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# Towards a Competitor-Aware RMS

Thomas FIIG
Michael WITTMAN
Clement TRESCASES

Amadeus IT Group

AGIFORS RM Study Group
Panama City, Panama
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# Motivation for a Competitor-Aware RMS (CARMS)

## Proof of concept for a new vision for RMS

- **Modelling of customer behavior**
  - Choice model that reflects the actual customer's choice behavior
  - Allow the full customer choice set
- **Modelling of other airline (OAL) prices**
  - More comprehensive data obtained by collecting OAL historical prices
  - Forecast of OAL prices and price reactions
- **Modelling of our airline's optimal policies**
  - Optimization incorporates OAL price reaction functions
  - Allows enhancement with Dynamic Pricing
- **New user roles**
  - Users can set pricing strategies separately by market and OAL
- **Literature**
  - Correcting RMS by an overlay logic: OAL matching; Forecast adjustments; Dynamic Pricing
  - Game theory: Proof of equilibrium properties in theoretical models
  - CARMS: Zhang, D. and Kallesen, R. (2007) simplified approach (non-reactive OAL, no real data)

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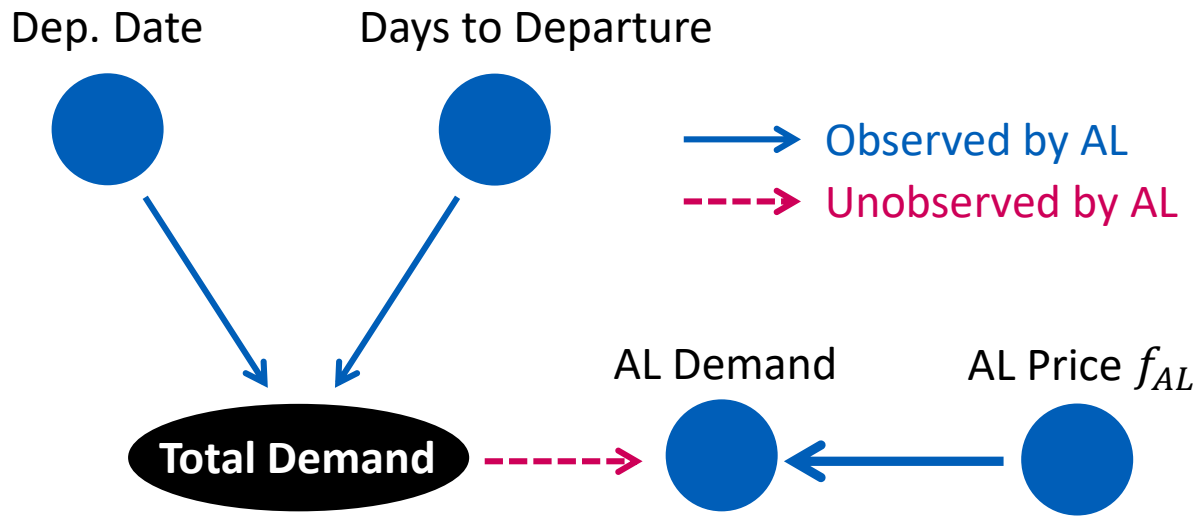
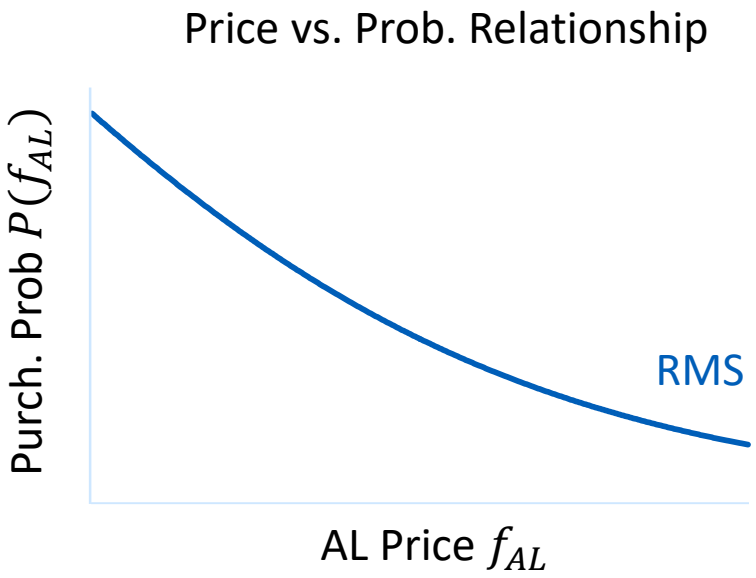
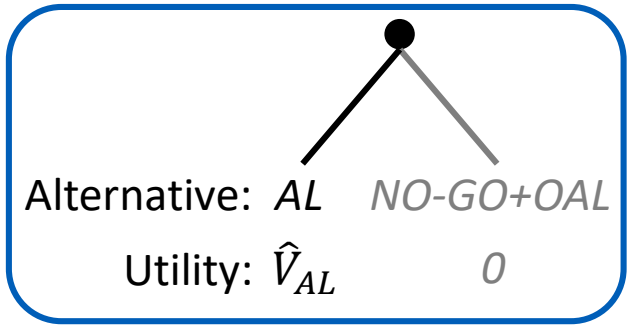
# Review of the RMS View of the World

## RMS assumes monopoly. Explanatory variables are: Departure date, days to departure, and AL price




$$\hat{V}_{AL} = \hat{\beta}_0 - \hat{\beta}_1 \times f_{AL}$$

$$P(f_{AL}) = \frac{e^{\hat{V}_{AL}}}{e^{\hat{V}_{AL}} + 1}$$

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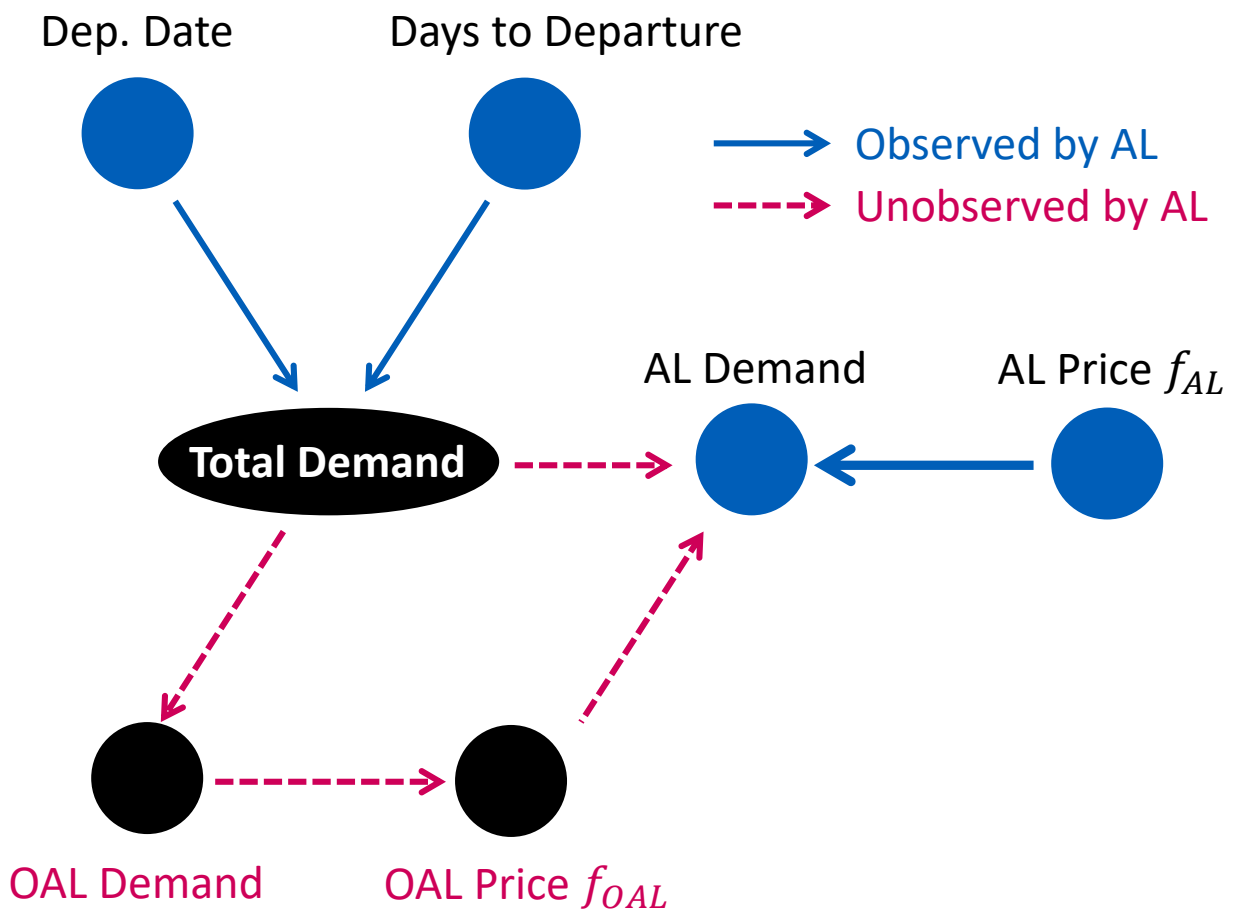
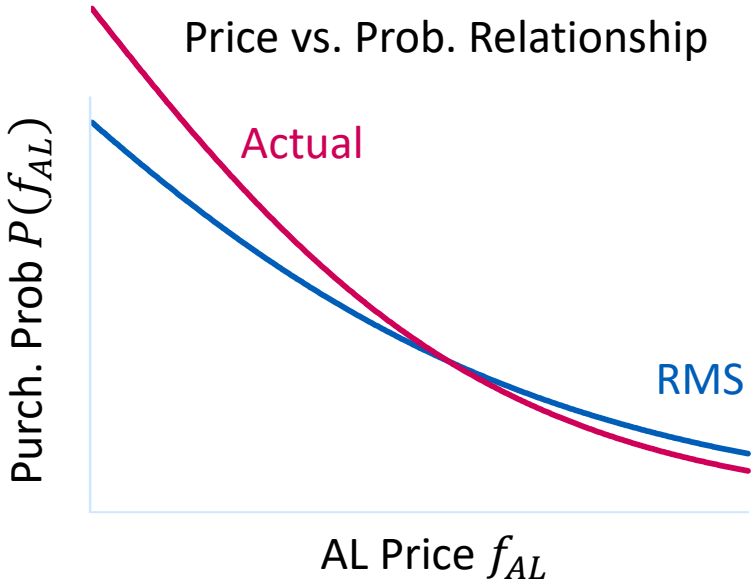
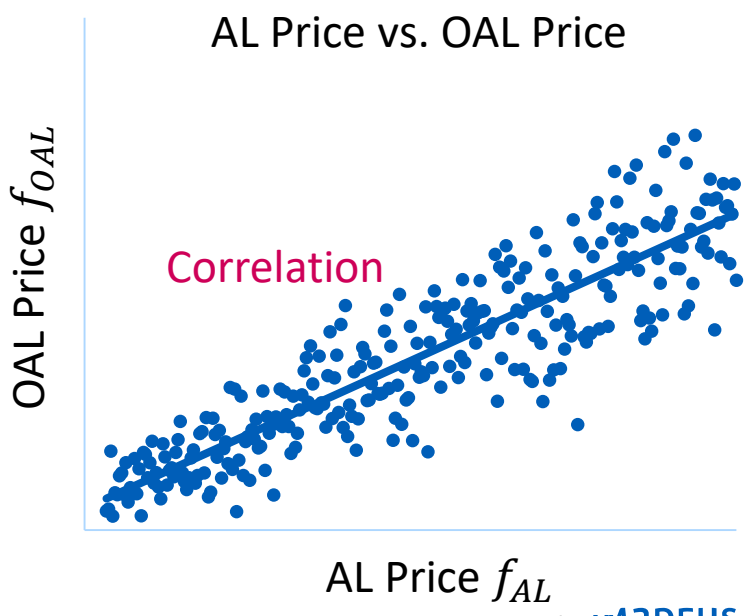
# RMS's Simplified View Gives Rise to Bias

