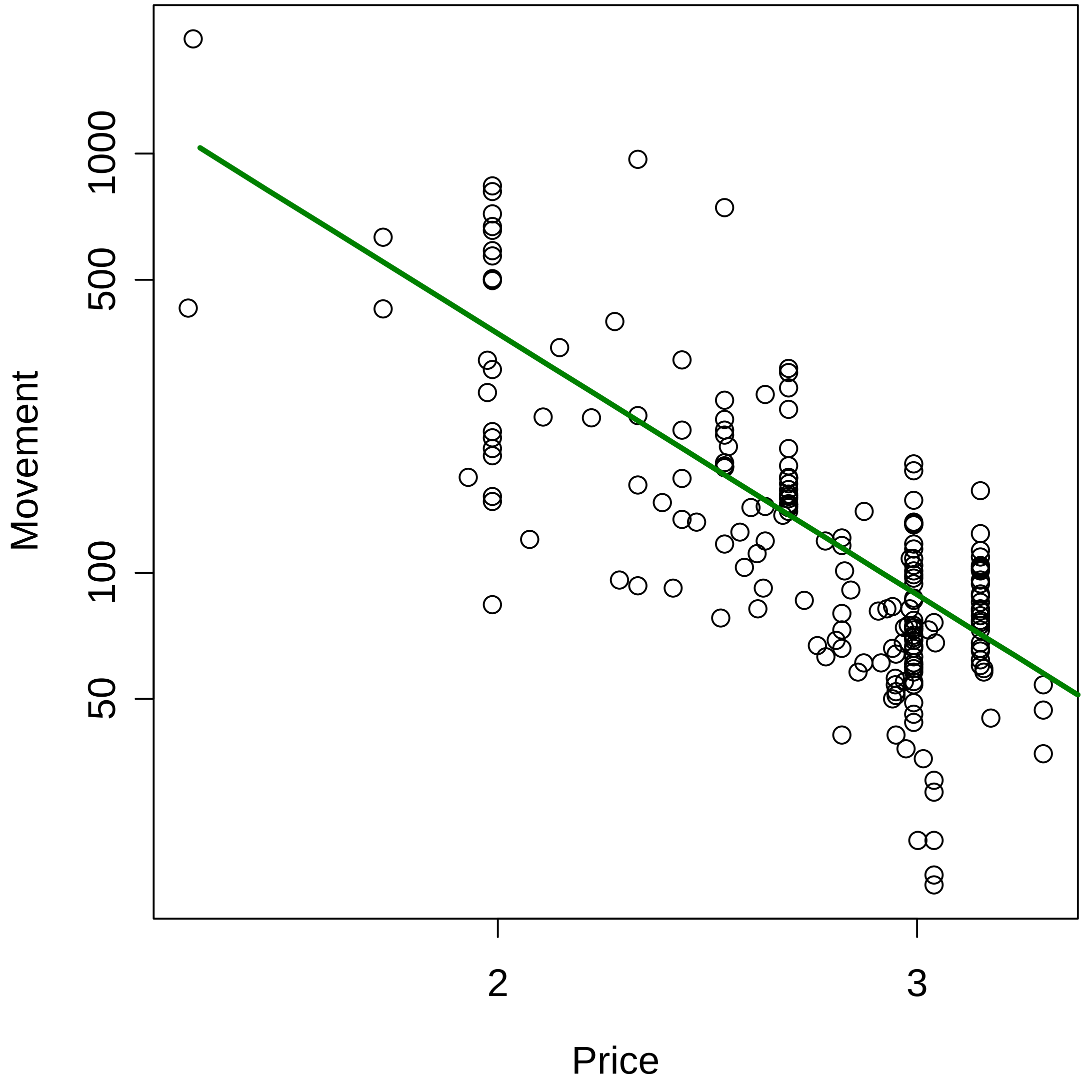
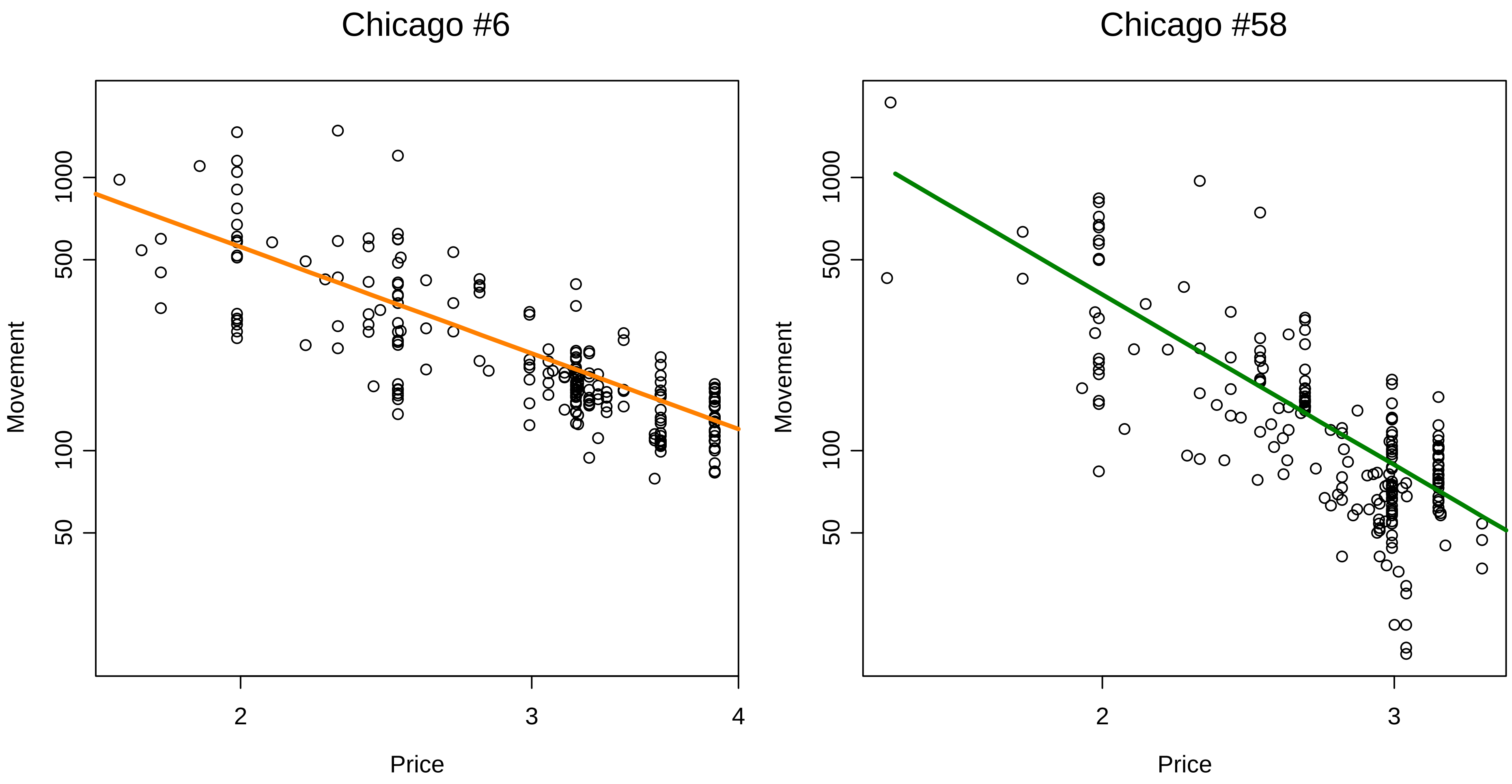
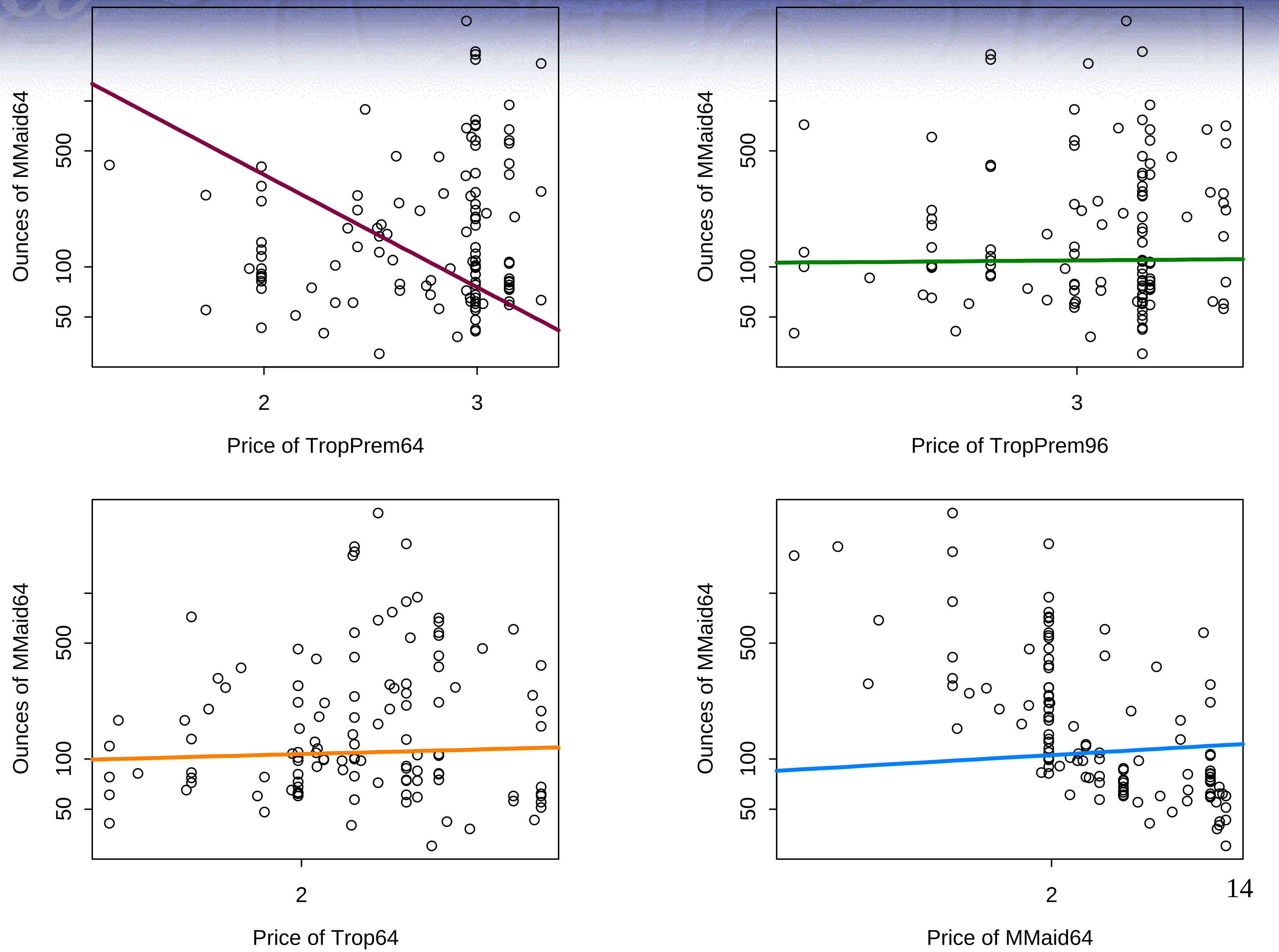


