# WHATS on Your menur 

Finding the value in your customer's complex choices

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## Introduction



## Ask or Observe

In-market product tests
Direct questions
Wait and see what your competitors do
Monitor what they are chatting about online
Hypothetical tests, such as conjoint analysis

## Standard Choice Models

## Which one of these options would you buy?

| Fettucini Alfredo |
| :--- |
| with Chicken |
| Includes 1 side |
| dish |
| $\$ 10.99$ |



| Teriyaki Salmon |
| :--- |
| Includes 2 side |
| dishes |
| $\$ 14.99$ |
|  |
|  |

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## Benefits of Choice Modelling

Able to test large number of combinations at little cost

Resulting models provide simulation capability, even for concepts not tested directly

But...
They are limited to a single independent choice


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## But what about these situations?

Cell phone plan/phone purchase
Bundling telecommunications
Restaurant menus
Choosing features to add to a new car
Multi-subscription bundles
Business software suites
Cruise inclusions vs. add-ons
Insurance policy riders
Transportation
...and on and on

## Menu Based Choice

Menu Based Choice exercises allow you to simultaneously measure multiple correlated decisions in situations where the consumer "creates" their own product bundle.

## Delmonico's, New York City, 1899

Goal: Create a model for each item on the menu

Menu choices dependent on its price, configuration, but also other items price, configuration.


PD-US, https://en.wikipedia.org/w/index.php?curid=5848801

## Top Sky deals in February

| GREAT VALUE | NETFLIX INCLUDED | ONLINE EXCLUSIVE OFFER |
| :---: | :---: | :---: |
|  |  |  |
| Sly Sky Entertainment TV | Sky Entertainment TV + Ultimate On Demand \& Netflix | Shy $\begin{aligned} & \text { Sky Entertainment TV + } \\ & \text { Sports + HD }\end{aligned}$ |
| $\checkmark$ Sky Entertainment TV | $\checkmark$ Entertainment \& Box Sets | $\checkmark$ Entertainment \& HD \& Sports |
| $\checkmark 388$ channels + 20 HD | $\checkmark 388$ channels + 20 HD | $\checkmark 430$ channels + 62 HD |
| £22.00 | f34.00 | £50.00 sly |
| for 18 months | for 18 months | for 18 months |
| Prices may change during this period | Prices may change during this period | Prices may change during this period |
| (usually $£ 27.00$ ) | (usually $£ 39.00$ ) | (usually $£ 61.00$ ) |
| Upfront cost: $£ 25.00$ | Upfront cost: $£ 20.00$ | Upfront cost: $£ 25.00$ |
| See deal | See deal | See deal |
| Over 300 channels including exclusive Sky Originals | Over 1,000 shows on demand from Sky Box Sets and Netfix all in a single pack - in stunning HD. | Watch live action from all 8 Sky Sports channels, in HD as standard, with the Complete Sports pack. |



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Ipsos



## Benefits of Menu Approach

Still get price elasticity, cross effects, all the benefits of conjoint models
But now we can model the real-world complexity of actual decision making process

## Case study



Founded
in 1965


850
restaurants
c. 60 countries worldwide 80+ UK restaurants


Value for money, quality and enhanced customer dining


Commissioned research to optimise the pricing of key dishes on their menu in order to maximise profit

In addition to individual dishes, Set menu deals which bundle together multiple courses also offered

Analysis needed to further take in to account cannibalisation to and from key competitors

## .

## Study details

Sample


Choice Design


## Questionnaire flow

## 1 . Screening

U\&A demographic and screening questions

Most recent occasion
Satisfaction ratings

## 2. Stage 1 - CBC

## Determine cannibalisation to/from TGI Fridays

Choose most preferred competitor
menu (Fixed price - Single choice)
Choice Based Conjoint exercise with
TGI Fridays menu vs. winning competitor menu

Only TGI Friday's prices changing

## 3. Stage 2 - MBC

Determine choice/price sensitivity within the TGI Fridays menu

MBC exercise with the price of all dishes varying each time

Option to choose none of the dishes and leave the restaurant

## Example screenshots

Stage 1 - CBC

$\theta$


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Stage 2 - MBC


[^0]
## Modelling considerations


$\square$ Given the choices above, I would leave this restaurant without eating

Note: Survey data on last occasion suggested c.96\% chose a main course

## Analysis Stage 1



CBC model to gauge change in footfall as a result of changes in menu price

At the base case TGI Fridays obtained $32 \%$ preference share

Changes to this value would alter the number of customers that would go in to a TGI Fridays in an average month which then feeds in to profit calculation