## Price endogeneity due to omitted variables (OAL prices $f_{OAL}$)

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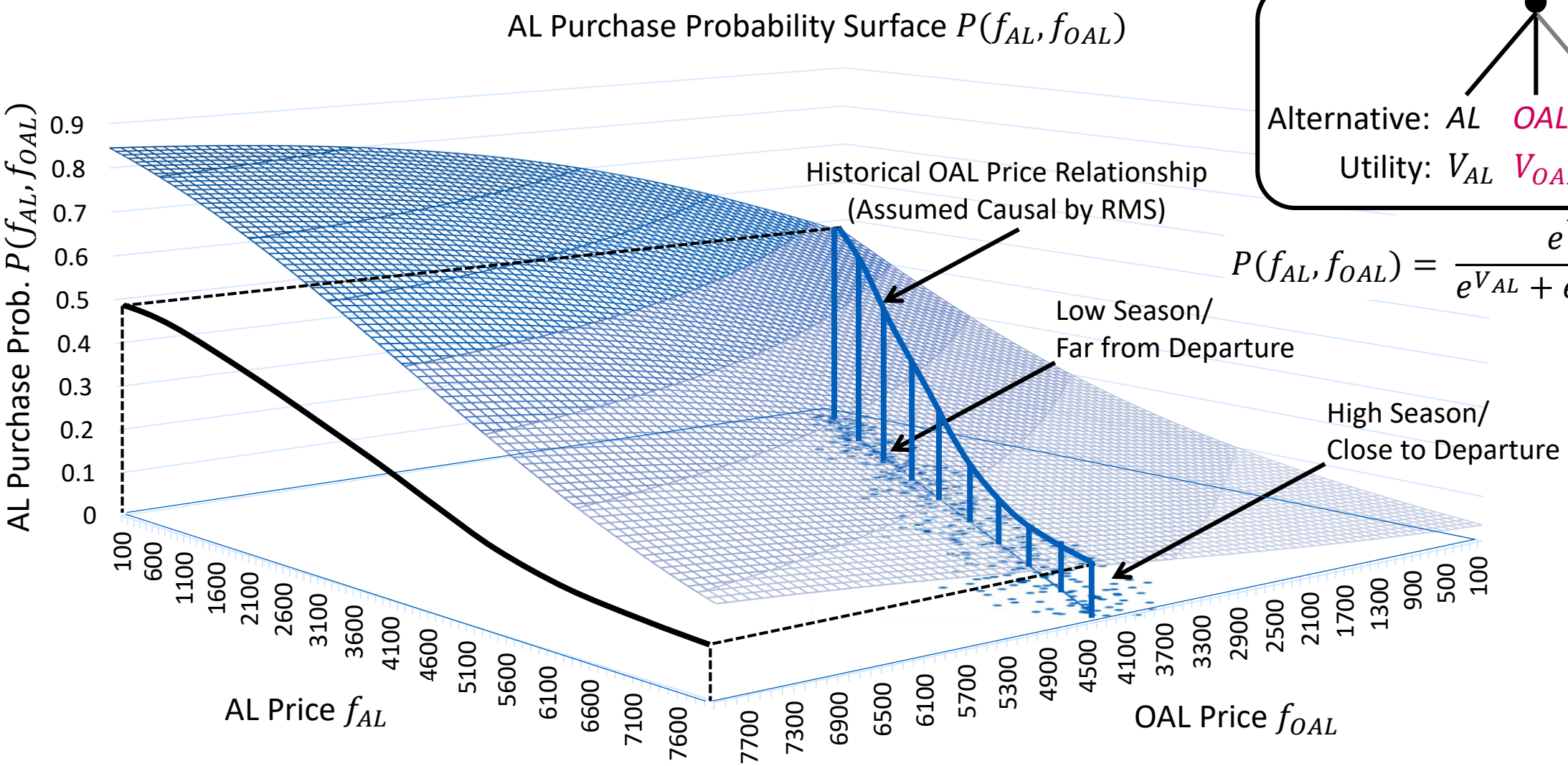
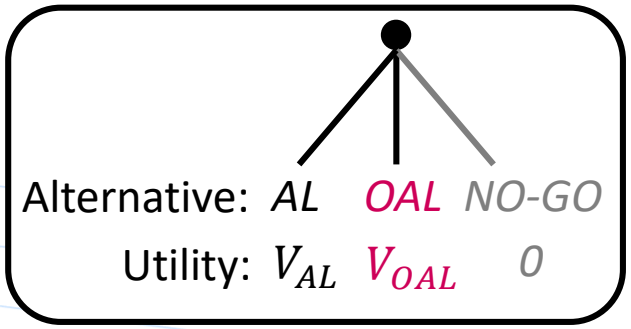
# Actual Choice Probability Depends on Both AL and OAL Prices

## RMS assumes the historical relationship with OAL prices is causal




$$P(f_{AL}, f_{OAL}) = \frac{e^{V_{AL}}}{e^{V_{AL}} + e^{V_{OAL}} + 1}$$

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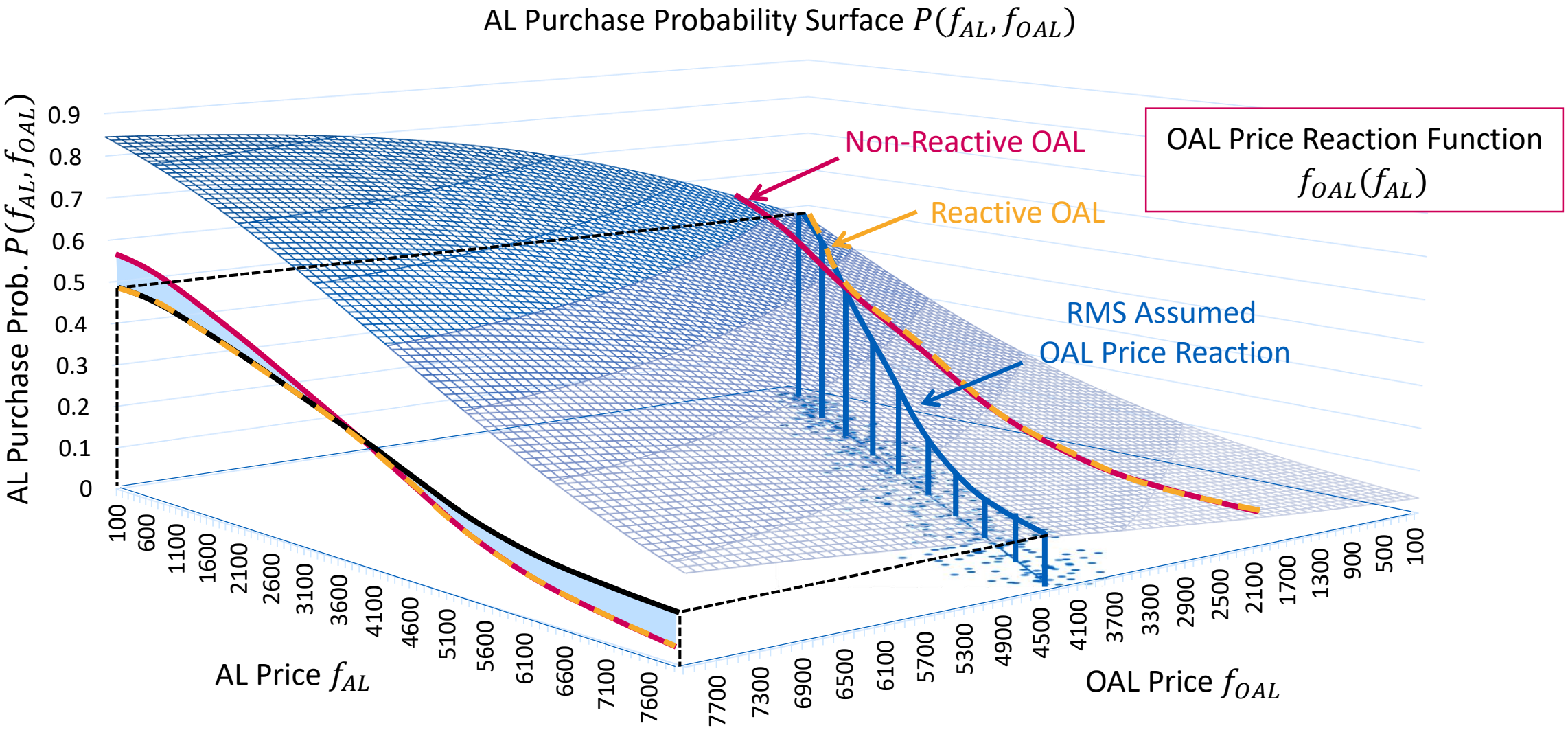
# OAL's Price Reaction Behaviors Depend on Market and OAL Strategy

## RMS bias results from its assumption that OAL's prices will always follow AL's

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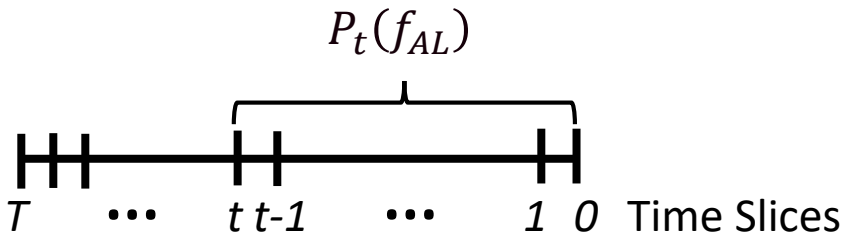
# Evolution from RMS to CARMS

RMS

**Choice-Based RMS**

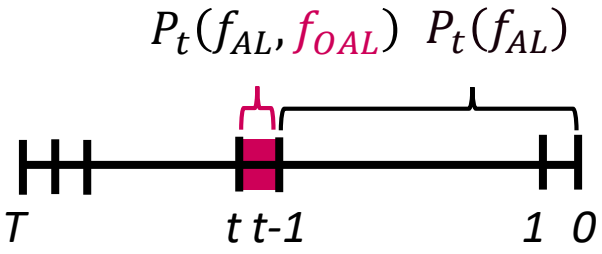
$$J_{t-1}(x) = J_t(x) + \lambda_t \max_{f_{AL}}[TR_t(f_{AL}) - BP_t(x)P_t(f_{AL})]$$




RMS+DP

**RMS with Dynamic Pricing (RMS + DP)**

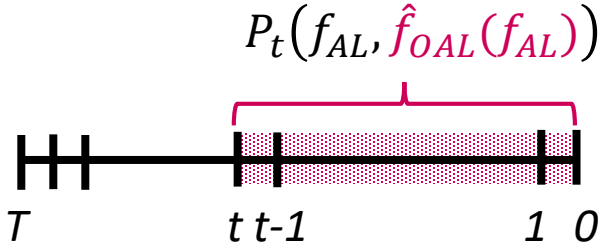
$$\max_{f_{AL}}[TR_t(f_{AL}) - BP_t(x)P_t(f_{AL}, f_{OAL})]$$




CARMS

**Competitor-Aware RMS (CARMS)**

$$J_{t-1}(x) = J_t(x) + \lambda_t \max_{f_{AL}}[TR_t(f_{AL}) - BP_t(x)P_t(f_{AL}, \hat{f}_{OAL}(f_{AL}))]$$



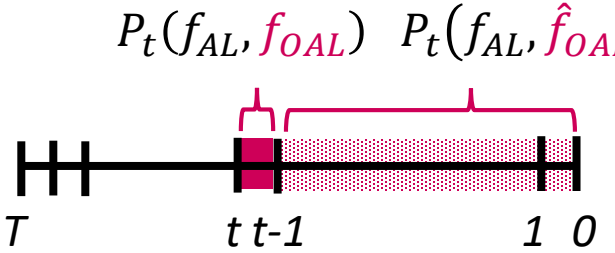

$f_{OAL}$: Observed OAL price

$\hat{f}_{OAL}(f_{AL})$: Forecast OAL price

CARMS + DP

**Competitor-Aware RMS with Dynamic Pricing (CARMS + DP)**

$$\max_{f_{AL}}[TR_t(f_{AL}) - BP_t(x)P_t(f_{AL}, f_{OAL})]$$

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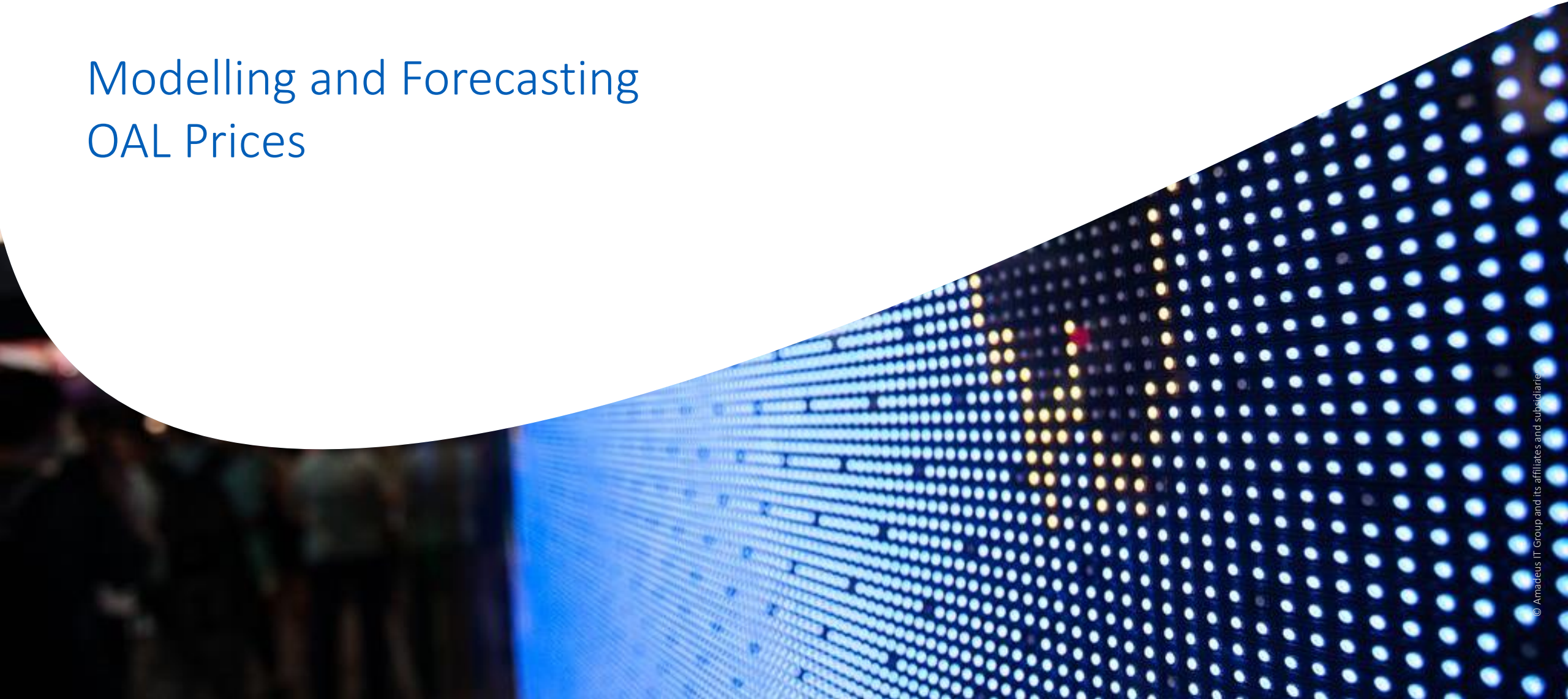
# Modelling and Forecasting OAL Prices