Movement vs Price of TropPrem64




Ounces of MMaid64
500
100
50
2
3
Price of TropPrem64
Ounces of MMaid64
500
100
50
3
Price of TropPrem96
Ounces of MMaid64
500
100
50
2
Price of Trop64
Ounces of MMaid64
500
100
50
2
Price of MMaid64

Statistical Demand Models

- Relate movement of each product to its price changes
- Consider prices of other products within the category
- Estimate the effects of feature ads, in-store displays, and shelf-tags

$$\ln(q_{bst}) = \alpha_{bs} + \mu_{bs}\ln(x_{bst}) + \sum_{i=1}^{M}\eta_{bis}\ln(p_{ist}) + \varphi_{bs} f_{bst} + \delta_{bs} d_{bst} + \varepsilon_{bst}$$

quantity volume

total store expenditures

own + cross price effects

out-of-store features/ads

in-store deals/ads

Evaluating This Approach

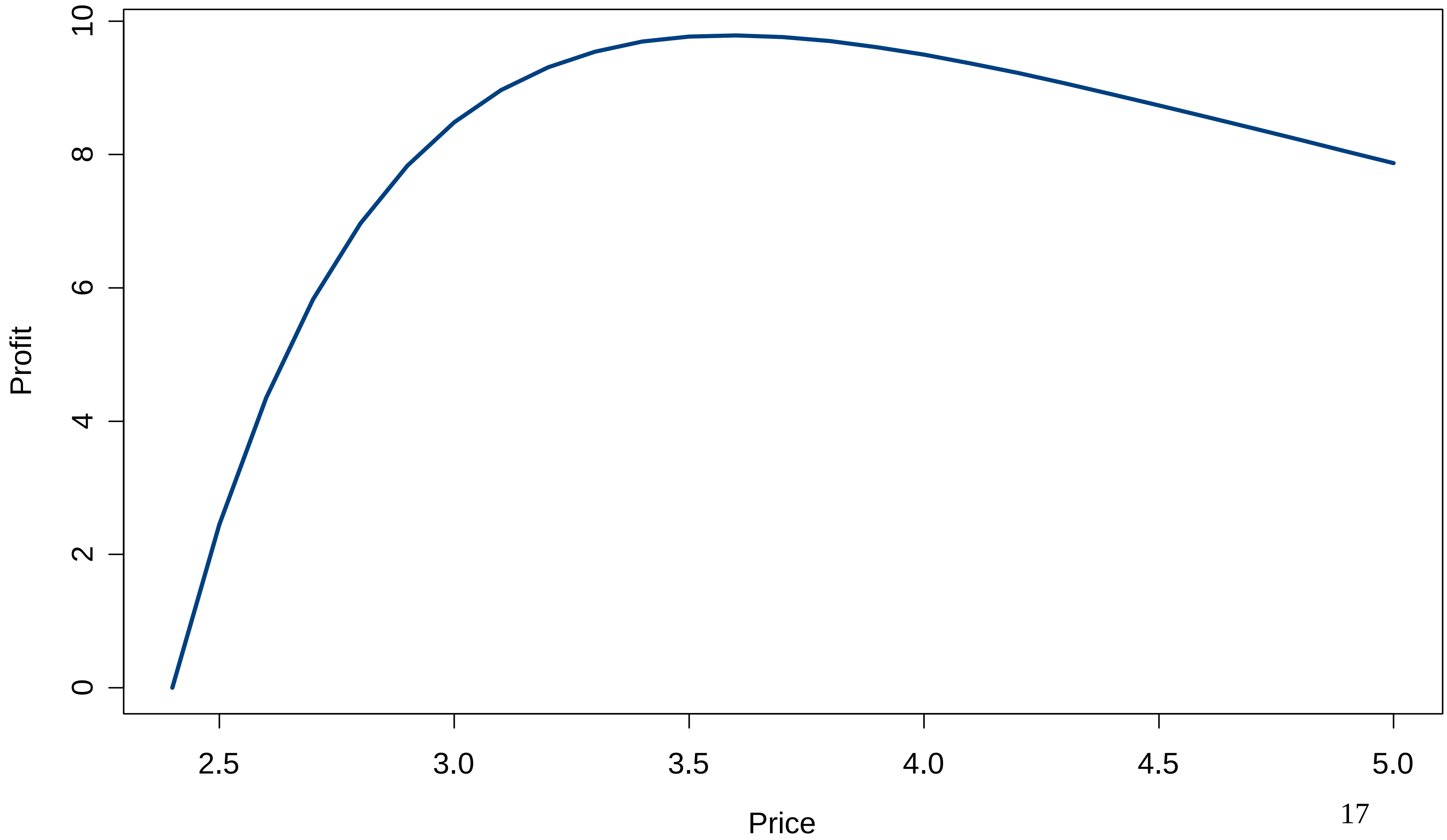
Advantages

- Can “learn” about consumers based on their past behavior
- Leverages data warehouse
- Summarizes complicated behavior
- Easy to use

Disadvantages

- Complicated to build
- Forecasts can be wrong
- Can conflict with our intuition
- How do we “prove” the models are correct

Profitability of TropPrem64 at Pittsburgh #637 (Cost=$2.40)



Decision Support Systems for Retail Pricing

Massive Datasets and

Massive Decision Problems

Goal

- How can we better exploit the *installed base* of data:
  - Point-of-Sale Data (Scanner/Loyalty programs)
- To make these types of decisions at *low cost*:
  - Everyday pricing
  - Zone/store pricing decisions
  - Planning the promotional calendar
  - Trade promotions

Decision Support Systems must be...