## Analysis Stage 2



MBC model to gauge change in preference for the different menu items as price changes

Data weighted by how often they go to TGI Fridays

## Checking results

Sensitivity of each item as other items change price

|  |  | Effect on dish |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | S1 | S2 | S3 | S4 | S5 | VM1 | VM2 | M1 | M2 | M3 | M4 | M5 | M6 | M7 | M8 | M9 | M10 | D1 | D2 | DR1 |
|  | S1 |  | 0.7 | 0.1 | 1.1 | 0.0 | -.0.5 | -0.3 | -0.6 | 0.0 | -0.1 | 0.0 | -0.1 | 0.1 | 0.0 | -0.1 | -0.2 | 0.0 | 0.1 | -0.4 | -0.1 |
|  | S2 | 0.4 |  | 1.0 | 2.8 | 0.1 | -0.9 | -0.5 | -0.8 | -0.4 | 0.1 | -0.3 | 0.1 | 0.1 | 0.0 | 0.1 | 0.1 | 0.0 | -0.4 | 0.2 | 0.8 |
|  | S3 | 0.1 | 1.2 |  | 0.9 | 0.0 | 0.5 | 0.7 | -0.6 | -0.1 | -0.2 | -0.1 | 0.1 | 0.1 | 0.0 | -0.2 | -0.3 | -0.2 | 0.0 | 0.1 | -0.2 |
|  | S4 | 0.7 | 0.7 | 0.8 |  | 0.2 | -0.4 | 0.3 | -0.7 | -0.4 | 0.1 | -0.4 | -0.1 | -0.1 | -0.2 | -0.1 | -0.2 | -0.2 | -0.2 | -0.2 | -0.1 |
|  | S5 | 0.0 | 0.1 | 0.0 | 0.2 |  | 0.0 | -0.3 | -0.2 | 0.0 | 0.1 | 0.0 | -0.2 | 0.0 | -0.1 | 0.2 | 0.0 | -0.3 | -0.5 | 0.7 | 1.1 |
| - | VM1 | 0.3 | 0.5 | 0.2 | 0.4 | 0.5 |  | 2.9 | 1.3 | 0.1 | 0.1 | 0.5 | 0.3 | 0.1 | 0.0 | 0.3 | 0.5 | 0.4 | 0.8 | 0.6 | 0.5 |
| - | VM2 | 0.0 | 0.3 | 0.1 | 0.1 | -0.1 | 4.1 |  | -0.1 | 0.0 | 0.0 | 0.2 | -0.1 | -0.1 | 0.0 | -0.1 | 0.0 | 0.1 | -0.5 | -0.1 | -0.6 |
| $\stackrel{\circ}{7}$ | M1 | -0.2 | -0.8 | -0.1 | -0.5 | 0.0 | 1.9 | 0.3 |  | 1.8 | 0.2 | 1.4 | 0.1 | 0.1 | 0.1 | 0.3 | 0.8 | 0.9 | -0.9 | -0.9 | 0.2 |
| 응 | M2 | -0.1 | -0.1 | -0.1 | 0.1 | 0.0 | 0.2 | 0.2 | 22 |  | 0.1 | 0.9 | 0.1 | 0.2 | 0.1 | 0.5 | 0.5 | 0.8 | -0.8 | -0.5 | 0.5 |
| 은 | M3 | -0.1 | -0.3 | 0.0 | 0.4 | 0.0 | 0.0 | -0.2 | 0.1 | 0.0 |  | 0.1 | 0.1 | 0.0 | 0.0 | 0.1 | 0.0 | 0.0 | 1.0 | 0.3 | 0.3 |
| $\stackrel{C}{0}$ | M4 | 0.1 | -0.3 | -0.2 | 0.1 | 0.0 | 0.2 | 0.3 | 0.9 | 0.5 | 0.3 |  | 0.2 | 0.1 | 0.1 | 0.2 | 0.3 | 0.4 | 0.1 | 0.0 | -0.4 |
| " | M5 | 0.2 | 0.4 | 0.1 | -0.1 | 0.1 | 0.1 | -0.2 | 0.0 | 0.0 | 0.1 | 0.2 |  | 0.0 | 0.0 | 0.1 | 0.0 | 0.0 | 0.7 | -0.1 | 0.1 |
| - | M6 | 0.2 | 0.1 | 0.0 | 0.4 | 0.0 | -0.4 | -0.1 | 0.1 | 0.1 | 0.0 | 0.3 | 0.1 |  | 0.2 | 0.2 | 0.2 | 0.0 | -0.4 | -0.3 | 0.0 |
| - 득 | M7 | -0.1 | -0.6 | 0.0 | -0.6 | 0.2 | -0.9 | -0.5 | 0.1 | 0.2 | 0.0 | 0.2 | 0.0 | 0.2 |  | 0.4 | 0.2 | 0.0 | 0.4 | -0.1 | -0.8 |
| 둗 | M8 | 0.0 | 0.4 | 0.1 | 0.1 | 0.0 | -0.2 | 0.1 | 0.2 | 0.4 | 0.0 | 0.2 | 0.1 | 0.1 | 0.3 |  | 0.2 | 0.2 | 0.0 | 0.0 | 0.8 |
|  | M9 | 0.1 | -0.4 | -0.1 | -0.9 | 0.0 | 1.6 | 0.0 | 0.8 | 0.4 | 0.0 | 0.5 | 0.1 | 0.1 | 0.2 | 0.4 |  | 0.7 | -1.4 | -0.9 | -0.3 |
|  | M10 | 0.3 | 0.3 | 0.1 | 1.1 | 0.4 | 0.2 | -0.5 | 0.7 | 0.5 | 0.0 | 0.4 | 0.0 | 0.1 | 0.0 | 0.1 | 0.5 |  | 0.9 | 0.9 | 1.2 |
|  | D1 | -0.1 | -0.3 | 0.0 | -0.4 | 0.0 | 0.6 | 0.4 | 1.0 | -0.5 | -0.2 | -0.4 | -0.1 | -0.1 | 0.0 | 0.0 | -0.4 | -0.3 |  | 3.0 | 0.0 |
|  | D2 | 0.1 | 0.4 | 0.2 | 0.7 | -0.2 | -1.6 | 0.0 | -0.2 | 0.0 | 0.2 | 0.1 | 0.1 | 0.1 | 0.0 | 0.0 | 0.0 | -0.2 | 3.7 |  | 0.0 |
|  | DR1 | -0.1 | 0.3 | 0.0 | 0.4 | 0.0 | 0.7 | 0.1 | 0.1 | 0.0 | 0.1 | 0.1 | 0.0 | 0.0 | 0.1 | 0.1 | 0.1 | 0.0 | 0.6 | -0.1 |  |