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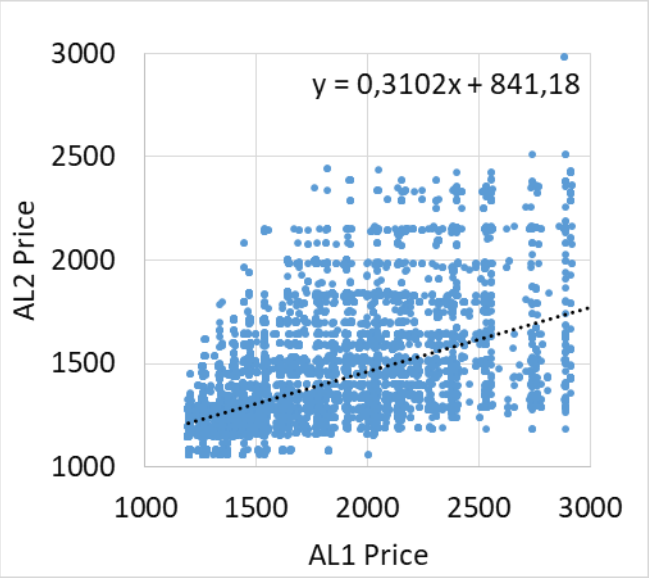
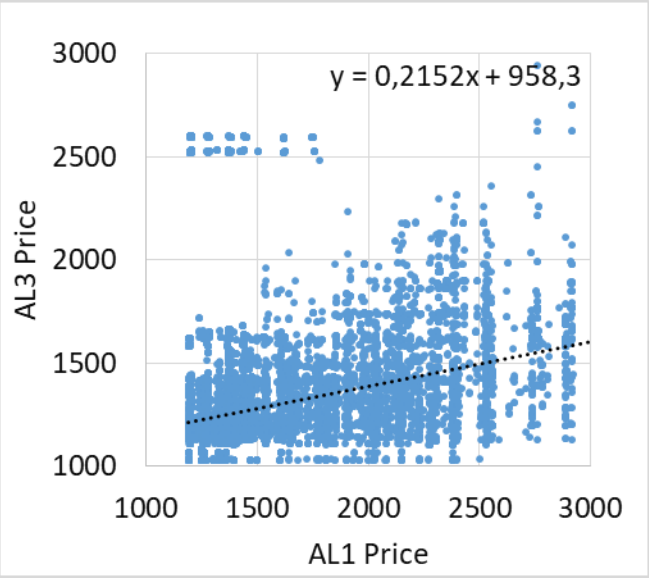
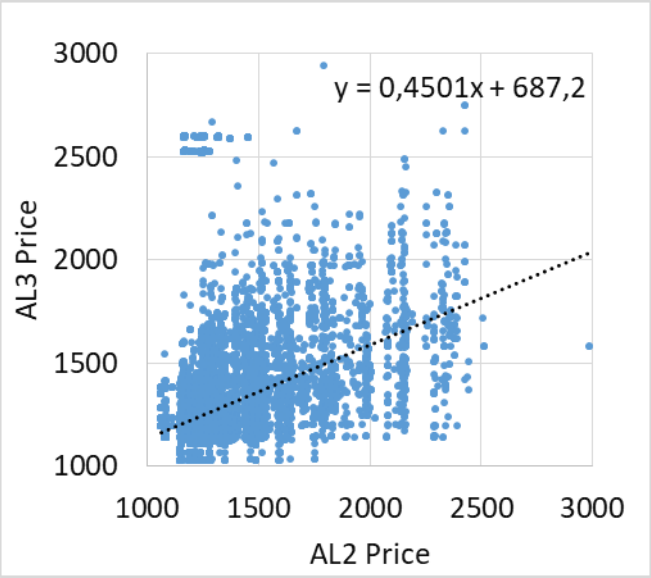
# Prices are Generally Correlated Between Airlines in the Same Market




| | AL1 | AL2 | AL3 | AL4 |
|---|---|---|---|---|
| AL1 | 100% | | | |
| AL2 | 67% | 100% | | |
| AL3 | 36% | 35% | 100% | |
| AL4 | 36% | 57% | 20% | 100% |




- Long-Haul Market (Europe-Asia) served by 4 AL with non-stop service.
- Pricing Intelligence data from INFARE. Market prices (by AL, dep. date, dtd) recorded daily.

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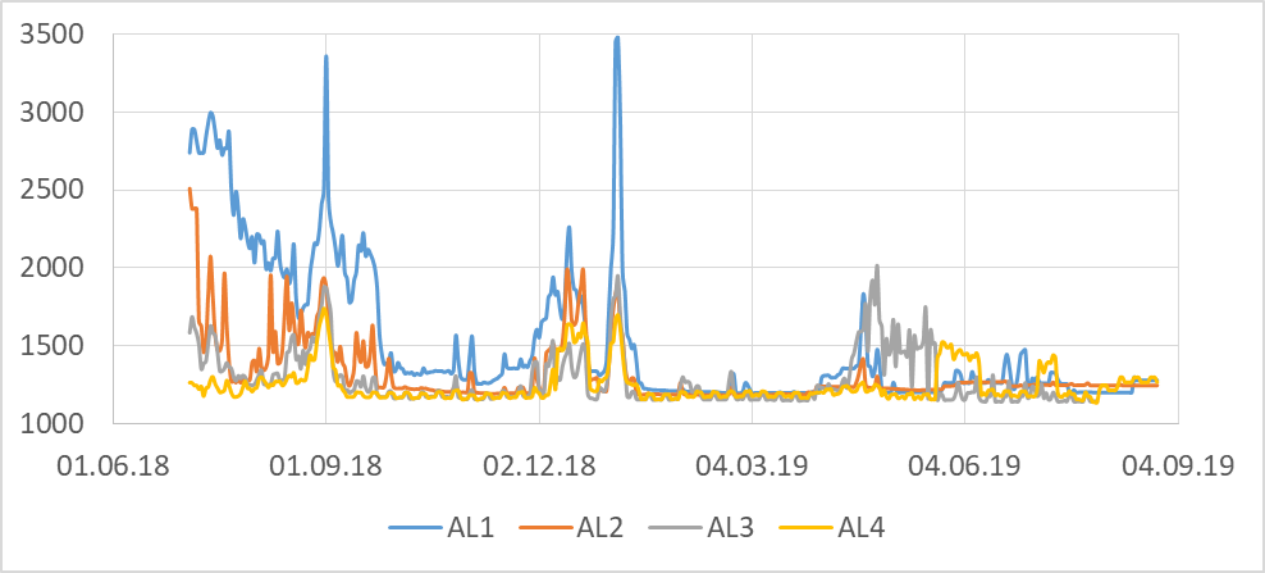
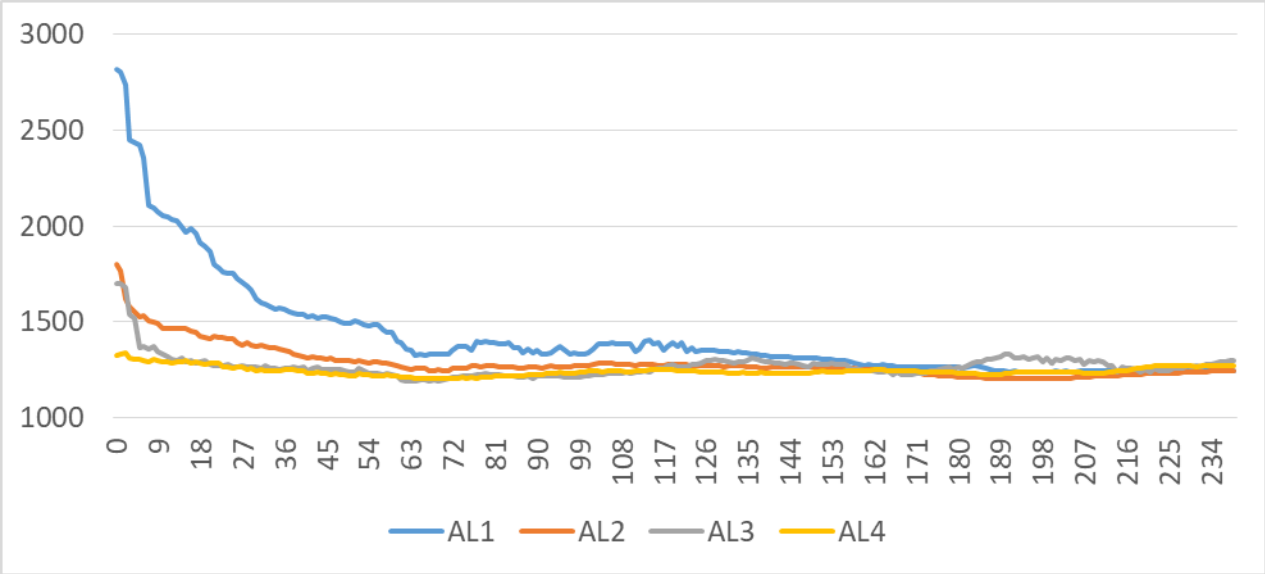
# Correlation Driven Largely By Seasonality and Days to Departure

**Prices versus Departure Date (doy)**




**Prices versus Days to Departure (dtd)**




## Model of OAL prices

$$\hat{f}_{OAL}(doy, dtd) = \mu_{OAL}(doy, dtd) + \varepsilon_{OAL}(doy, dtd)$$

↑ Systematic component

↑ Random noise

## Hypotheses

$$\varepsilon_{AL}(doy, dtd) \sim N(0, \sigma^2)$$

$$Corr(\varepsilon_{ALi}, \varepsilon_{ALj}) \sim 0, i \neq j$$

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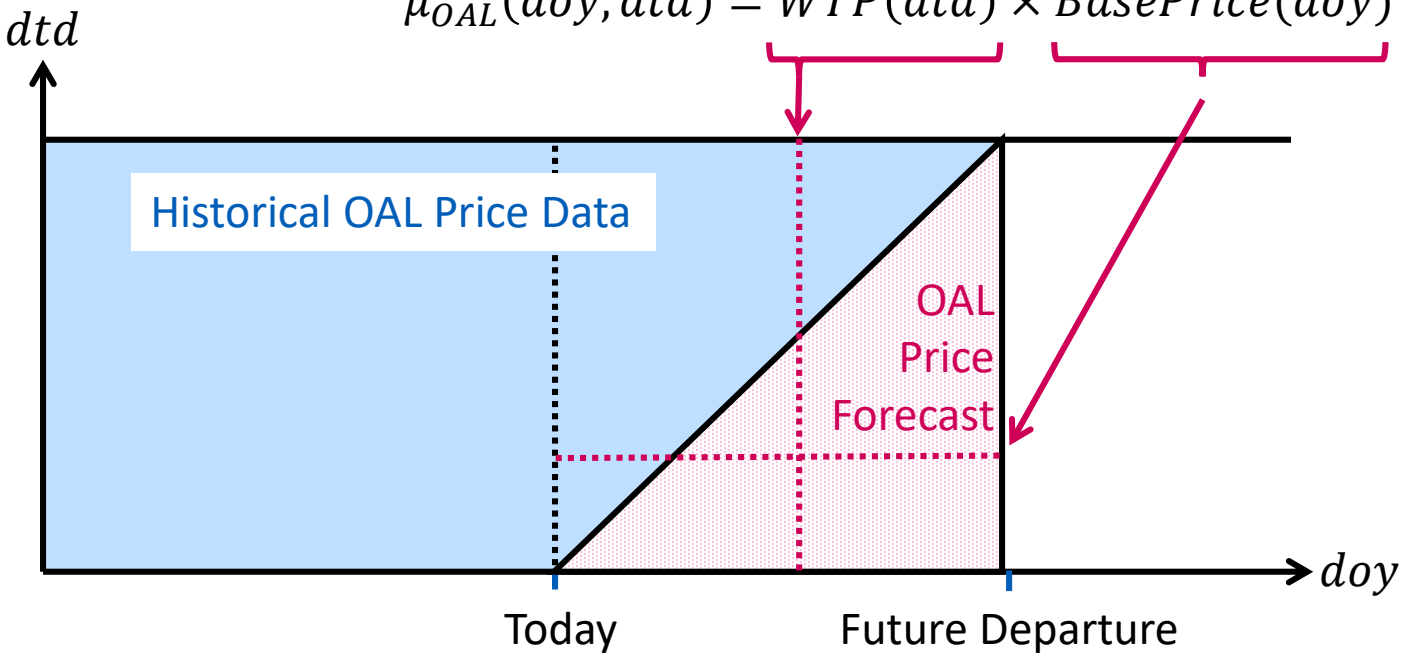
# Decomposing the Systematic Component of the OAL Price Forecast

## Forecast model decomposed into: *WTP(dtd)* and *BasePrice(doy)*

$$\hat{\mu}_{OAL}(doy, dtd) = WTP(dtd) \times BasePrice(doy)$$




$$WTP(dtd) = 1 + \alpha_{dow}\, e^{-\beta_{dow} \times dtd}, dow = 1, \dots, 7$$

$$BasePrice(doy) = RefPrice \times SP \left[ 1 + \sum_{i=1}^{5} a_i \sin\left(2\pi i \times \frac{doy}{365}\right) + b_i \cos\left(2\pi i \times \frac{doy}{365}\right) \right]$$

Normal, Easter, Summer, New Year

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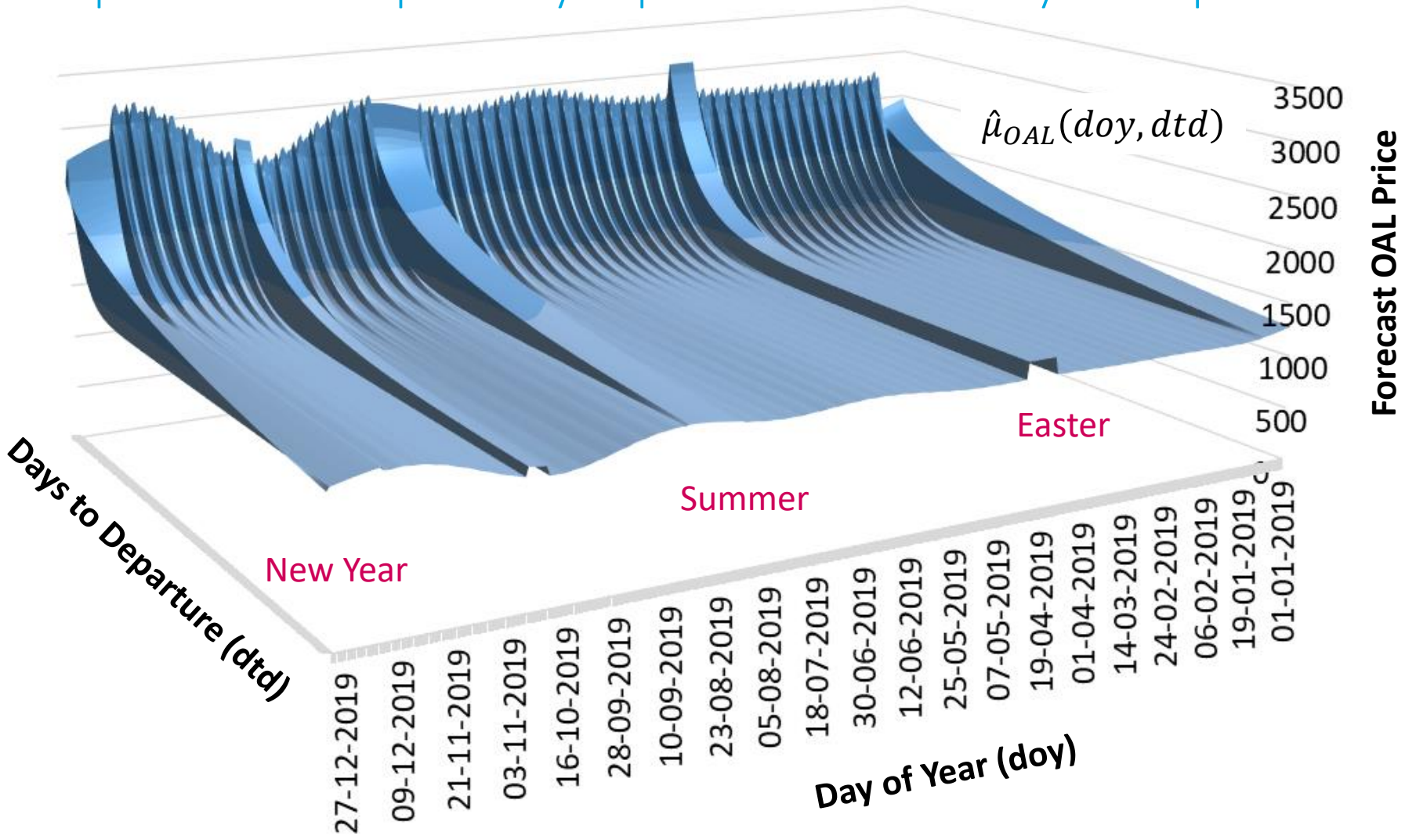
# Forecasting OAL Prices