- Simple
- Robust
- Easy to control
- Adaptive
- As complete as possible
- Easy to communicate with

See Little (1970, 1979)

Pricing Decision Support

Market Simulation Model

Decision Variables

Brand Description	Carton Price	Feature Ad	In-Store Display	Expected Movement	Wholesale Cost	Profits
1 TropPrem64	$2.89	No	Yes	12248	$1.75	$217.27
2 TropPrem96	$3.79	Yes	No	21139	$3.32	$103.01
3 TropReg64	$2.29	No	No	3566	$1.49	$44.64
4 MinMaid64	$2.24	No	No	8459	$1.67	$75.52
5 Store64	$1.79	No	No	9106	$1.20	$83.96
					Category Profits:	$524.41

- Dynamically forecast movement, revenue, profit
- Manipulate price, display, advertising, wholesale cost
- Produce forecasts for store, chain, zone level
- Provide multi-week planning horizon
- Measure both acquisition and wholesale costs
- Manage promotional calendars
- Optimizer to suggest best pricing strategy (either by groups or all)

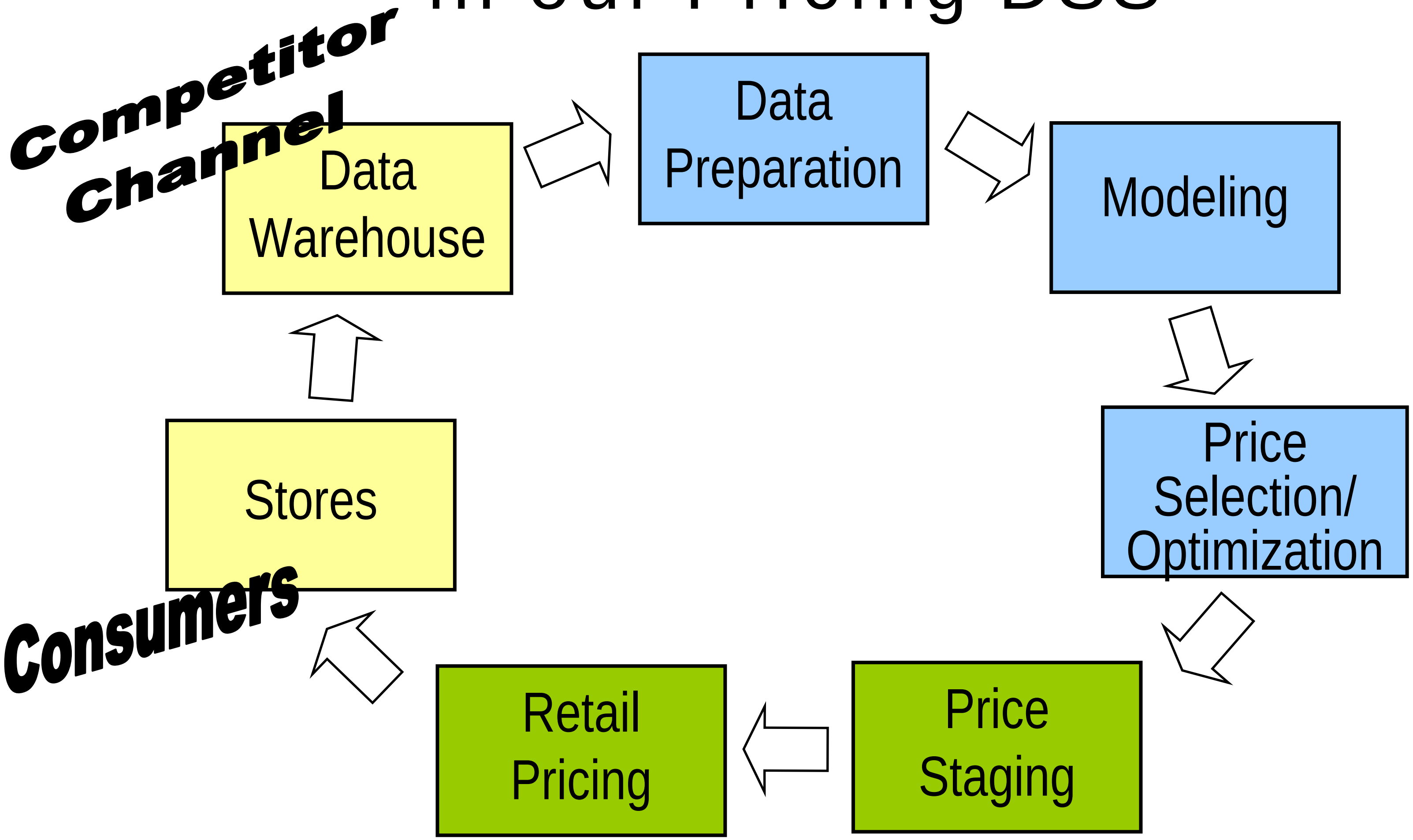
Pricing DSS

- Detect price response using historical transaction data
- Forecast movement, revenue, profit in real-time
- Produce weekly forecasts at the chain, zone, and store level
- Manipulate price, feature, display, and wholesale cost in an interactive environment
- Change prices for groups of products
- Provide a multi-week planning horizon in order to manage promotional calendars
- Work with incomplete information
- Coordination across categories and stores
- Integrate information from many sources
- Scalability
- Recommend price strategies

Problems

- **Data**
  - Historical data from the warehouse
  - Current inventory
  - Anticipated prices from promotions/competitors
  - Continually changing inventories/product assortments
- **Modeling**
  - How to model 200-10,000 SKUs per category?
  - What about 100-2,000 stores in the chain?
  - Over 300 categories per store?
  - Seasonal patterns
- **Inference**
  - Prevent model from making bad predictions
  - Need to consider promotional calendar
  - Making Optimization Decisions

Illustrating our Information Flow in our Pricing DSS



Companies offering Pricing Optimizers

Company	Location	Website	Founded
ACNielsen	New York, NY	Acnielsen.com	1923, 1995*
Applied Predictive Technologies	Arlington, VA	predictivetechnologies.com	1999
DemandTec	San Carlos, CA	Demandtec.com	1999
I2	Dallas, TX	i2.com	1988
Evant	San Francisco, CA	nonstop.com	1994
KhiMetrics	Scottsdale, AZ	khimetrics.com	1993, 2000*
Knowledge Support Systems	Florham Park, NJ	kssg.com	1993
Manugistics	Rockville, MD	Manugistics.com	2001*
Marketmax	Wakefield, MA	marketmax.com	2003*
Maxager Technology	San Rafael, CA	maxager.com	
Metreo	Palo Alto, CA	metreo.com	2000
ProfitLogic	Cambridge, MA	profitlogic.com	1984, 2001*
Retek	Minneapolis, MN	retek.com	1986, 1996*
Zilliant	Austin, TX	zilliant.com	1998

Our Modeling Contributions

- Hierarchical Bayesian Models
  - Estimation of product X store level models
  - Use of Monte-Carlo Markov Chain methods for estimation and inference
- Real-time Inference
  - Use of simulated estimates incorporates uncertainty over parameter estimates and prior information. Avoids approximations commonly used in practice.
- Informative Priors
  - Shrinkage estimators allow borrowing of information across stores to improve estimates
  - Allow managers and analysts to incorporate prior information about parameter values and optimal prices

The Determinants of Price Elasticity

Why do price elasticities vary?

- Do all stores have the same price response profiles?
- What explains these differences?
- How do you customize a pricing strategy that appeals to a store's trading area?

Implementing a Micro-Marketing Strategy

Are there really differences across stores and brands?

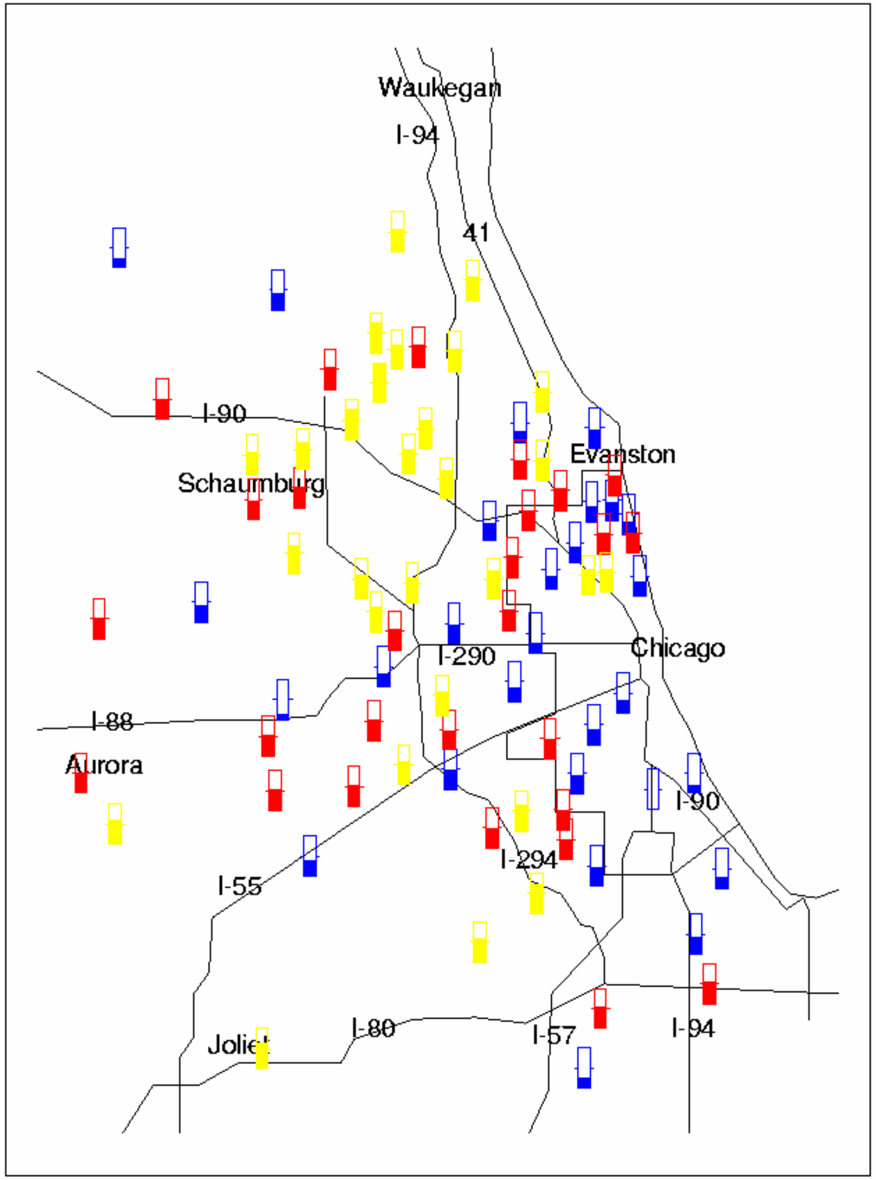
Legend:

Very Price Sensitive

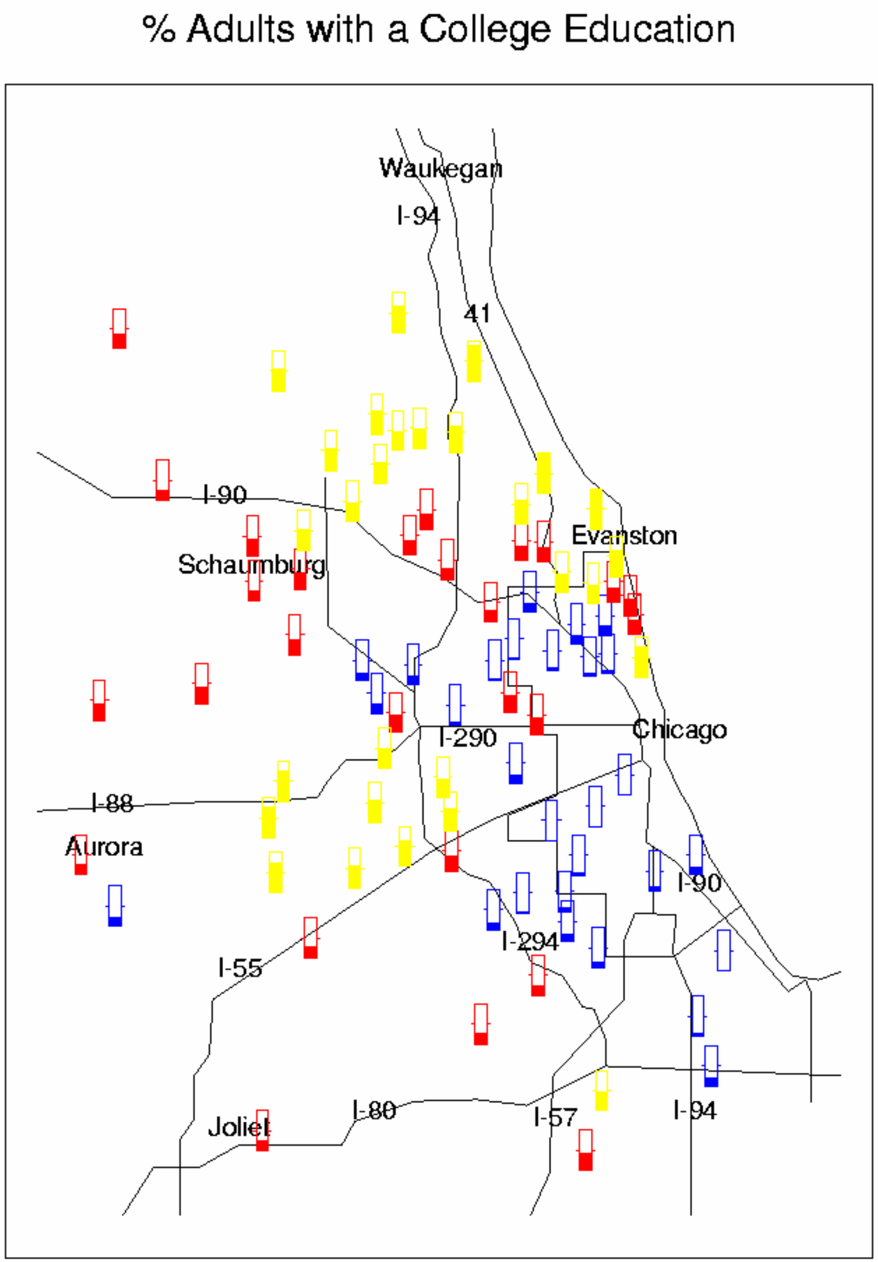
Moderate Price Sensitive

Not Price Sensitive

Category Price Elasticity



What explains these differences?
Demographics +
Unique Store Profiles



Legend:

- Few College Educated Adults
- Moderate Education Levels
- Highly Educated Areas

©

Summary of Results

+	Elderly	Can devote more time to price search and shopping
-	Education	Higher opportunity costs, less attention to shopping
+	Ethnic	Proxy for other causal factors
?	Income	Dependent upon category
+	FamilySize	Larger share of disposable income on groceries, increased returns to search
+	Working Women	Tighter constraints on household budget
-	House Value	Fewer income constraints
-	Competitor Dist.	Isolated stores less price sensitive
+	Relative Volume	Consumers self-select for location and convenience or price and assortment