Within category all cross-effects should be positive

Cross-effects outside category
should be a mixture of positive and negative effects

## Profit optimisation

Ultimate goal of the project was to increase net profit so analysis needed to show best combination of prices

## 1

## Stage 1

- Determine \# monthly covers


## Stage 2

Determine volume of each dish

## 3

Client data
Provided all fixed and variable costs

Optimisation analysis done via Oracle Crystal Ball software


## In 3 months, net profit

 has increased by31\%
vs. previous year (same stores), and significantly higher than in the control restaurants $(12 \%)$

## Real world results

In 3 months, net profit has increased by $31 \%$ vs. previous year (same stores), and significantly higher than in the control restaurants

|  | Test restaurants <br> Jan - Mar | Control restaurants <br> Jan - Mar |
| :--- | :---: | :---: |
| Average number of covers | 118 | 106 |
| Average total weekly sales | 114 | 106 |
| Average total weekly profit | 131 | 112 |
| Average spend per head (core food) | 96 | 99 |
| Average customer satisfaction score | 125 | 121 |

[^1]

## MBC Tips

# MBC projects can become complex and expensive very quickly. Be pragmatic! 

## MBC Tips

## Simpler models i.e. less cross-effects tend to work better. Only include significant effects

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## Context is extremely important - What is the occasion? Who is buying? Are there different menus by time?

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## MBC Tips

## Don't under-estimate the time needed in the set-up phase

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## IHANK YOU.


[^0]:    $\square$ Given the choices above, I would leave this restaurant without eatin

[^1]:    Note: Index score vs. previous year (100) - Profit adjusted for uncontrollable costs