## Systematic component of OAL prices by departure date and days to departure

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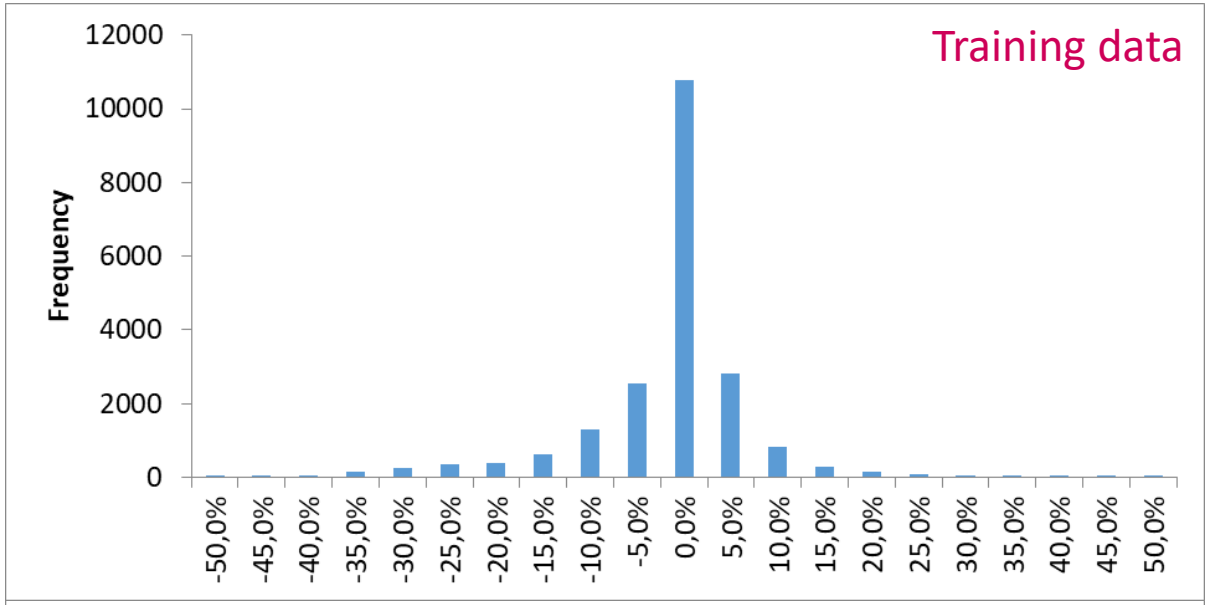
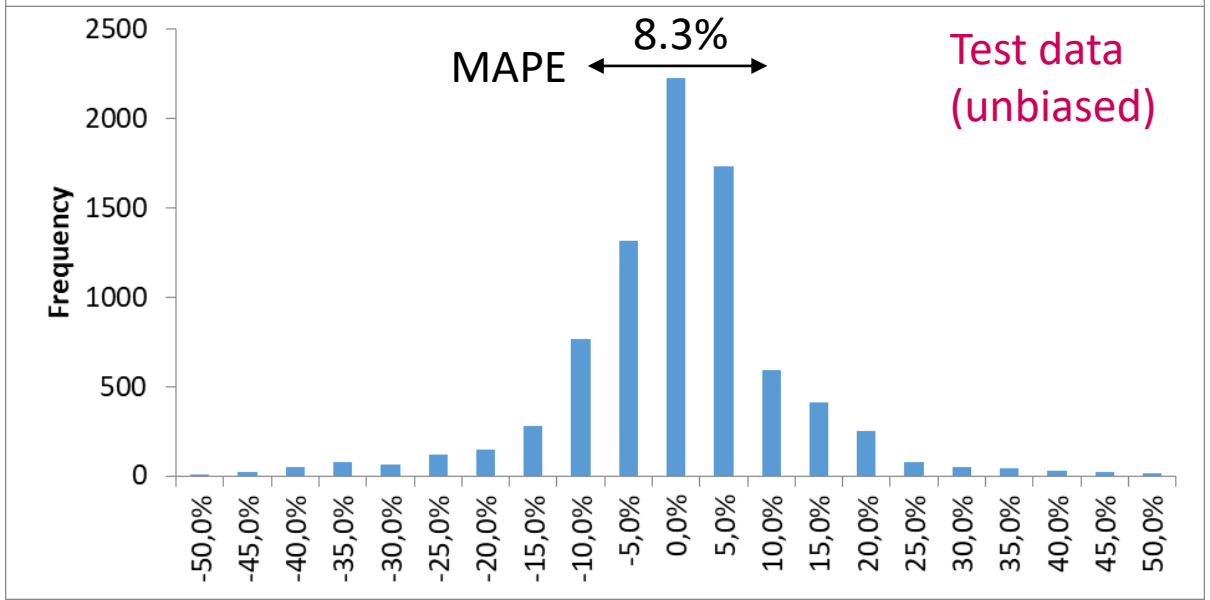
# Forecast Model Validation

## Frequency plots of residuals




$$\varepsilon_{OAL}(doy, dtd) = \frac{f_{OAL}(doy, dtd) - \hat{\mu}_{OAL}(doy, dtd)}{\hat{\mu}_{OAL}(doy, dtd)}$$

| Market | Airline | MAPE*) (Test data) |
|---|---|---|
| M1 | AL1 | 8.3% |
| | AL2 | 8.6% |
| | AL3 | 11.2% |
| | AL4 | 8.1% |
| M2 | AL1 | 9.8% |
| | AL5 | 9.6% |
| | AL6 | 9.7% |
| M3 | AL1 | 10.0% |
| | AL5 | 7.9% |
| | AL7 | 24.0% |

Note: TEST data made overall unbiased for MAPE

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# Our Modeling Hypotheses are Confirmed

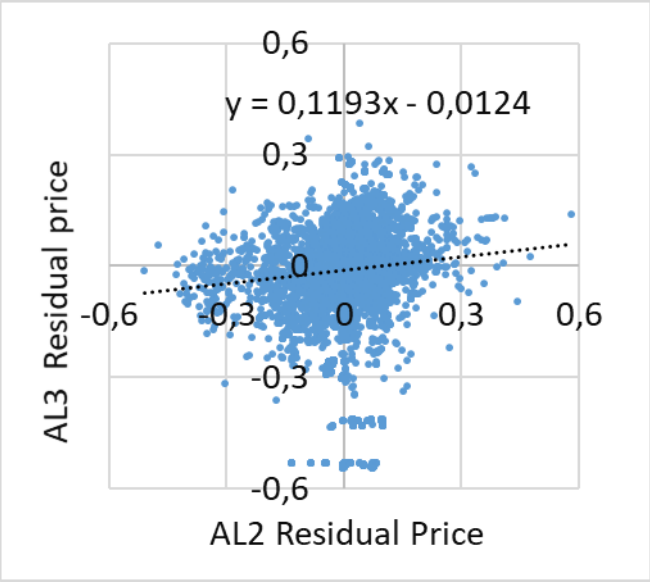
## Price residuals are approx. normally distributed and show little inter-AL correlation

Price Correlations

| | *AL1* | *AL2* | *AL3* | *AL4* |
|---|---|---|---|---|
| AL1 | 100% | | | |
| AL2 | 67% | 100% | | |
| AL3 | 36% | 35% | 100% | |
| AL4 | 36% | 57% | 20% | 100% |

Price Residuals Correlations

| | *AL1* | *AL2* | *AL3* | *AL4* |
|---|---|---|---|---|
| AL1 | 100% | | | |
| AL2 | 19% | 100% | | |
| AL3 | 14% | 8% | 100% | |
| AL4 | 6% | 18% | -9% | 100% |




- We are able to predict AL prices with a high degree of accuracy
- This forecast is a critical component that allows us to build CARMS

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# Simulating the Effects of Competitor-Aware RMS

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# Simulation Set-Up: Network, Scenarios, and Customer Choice Behavior

## _Network Structure:

- Single market served by two airlines with one flight each

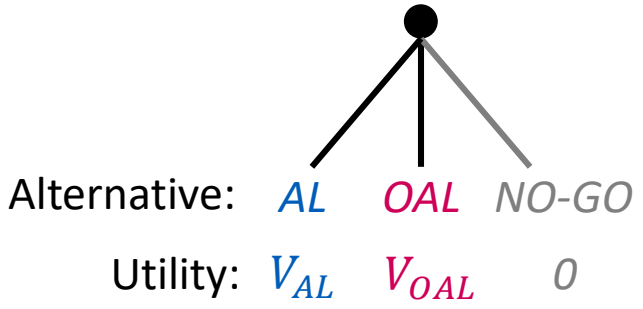
## _Customer Choice Behavior:

- Multinomial logit with time-dependent price sensitivity

$$V_i = \beta_0 - \beta_{1,t} \times f_i$$

$$\beta_{1,t} = N(\mu_t, \sigma_t^2)$$

$$P_t(f_{AL}, f_{OAL}) = \frac{e^{V_{AL}}}{e^{V_{AL}} + e^{V_{OAL}} + 1}$$




## _Scenarios Tested:

- AL: RMS or CARMS
- OAL: Non-reactive or reactive to AL's prices

| | |
|---|---|
| AL: RMS<br>OAL: Non-Reactive | AL: RMS<br>OAL: Reactive |
| AL: CARMS<br>OAL: Non-Reactive | AL: CARMS<br>OAL: Reactive |

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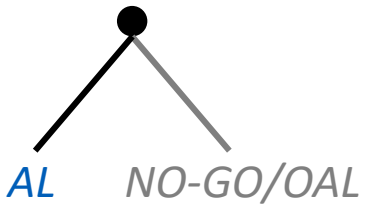
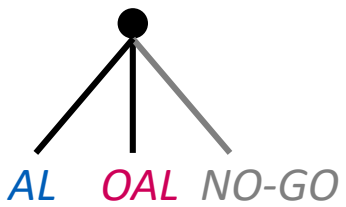
# Simulation Set-Up: RMS and CARMS

| | RMS | CARMS |
|---|---|---|
| **AL Fare Structure (Unrestricted)** | FC1: 500, FC2: 400, FC3: 350, FC4: 300, FC5: 250, FC6: 200, FC7: 175, FC8: 150, FC9: 125, FC10: 100 | |
| **Assumed Customer Choice Behavior** |   |   |
| **Data Used in Forecast Parameter Estimation** | Historic AL prices and AL bookings (prev. 200 dep. days) | Historic AL and OAL prices and AL bookings (prev. 200 dep. days) |
| **Estimated Demand Function** | $\lambda \frac{e^{(\hat{\beta}_0 - \hat{\beta}_{1,t} f_{AL,t})}}{e^{(\hat{\beta}_0 - \hat{\beta}_{1,t} f_{AL,t})} + 1}$ | $\lambda \frac{e^{(\hat{\beta}_0 - \hat{\beta}_{1,t} f_{AL,t})}}{e^{(\hat{\beta}_0 - \hat{\beta}_{1,t} f_{AL,t})} + e^{(\hat{\beta}_0 - \hat{\beta}_{1,t} \hat{f}_{OAL,t}(f_{AL,t}))} + 1}$ |
| **Optimizer** | Dynamic Programming | |

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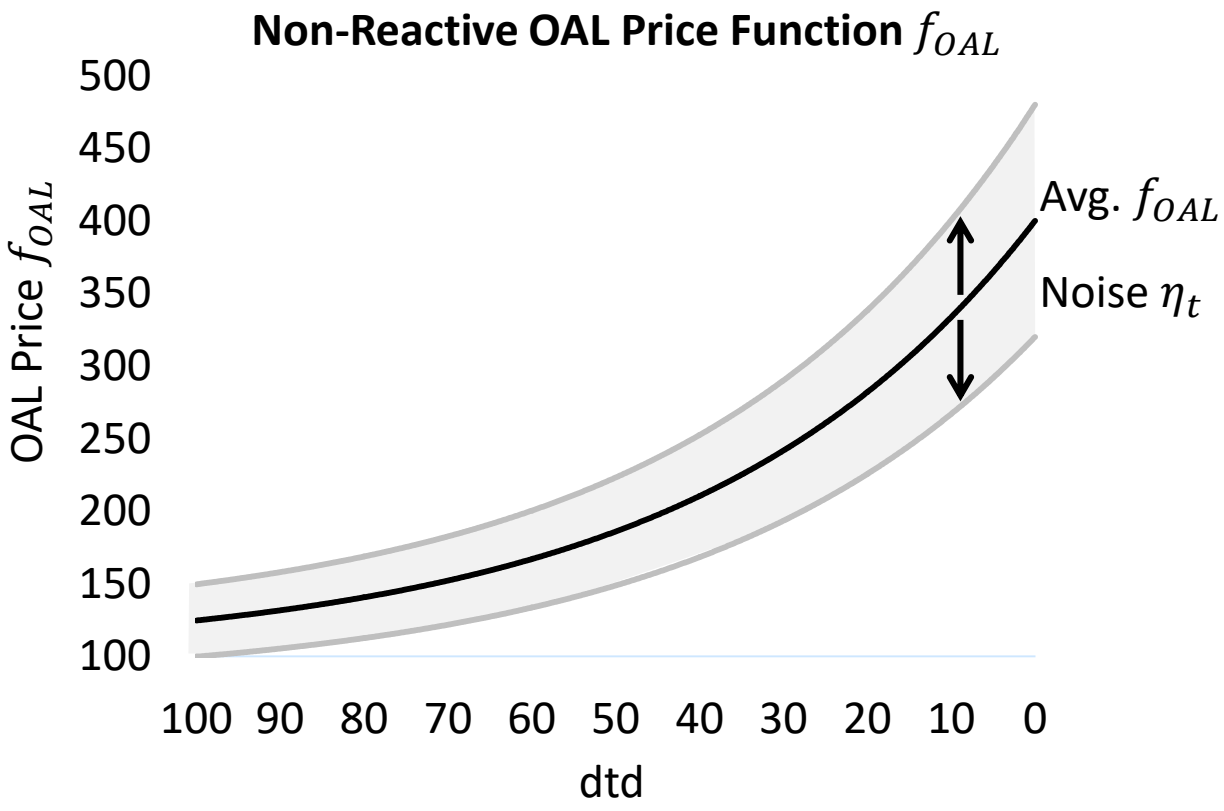
# Simulation Set-Up: OAL Price Reaction Behaviors