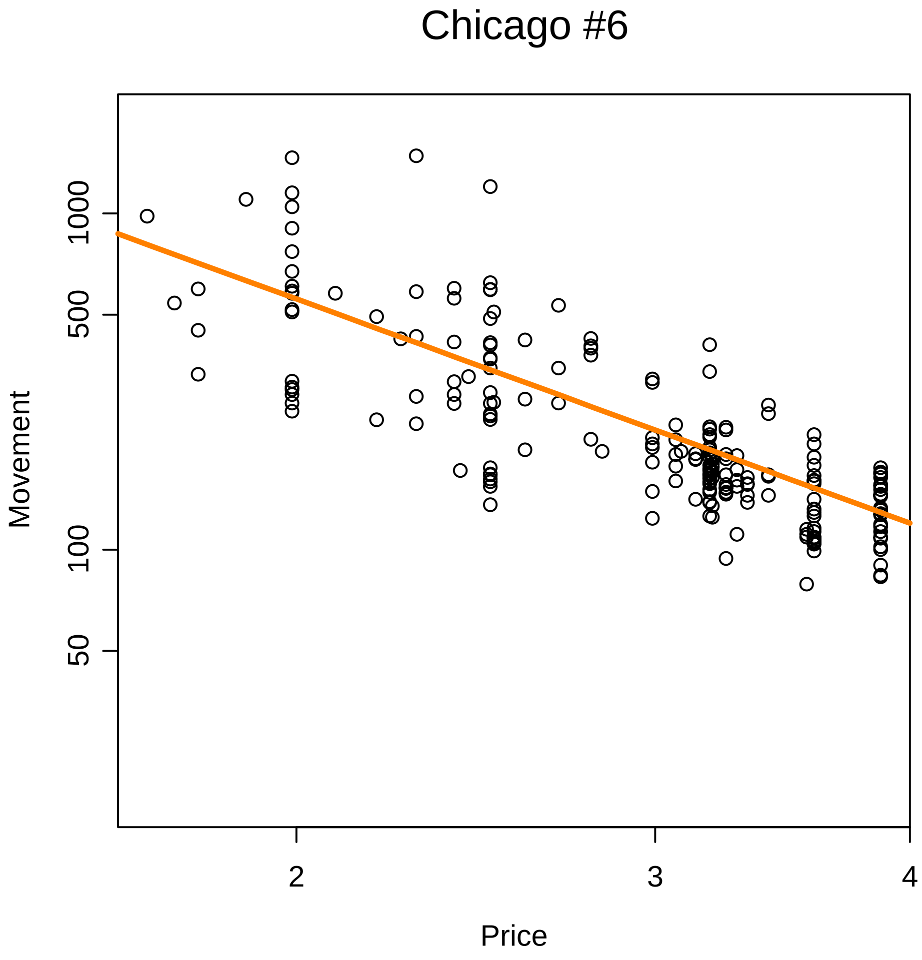
Micro-Marketing Pricing

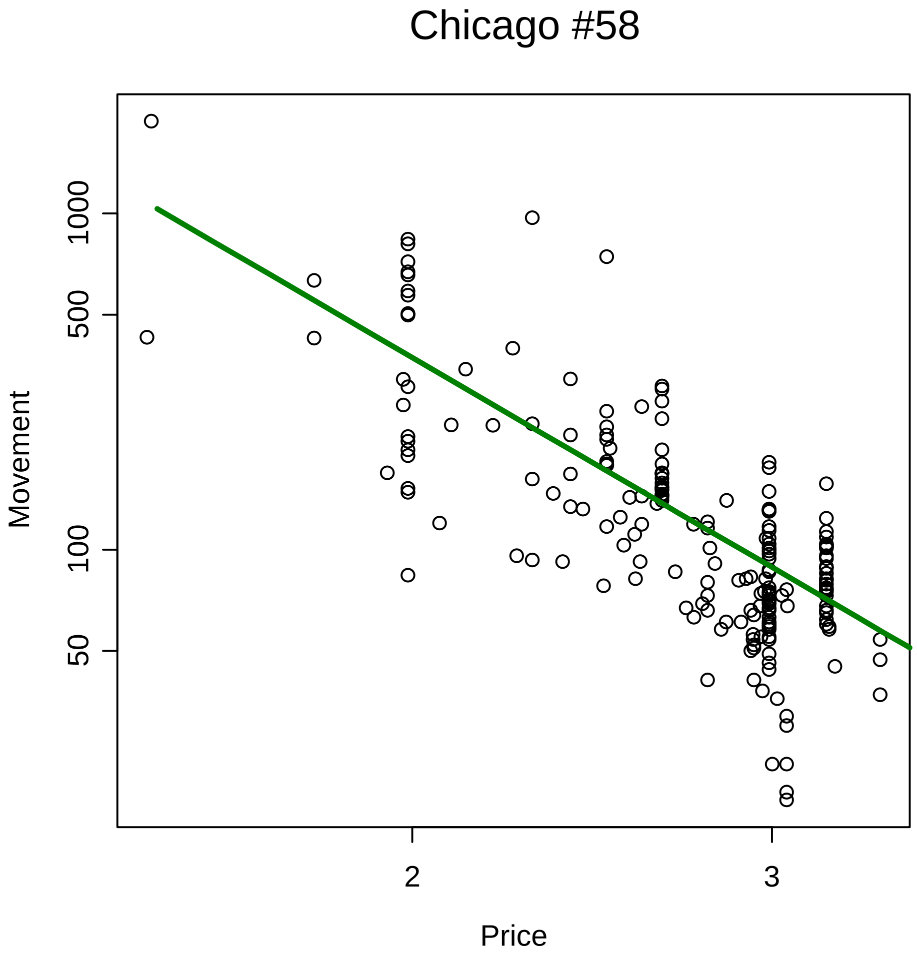
Developing Models for every Store x Item

Store-Level Strategies

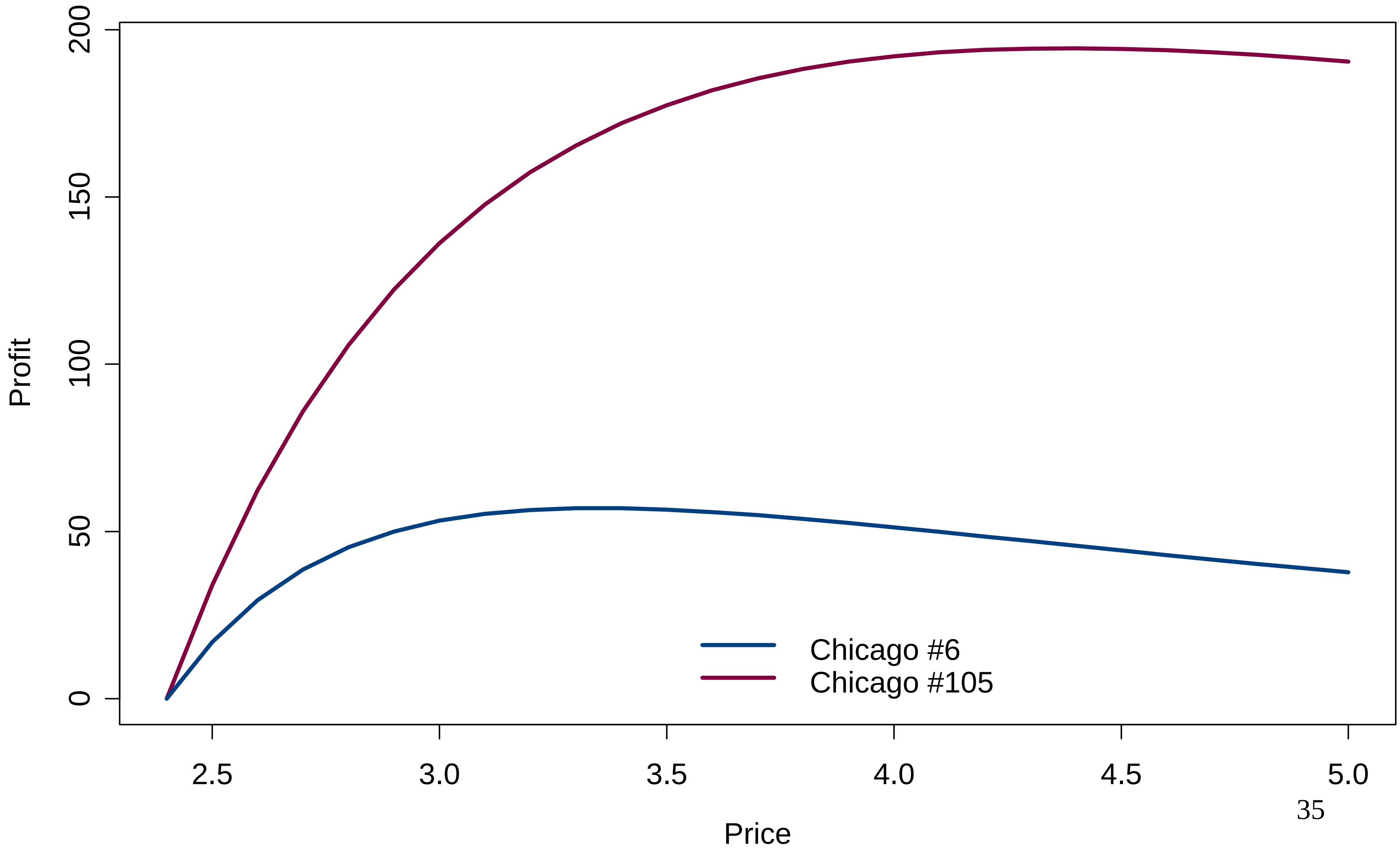
- The previous results show that there are differences in how consumers respond to price changes across stores
- How do you cater to neighborhood store preferences?
  - Different product assortments
  - Store-level everyday pricing
  - Unique in-store promotions
  - Customized store features

Movement vs Price of TropPrem64





Profitability of TropPrem64 (Cost=$2.40)



What is the problem with the usual regression approach?

Difficult to acquire reliable estimates for individual products at store-level

Model Dimension

Stores x Brands x Regressors

= 100 x 10 x 14 = 14,000 parameters

Data Dimension =

Stores x Brands x Weeks

= 100 x 10 x 156 weeks = 156,000 data points

Frustrated use of this data in industry!

What can be done?

Two extremes:

<u>Pooling</u>
Ignore all store differences

<u>Individual Store Models</u>
Difficult to estimate

Our Solution:

<u>Shrinkage</u>
Exploit commonalties across stores to improve individual store estimates

Hierarchical Bayesian Setup

$$y_{1,1} = X_{1,1}\beta_{1,1} + \varepsilon_{1,1}$$

$$\vdots$$

$$y_{s,m} = X_{s,m}\beta_{s,m} + \varepsilon_{s,m}$$

$$\vdots$$

$$y_{S,M} = X_{S,M}\beta_{S,M} + \varepsilon_{s,M}$$

$$\beta_{s,m} \sim N(\overline{\beta_m}, V_\beta)$$

How do we set our prior?

Quantity

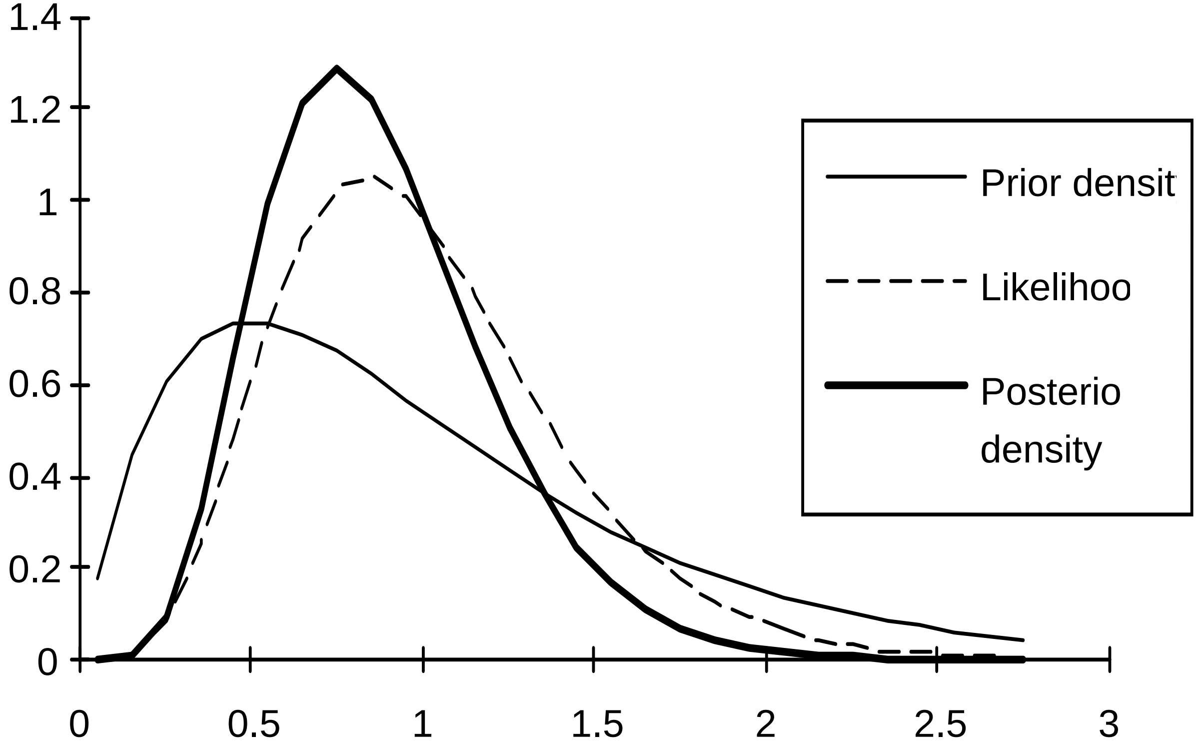
Expenditures,
Price, Feature, Deal

Elasticities

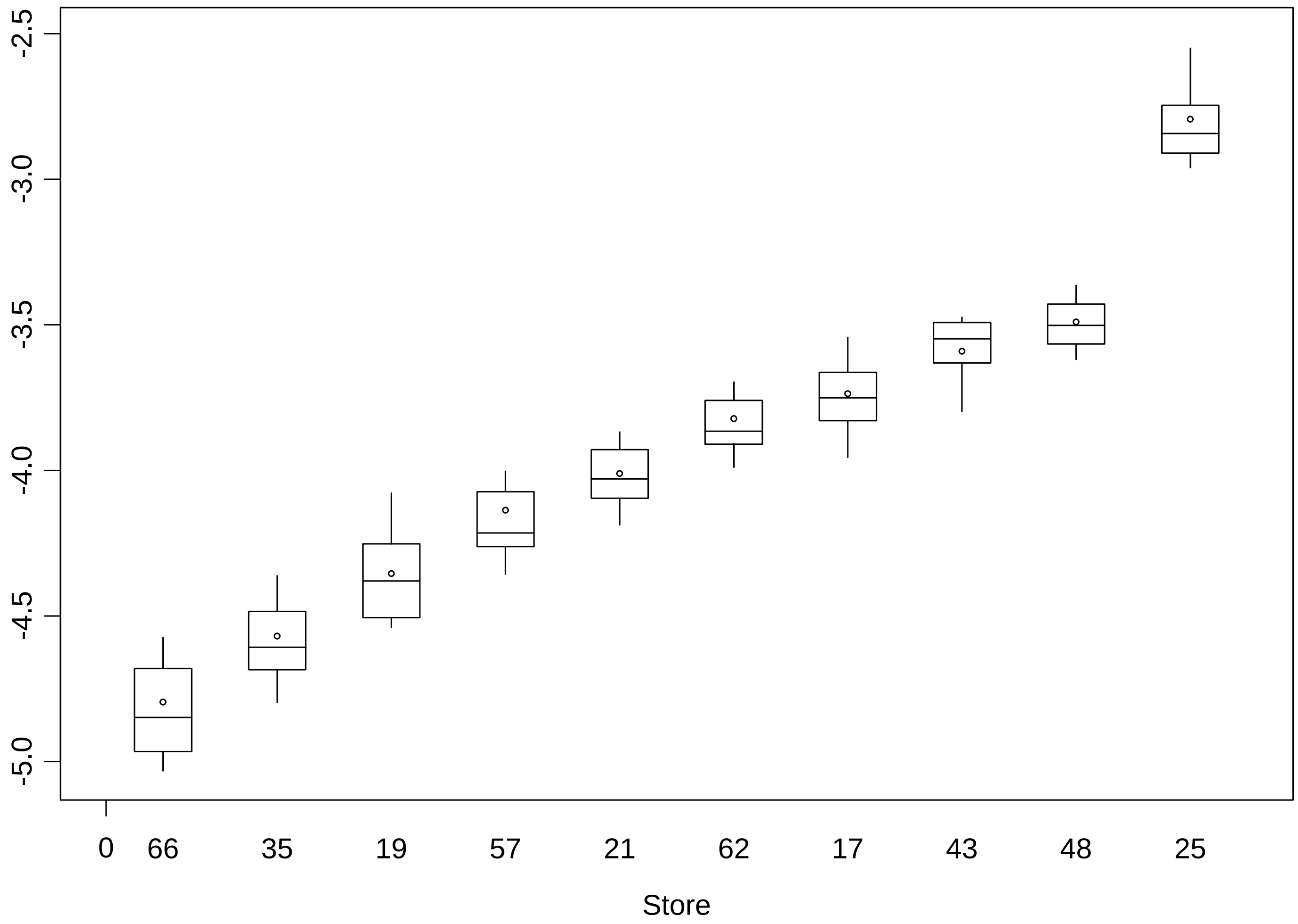
Shrinkage estimates

- We are exploiting commonalities across the stores to improve the estimates
- Our approach incorporates several new theoretical developments:
  - Shrinkage estimation using Monte Carlo Markov Chain methods
  - General approach to estimation
  - Incorporation of informative priors to specify similarities across stores, model structure, and information about price solution

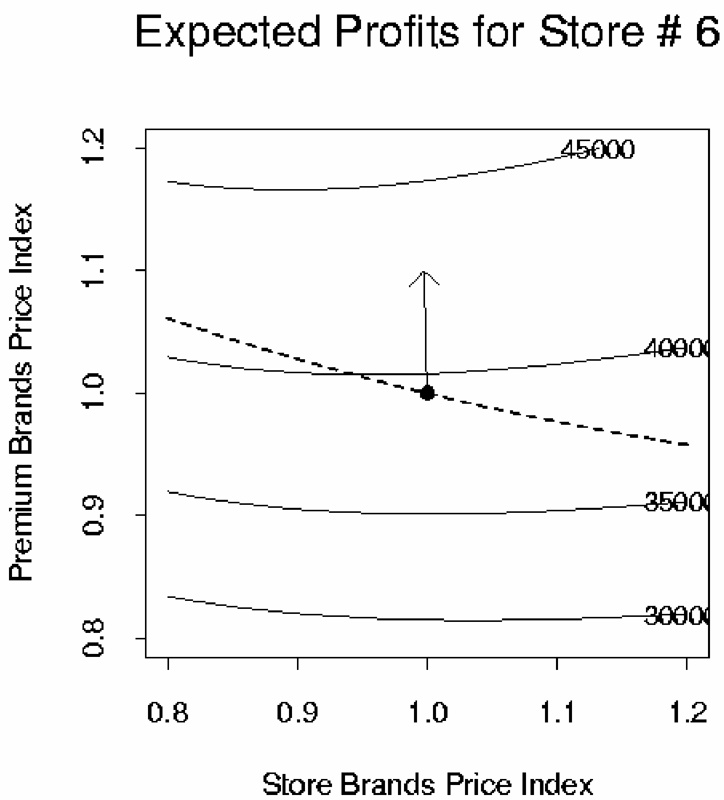
Visualizing the Priors Effect: Shrinkage toward the Prior