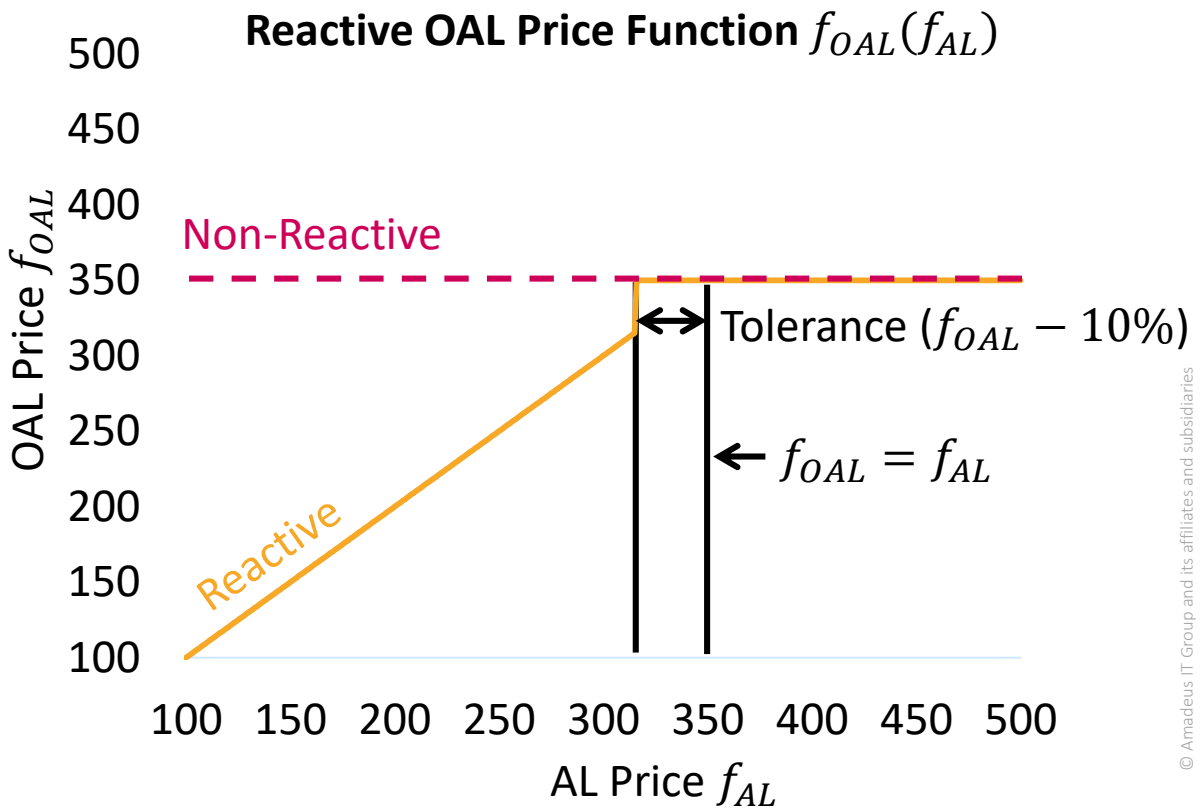
## _Non-Reactive OAL:

- OAL follows a given price curve (with noise)
- CARMS is aware of average OAL prices




## _Reactive OAL:

- OAL matches AL's price if it attempts to undercut
- CARMS is aware of OAL's price tolerance

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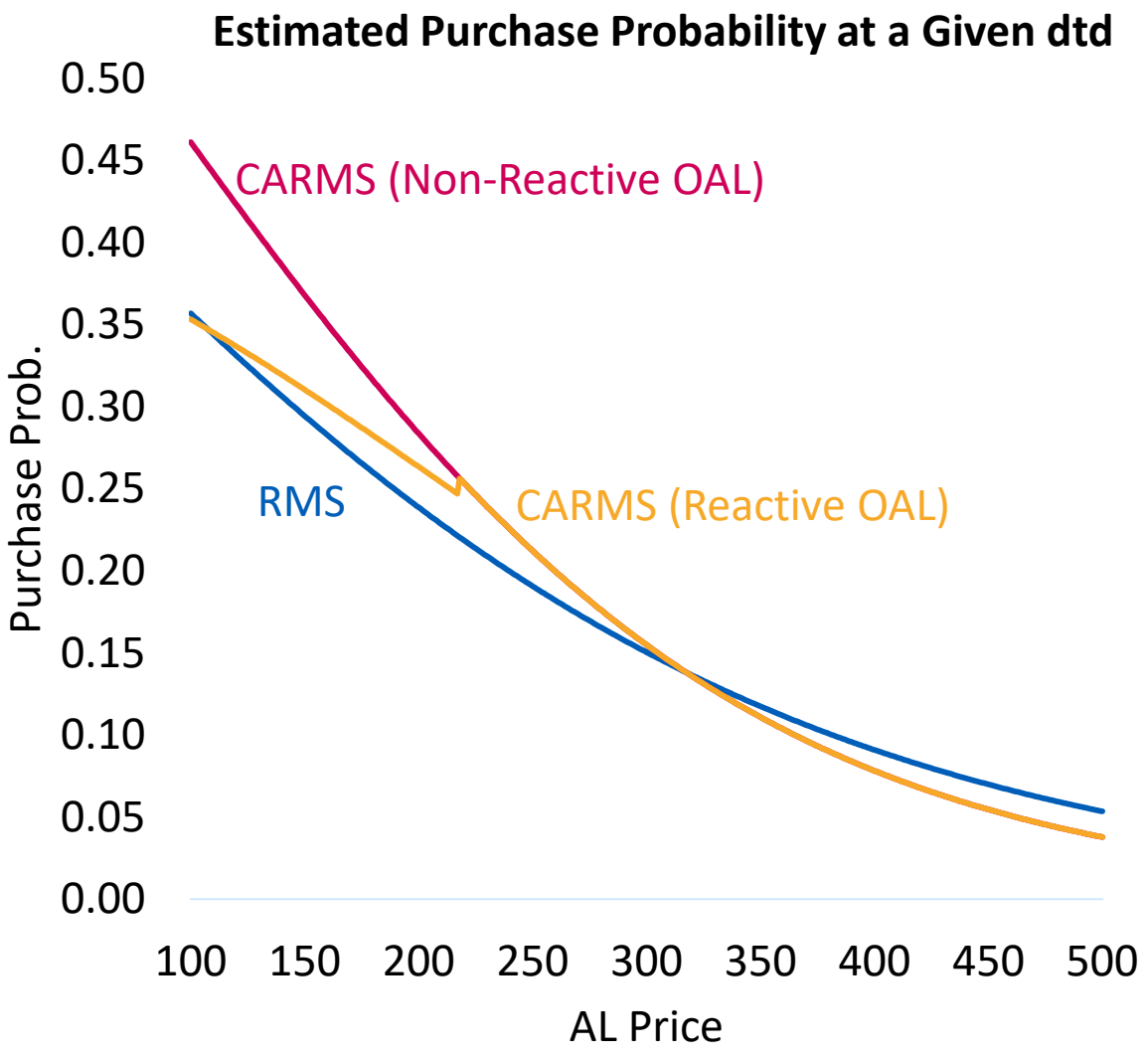
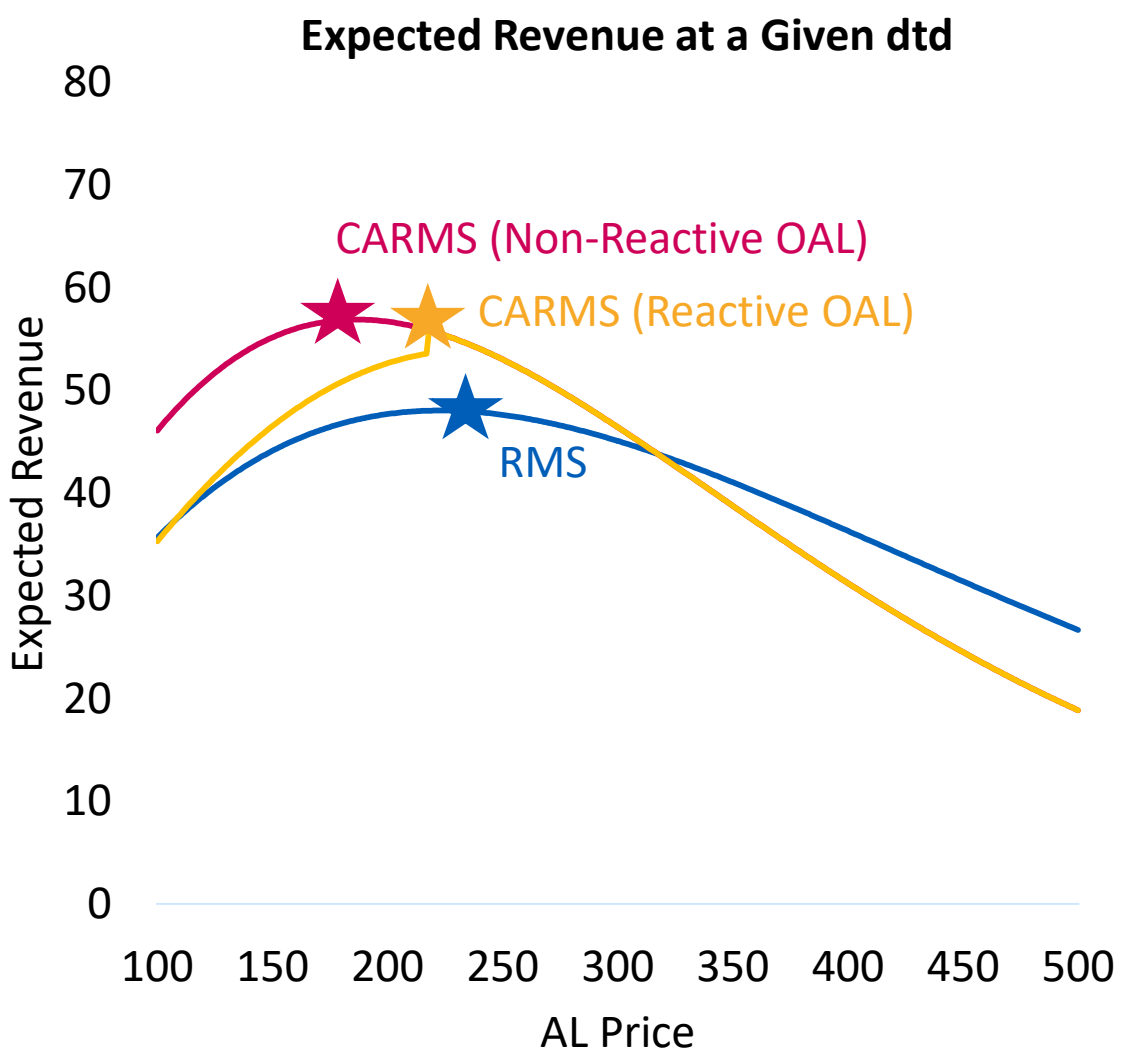
# Results: RMS Underestimates Price Sensitivity Compared to CARMS

## RMS tends to produce optimal prices that are too high

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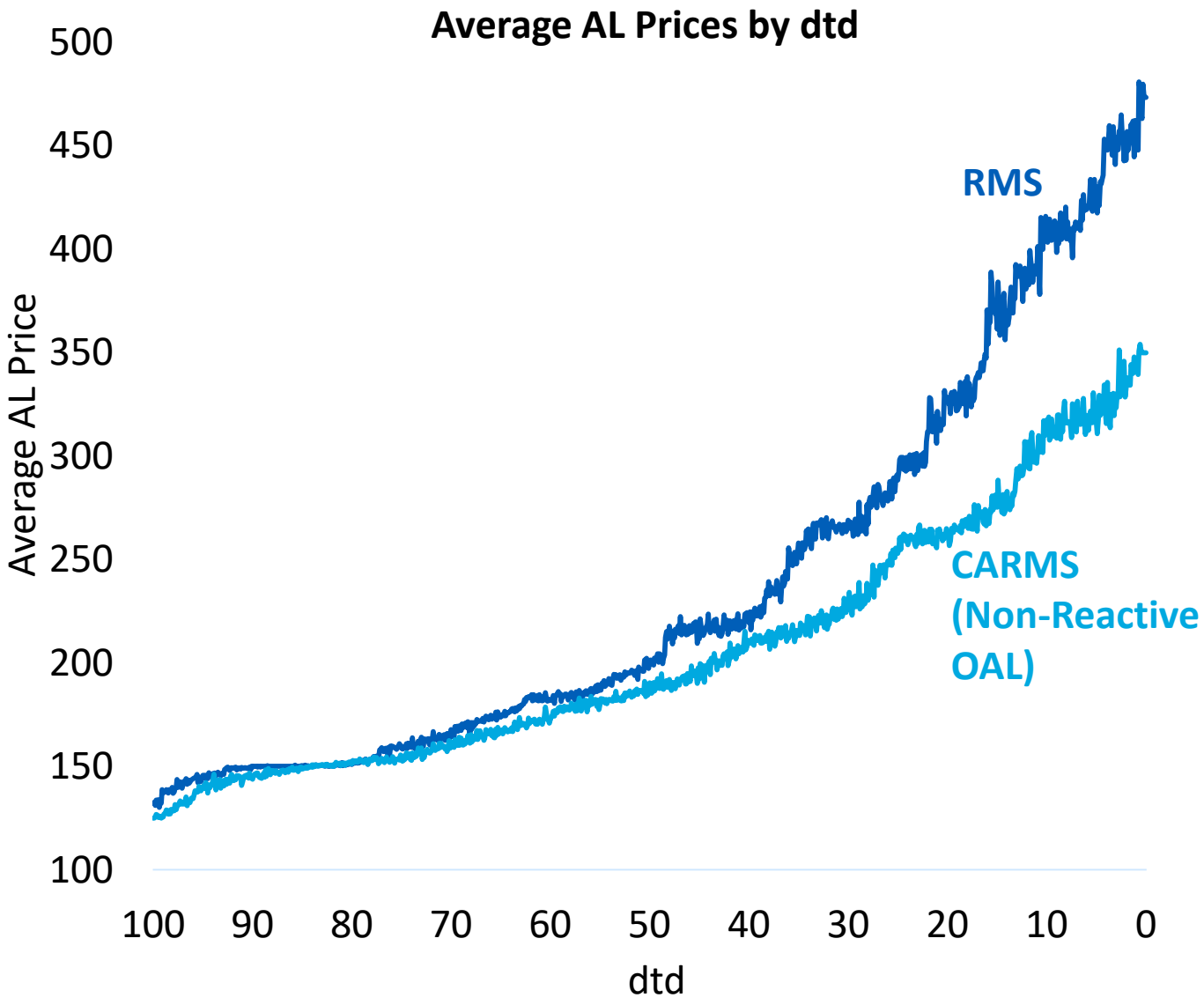
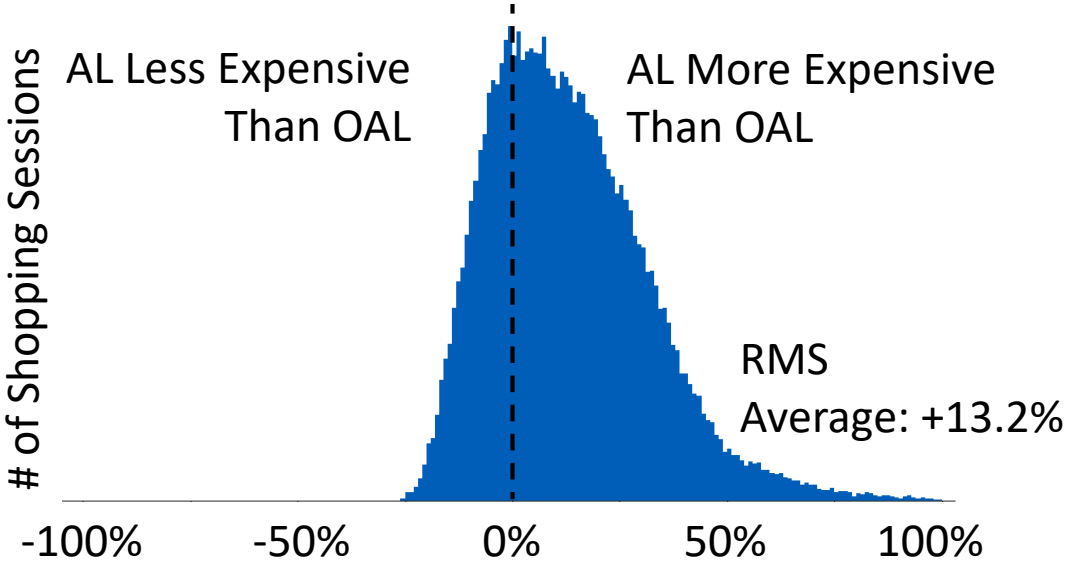
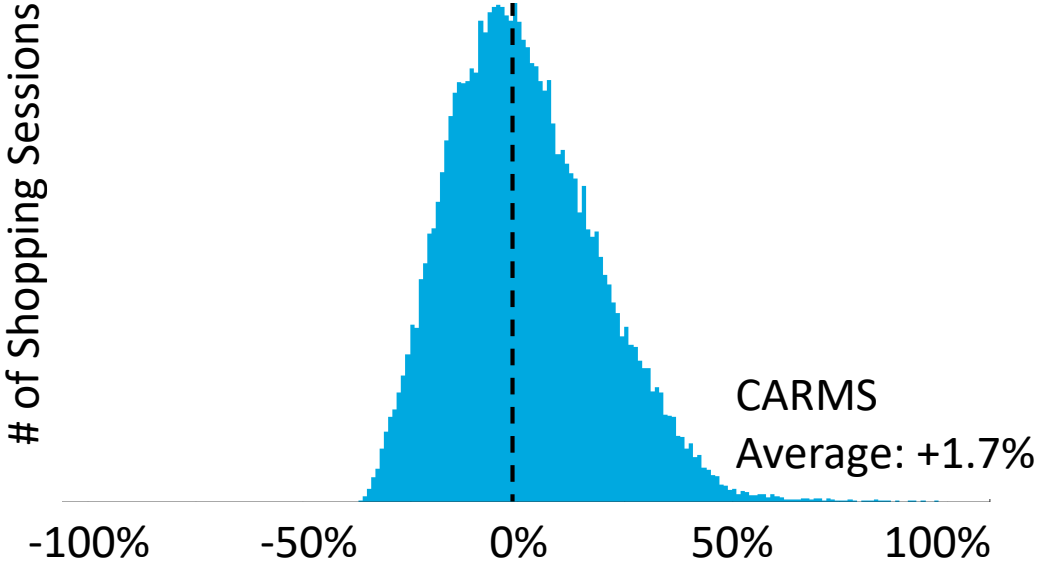
# RMS vs. CARMS Pricing (Non-Reactive OAL)

## CARMS prices are more aligned with market prices




$(f_{AL} - f_{OAL}) / f_{OAL}$

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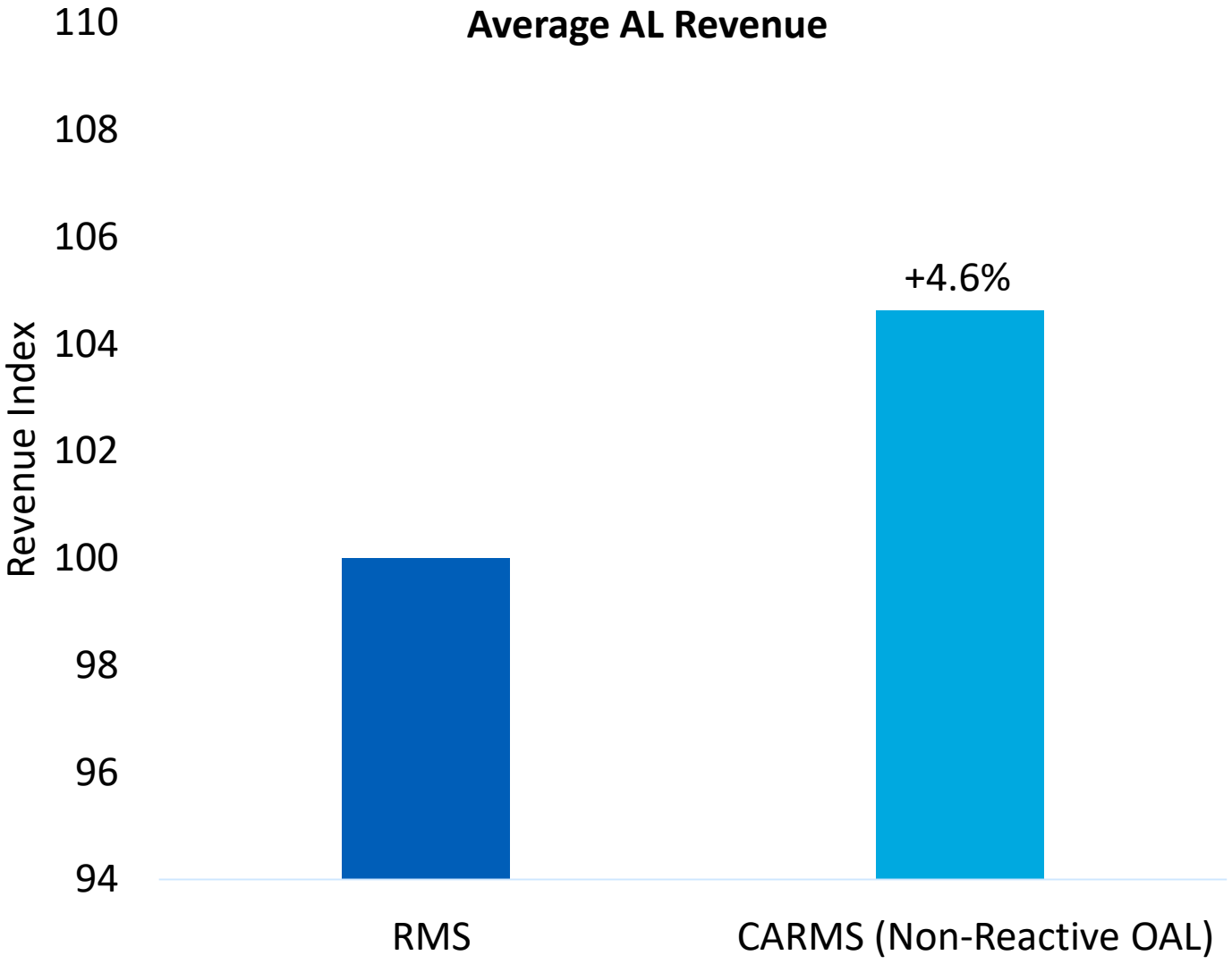
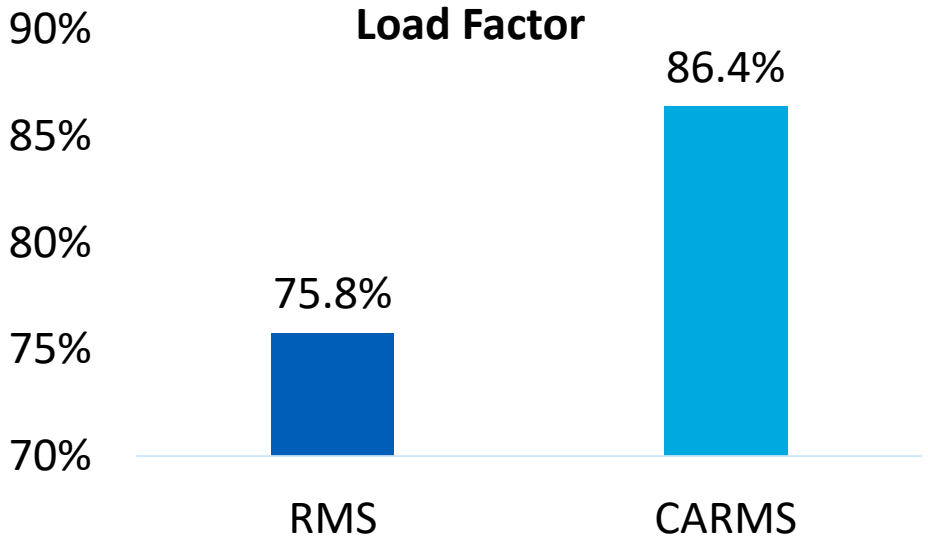
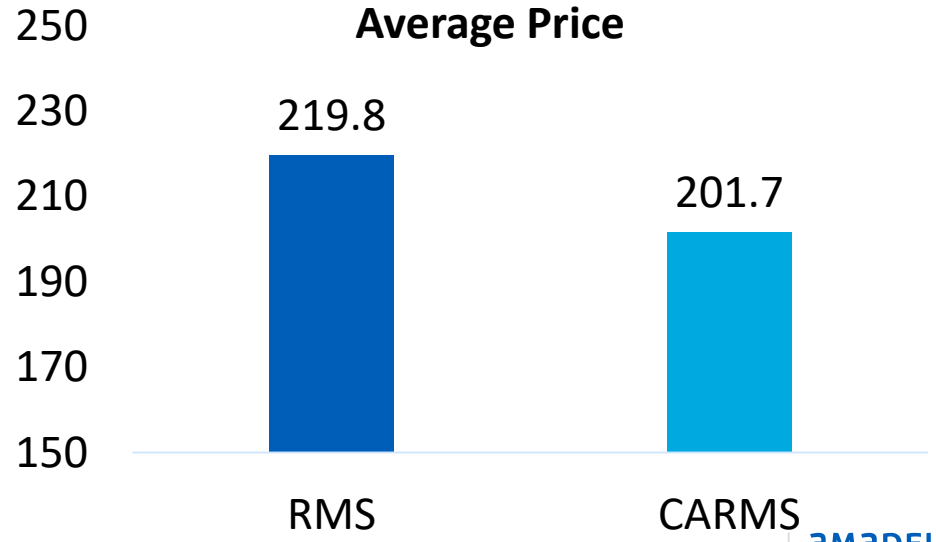
# Performance of RMS vs. CARMS (Non-Reactive OAL)