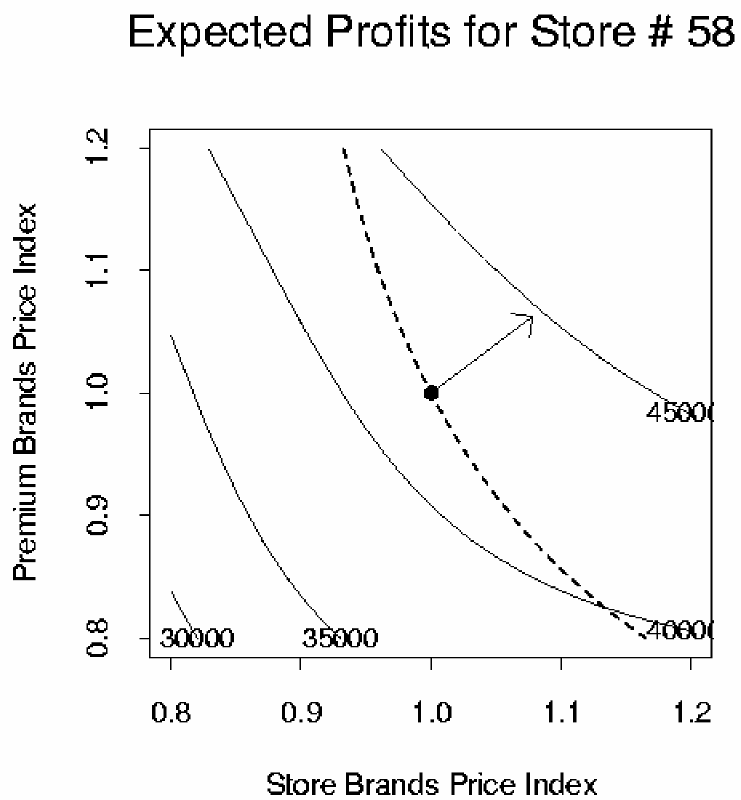


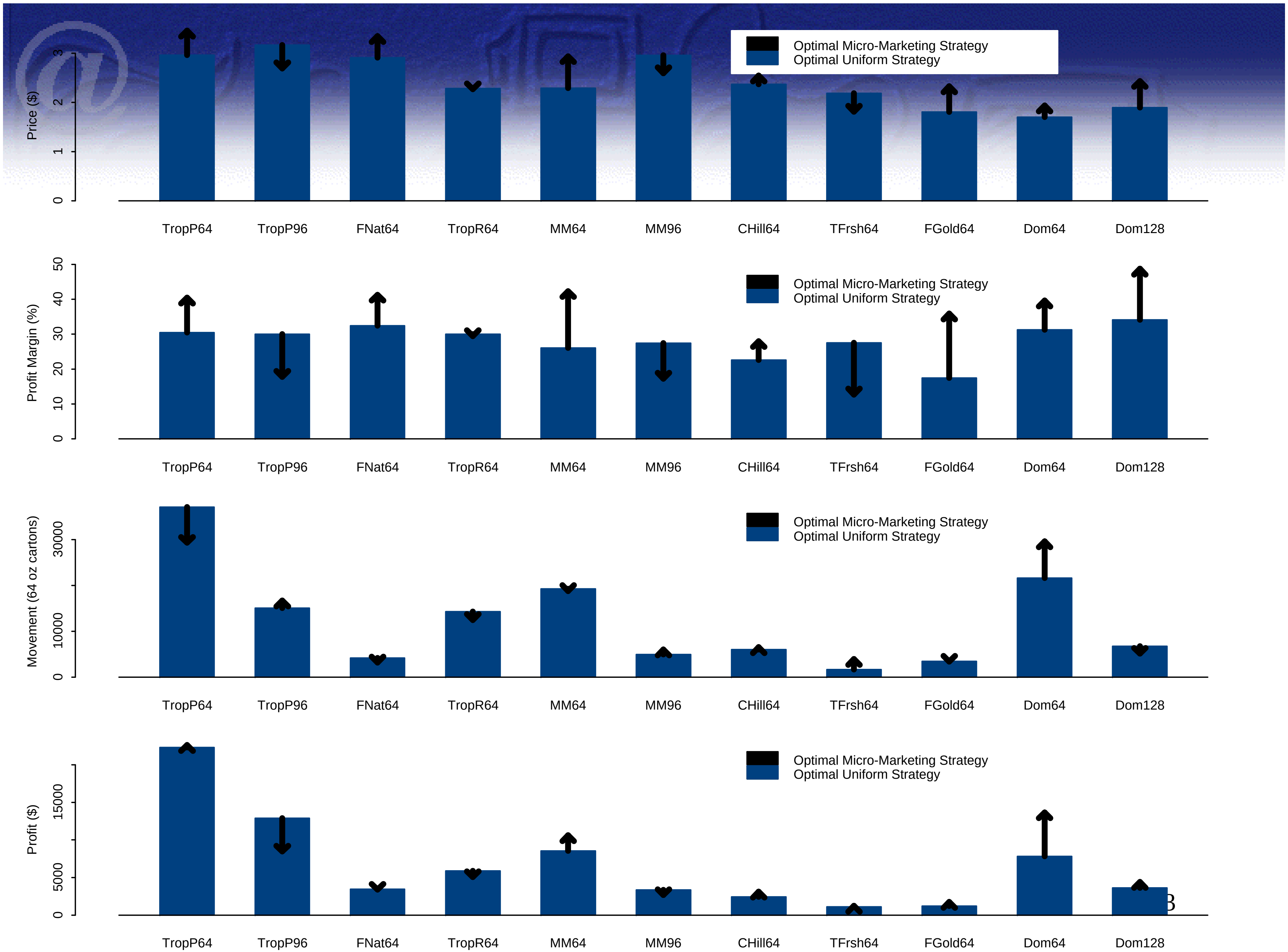
Variation in Tropicana Own Price Elasticity



Setting Store-Level National Brand/ Store Brand Price Gaps

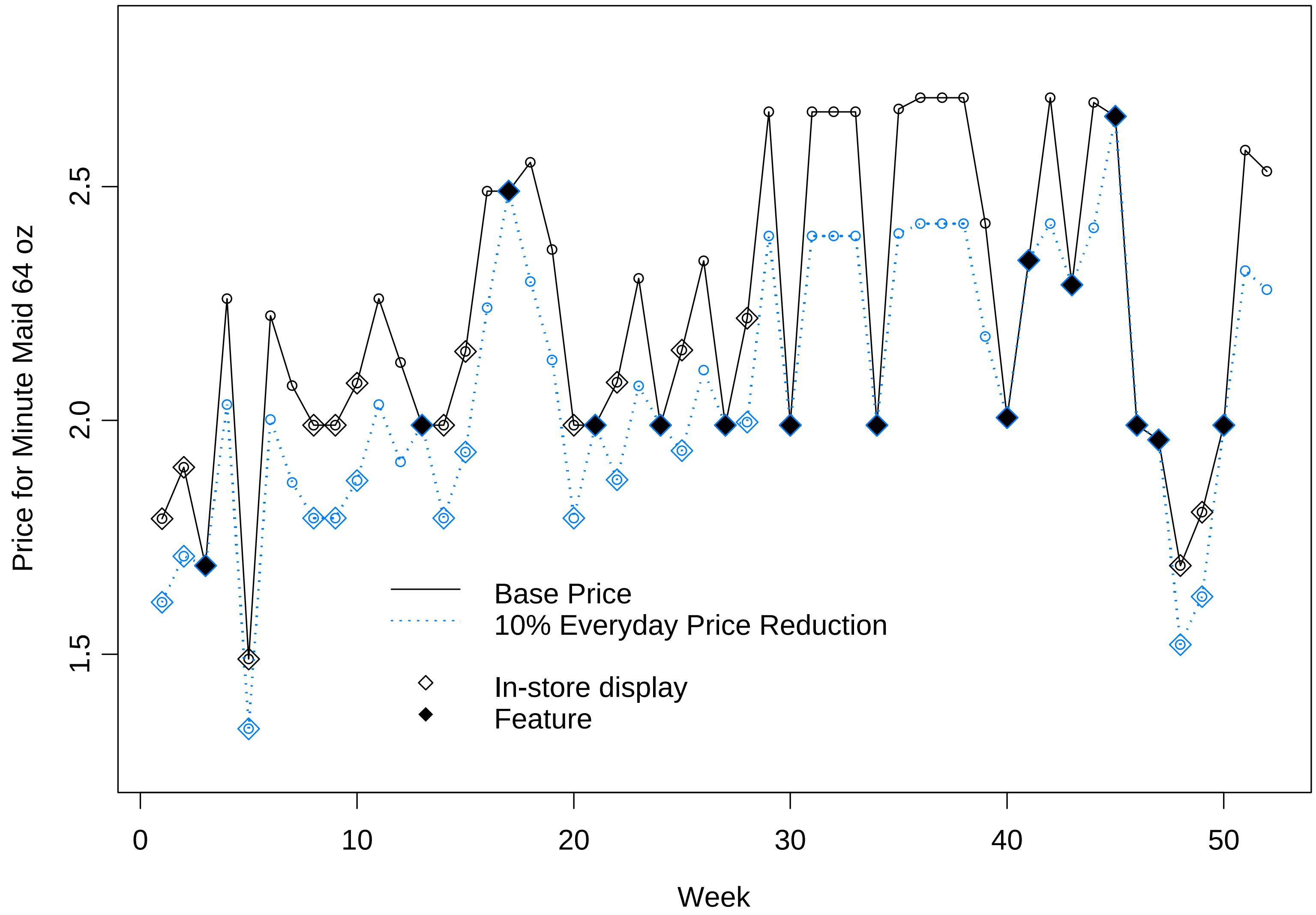






Optimal Micro-Marketing Strategy
Optimal Uniform Strategy
Price ($)
0
1
2
3
Profit Margin (%)
0
10
20
30
40
50
Movement (64 oz cartons)
0
10000
30000
Profit ($)
0
5000
15000
TropP64
TropP96
FNat64
TropR64
MM64
MM96
CHill64
TFrsh64
FGold64
Dom64
Dom128