## CARMS leads to a 4.6% increase in AL revenue through higher load factors

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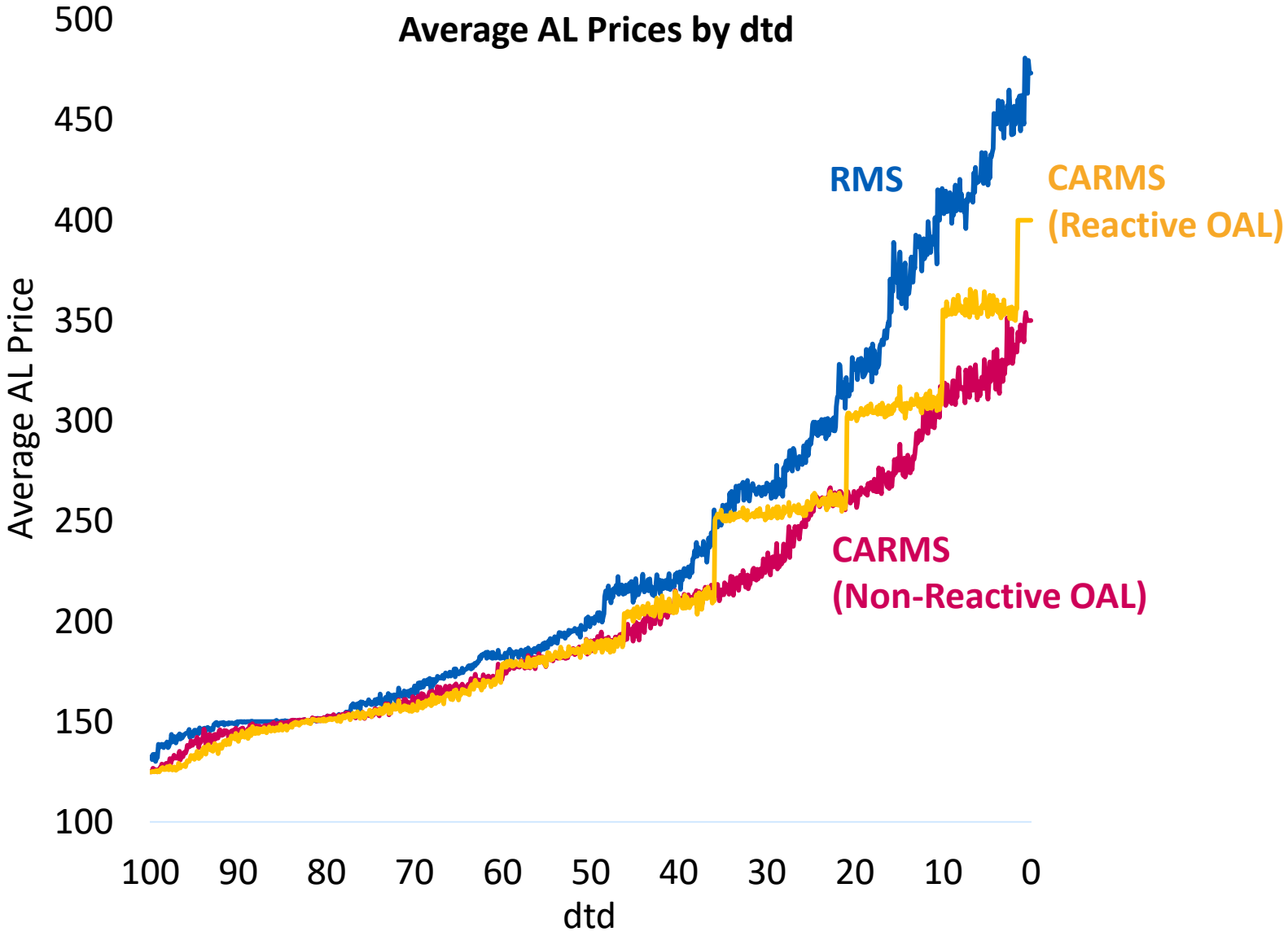
# RMS vs. CARMS Pricing (Reactive OAL)

## CARMS is more conservative if it anticipates OAL will react to being undercut




- CARMS produces lower prices than RMS with either OAL price reaction.
- CARMS is more conservative if it knows OAL will match low prices.
- With a reactive OAL, CARMS shows a “staircase” pattern in later dtd.

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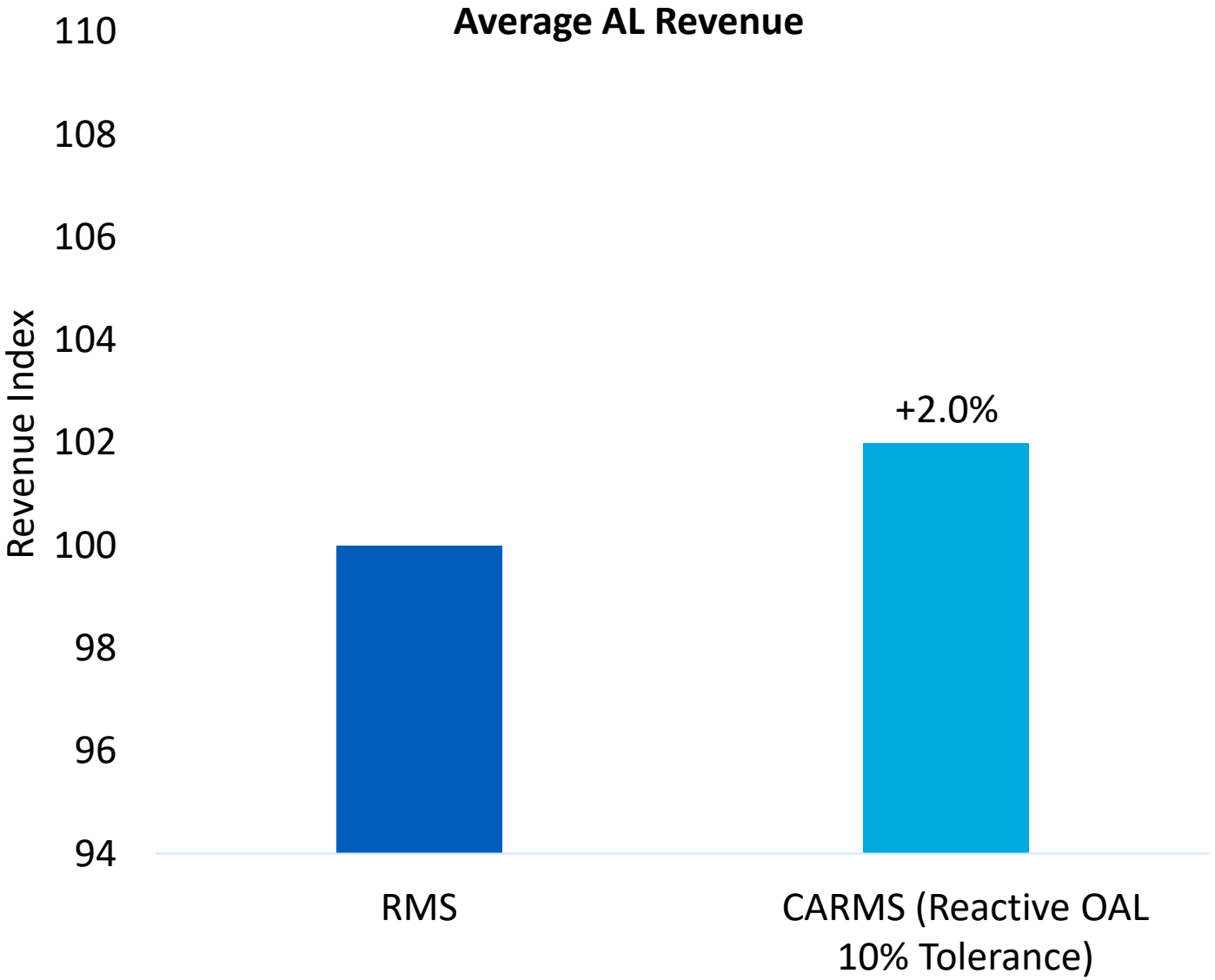
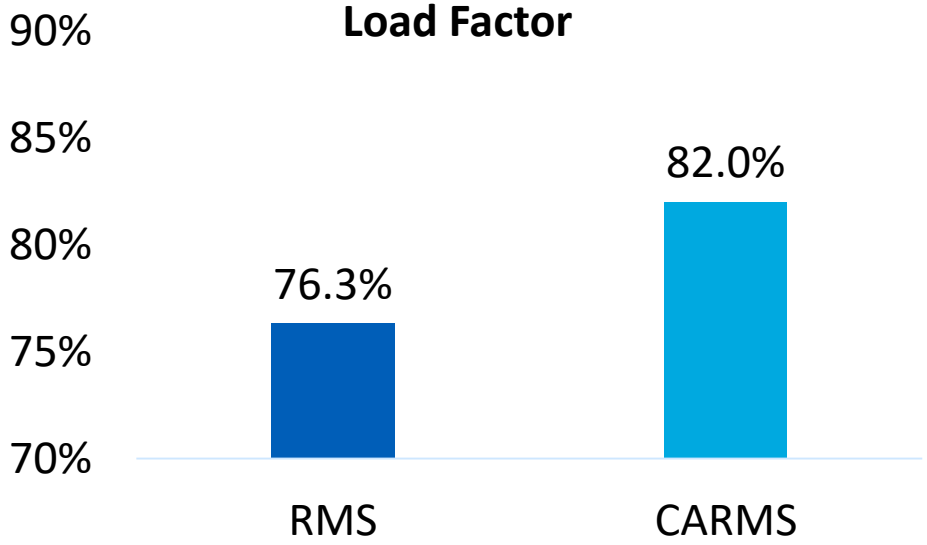
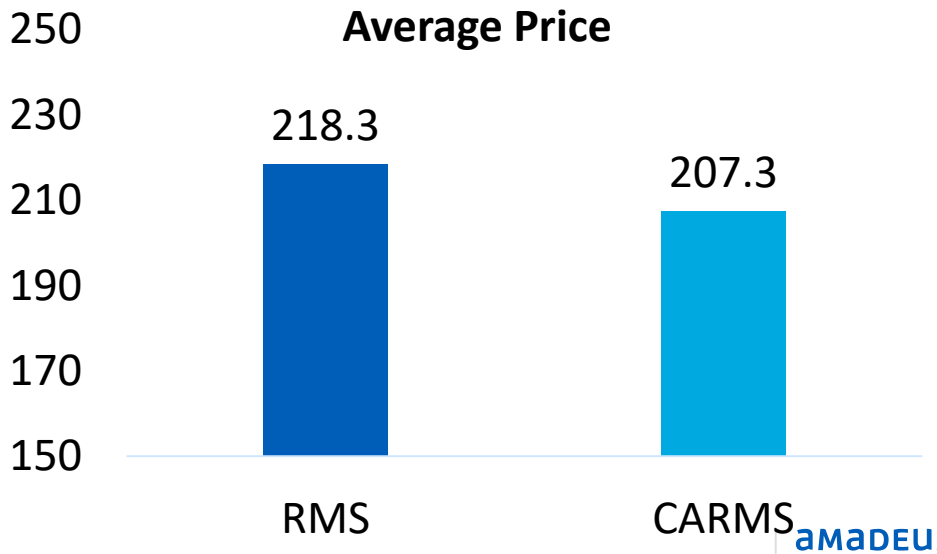
# Performance of RMS vs. CARMS (Reactive OAL)

## CARMS produces lower revenue gains with a reactive OAL than a non-reactive OAL

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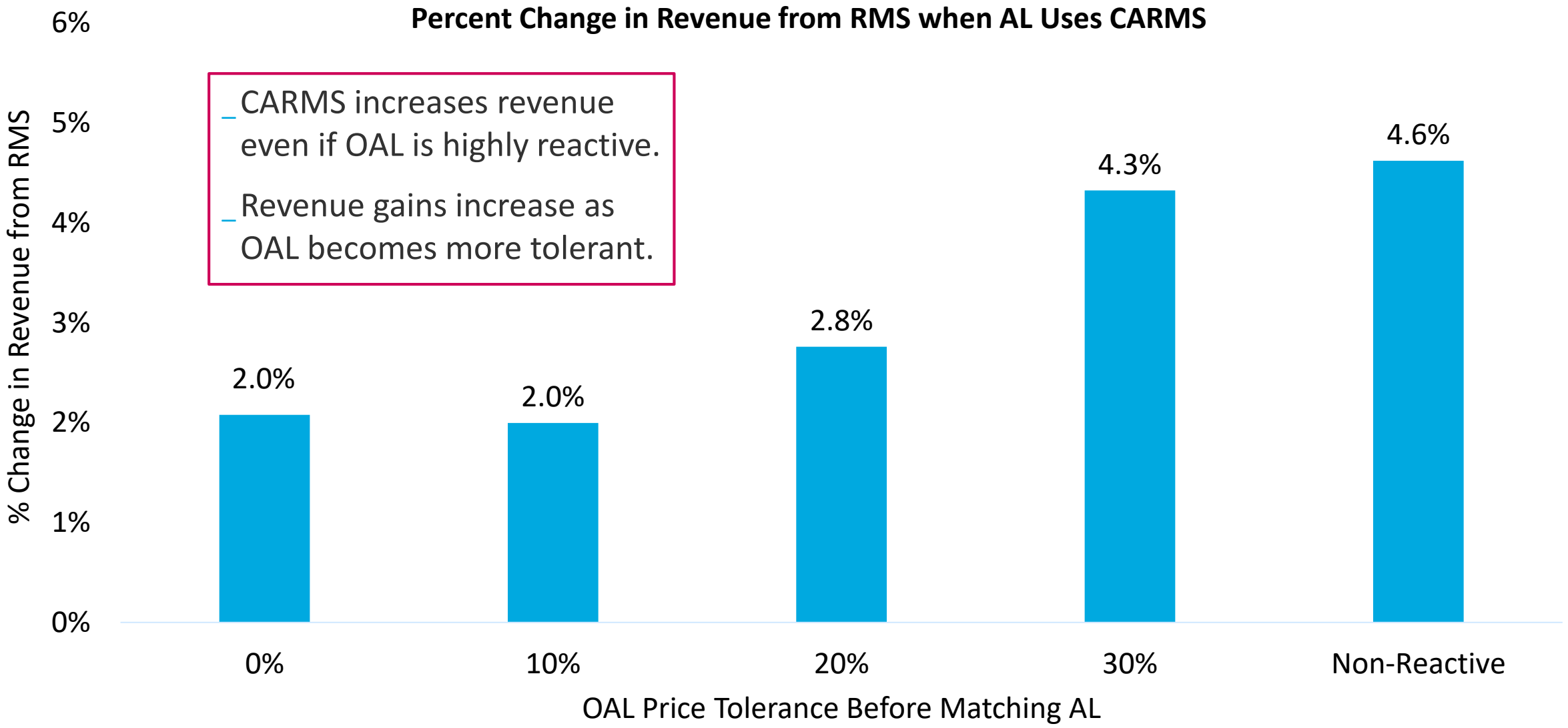
# CARMS is More Effective if OAL is More Tolerant to Being Undercut

## Increasing OAL's price tolerance approaches the non-reactive case




- CARMS increases revenue even if OAL is highly reactive.
- Revenue gains increase as OAL becomes more tolerant.

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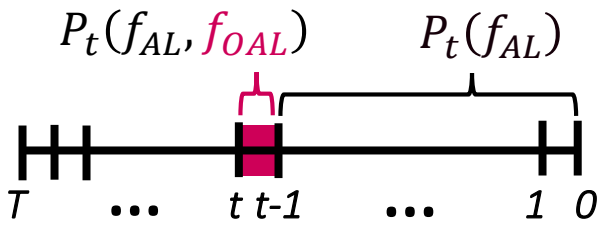
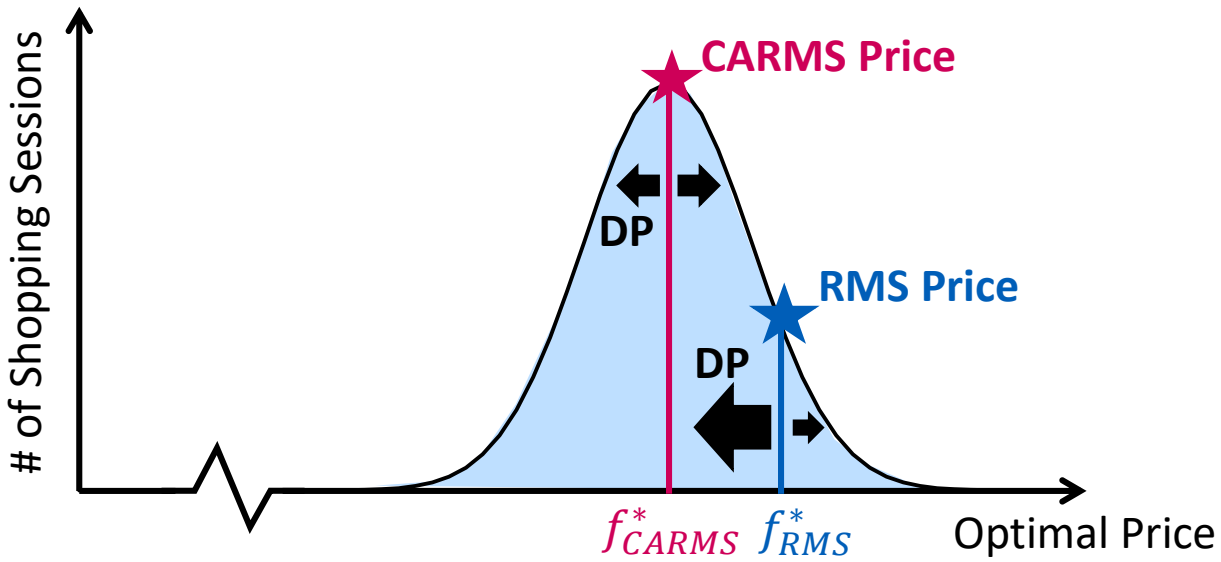
# RMS/CARMS and Dynamic Pricing are Complementary

## Dynamic Pricing computes adjustments to RMS/CARMS prices at the session-specific level

**RMS/CARMS with Dynamic Pricing**

$$\max_{f}[TR_t(f) - BP_t(x)P_t(f_{AL}, f_{OAL})]$$




- CARMS corrects RMS's price sensitivity bias, but does not have a session view
- DP fine-tunes CARMS using session-specific OAL prices and customer segmentation
- DP alone can also correct RMS's inherent bias, as seen in past work
  - RMS + DP: +6.0% revenue over RMS alone

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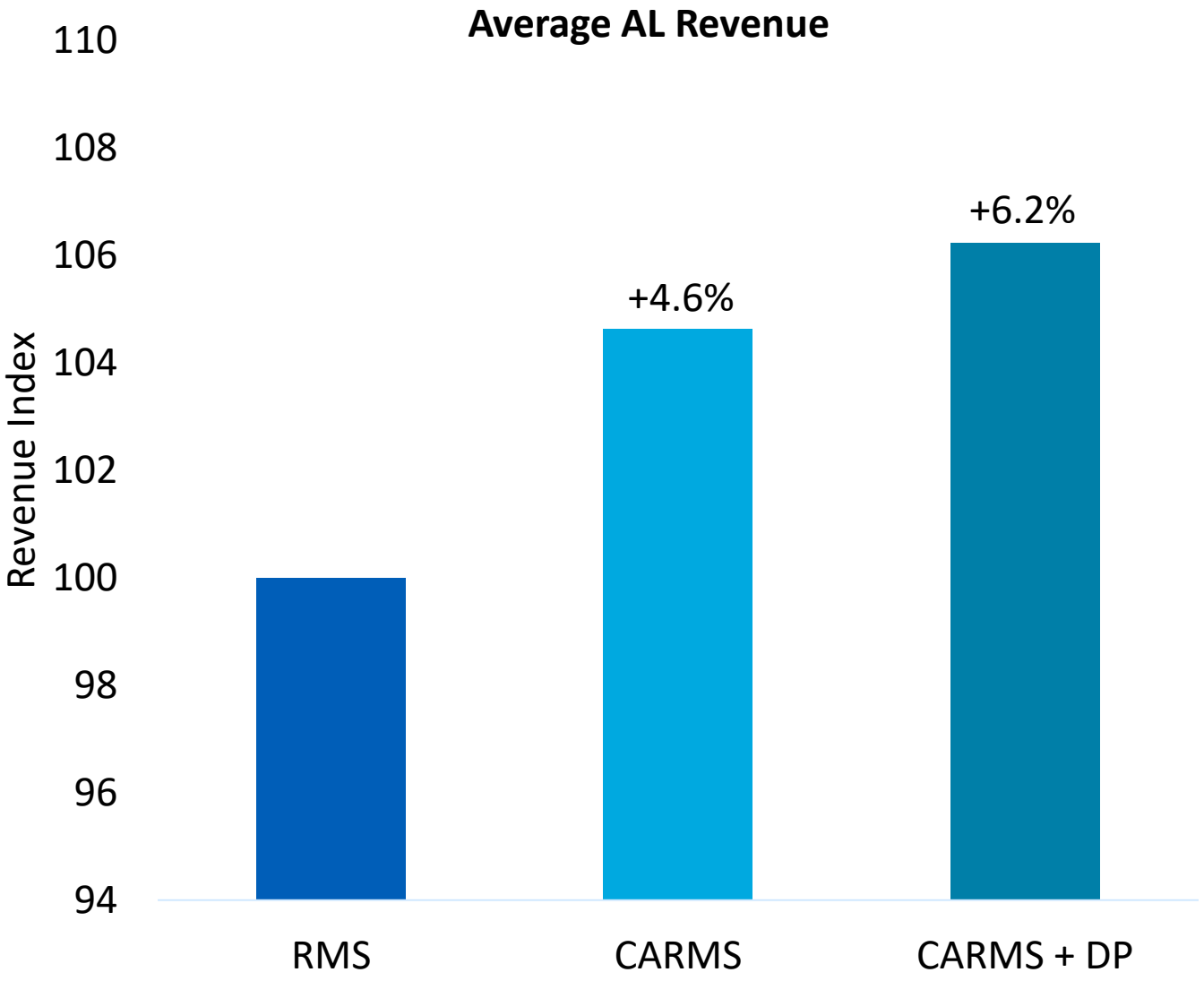
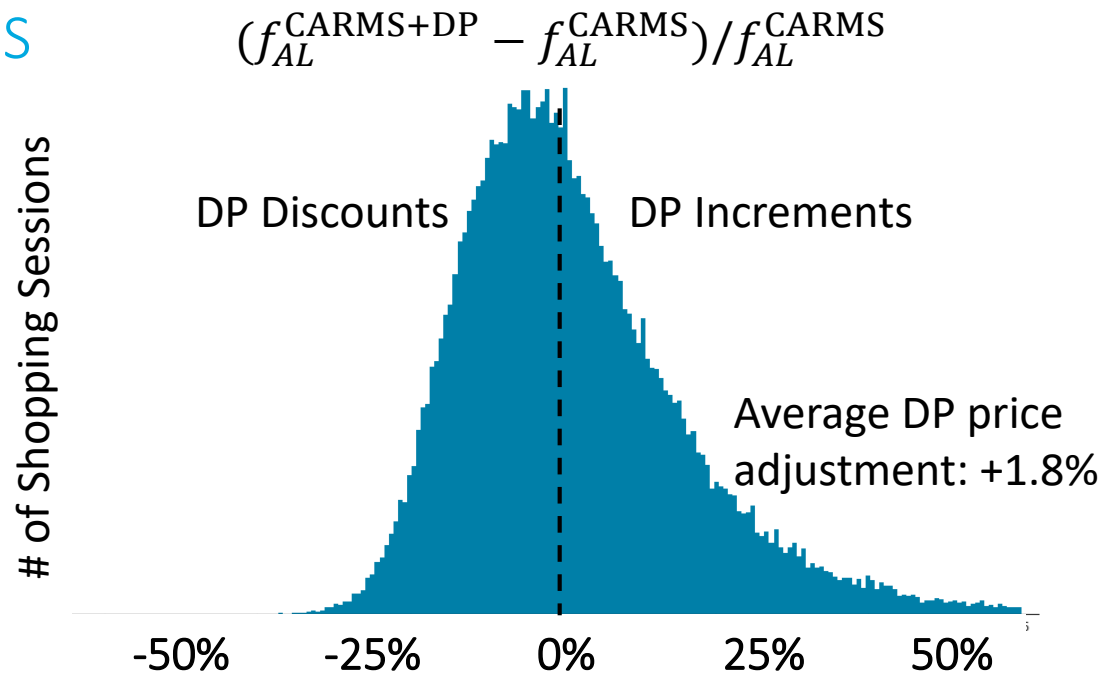
# CARMS with Dynamic Pricing

## DP provides additional revenue benefits over CARMS




- DP increases revenue by about 1.6% over CARMS alone.
- DP adjusts CARMS prices based on DP's view of actual OAL prices and customer price sensitivity.

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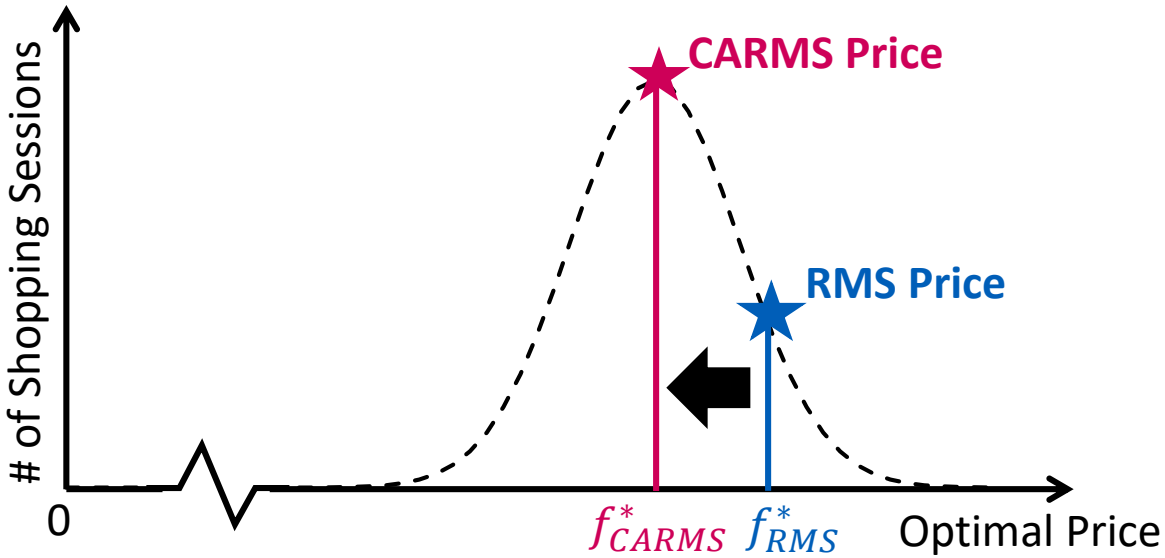
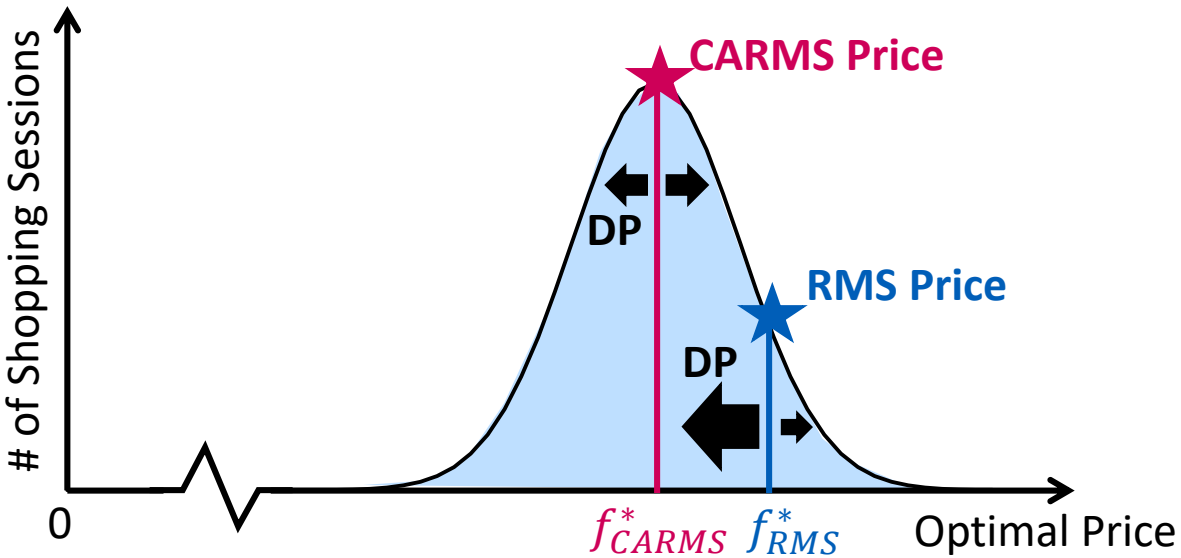
# Conclusions




## _CARMS corrects RMS's world view

- RMS has no visibility of OAL prices or reactions
- CARMS provides revenue gain of 2% – 5% over RMS

## _Future OAL prices can be forecasted

- Assumed impossible, but can actually be done with high accuracy using available data
- Anticipated OAL price reactions can be integrated into RM for the first time

## _Dynamic Pricing provides further value

- DP injects session-specific data into RMS or CARMS
- DP provides additional revenue gains of 1% – 2% over CARMS alone

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# Thank you!