Effects of a reduction in the price multiplier

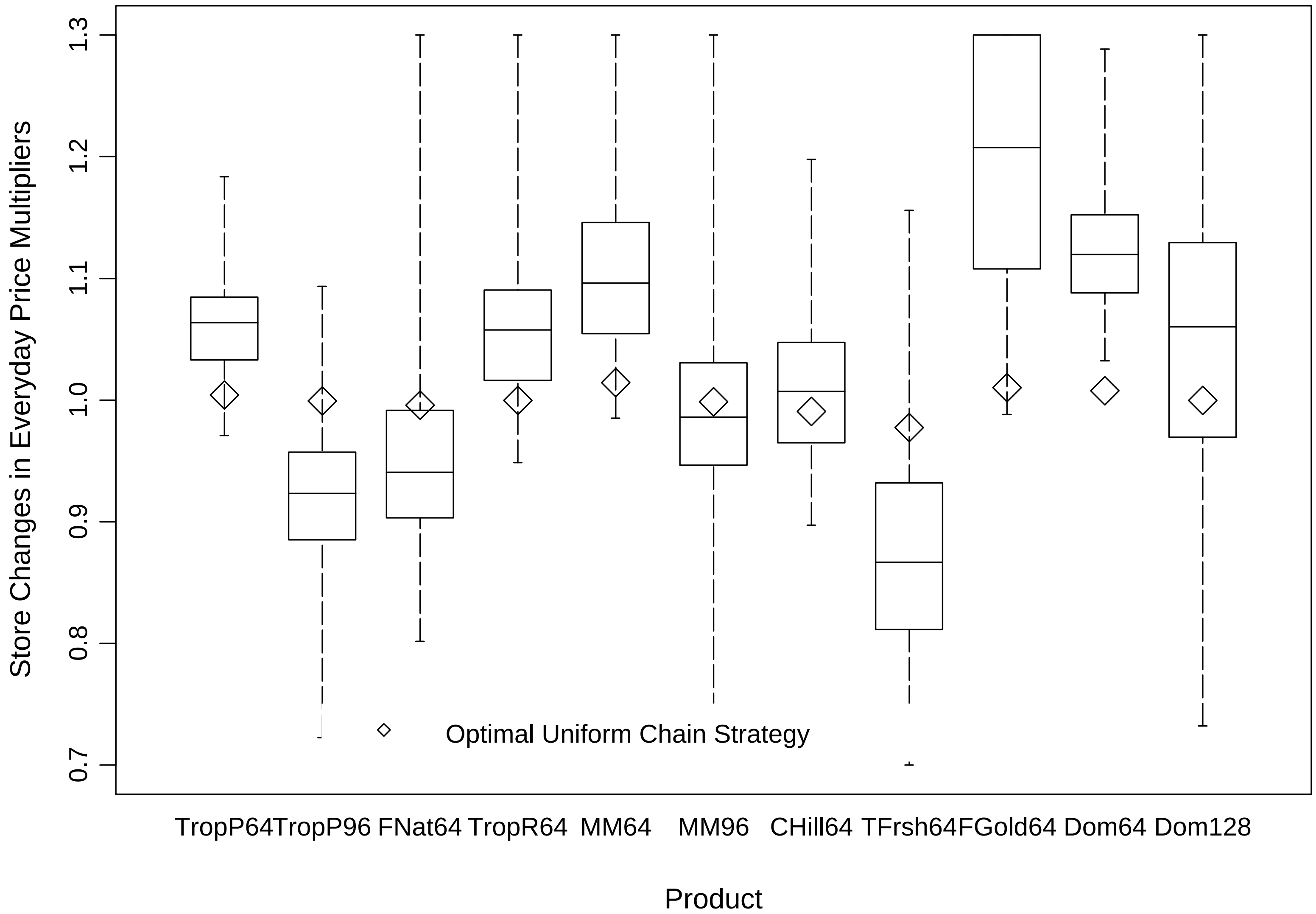


Expected Profits from Micro-Marketing Pricing Strategies

#	Description of Pricing Strategy	Expected Profits	Relative to a Uniform Chain Pricing Strategy: Expected Increase	% Change in Expected Profits	Prob[Expected Increase >0]
	Uniform Prices across all Stores	$3,330,900 (11,900)			
1	Optimal Uniform Strategy	$3,344,100 (11,600)	+$13,200 (1,700)	+.4% (.1)	1.00
2	Optimal Micro-Marketing Strategy	$3,459,000 (19,400)	+$128,100 (18,800)	+3.9% (.6)	1.00
3	Optimal Micro-Marketing Strategy with constraints at the Chain-level	$3,481,600 (20,900)	+150,700 (20,200)	+4.5% (.6)	1.00

Note: The standard deviation of the posterior are given in parentheses below the posterior means.

Effects of Price Changes from an Optimal Pricing Strategy



Findings

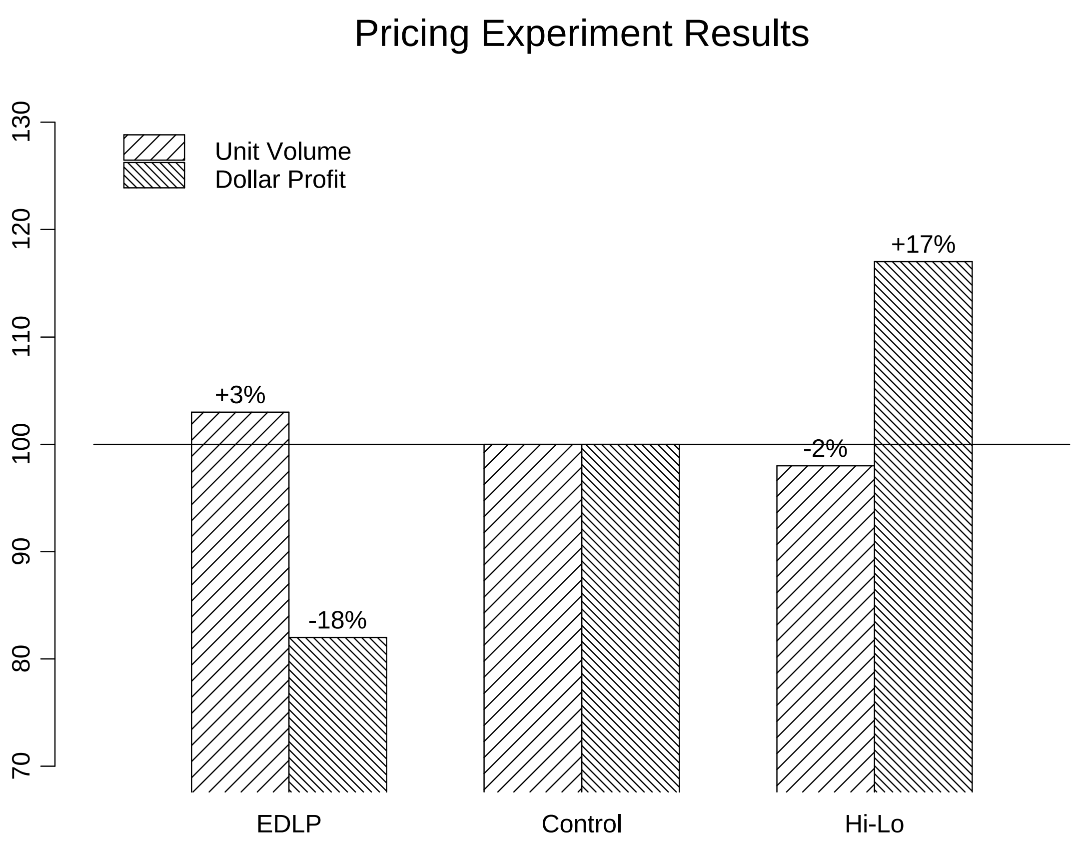
- Every store is different and has its own price response profile
  - We can identify the price profile of a store using historical data
  - The most important determinants are store demographics (to a lesser extent competitive characteristics)
- Micro-marketing presents a rich environment for store-level pricing
  - Do not simply increase all prices up or down
  - Manage the price gaps between the brands to encourage substitution towards more profitable baskets or products
- Can recommend better or optimal pricing strategies

Experimental Results

An Experimental Approach

- A simple and reliable method (albeit costly) to find a better pricing strategy is through experimentation:
  – Divide 86 stores into 3 treatments: Control (leave prices unchanged), EDLP (decrease prices by 7%), and Hi-Lo (increase prices by 7%)
  – Measure change in profits and movement and compare them to control group

Experimental Results



EDLP vs Hi-Lo

- Clearly Hi-lo is much more profitable
  - ***Why was Dominick's hesitant to implement these results?***

- What is driving these results is price sensitivity
  - If products were more price sensitive than EDLP would work (price decreases would dramatically increase sales)
  - ***What determines price sensitivity?***

Elasticity Based Zone Assignments

	Low Price Zone	Medium Price Zone	High Price Zone
High Price Sensitivity	2	14	4
Medium Price Sensitivity	6	25	11
Low Price Sensitivity	1	10	10

Conclusions

Findings

- The Retail Market is moving towards integrated supply-channel and demand-based pricing solutions
- Many challenging modeling problems have been addressed, however there are still much to be done
- Strong potential for increased profitability and efficiency that can benefit both the retailer and the consumer