Difficulty of the Conventional Approach

- Lack of invariance to the baseline condition
- Inference depends on the choice of baseline condition
- 3×2 example:
 - Treatment $A \in \{a_0, a_1, a_2\}$ and Treatment $B \in \{b_0, b_1, b_2\}$
 - Regression model with the baseline condition (a_0, b_0) :

$$\mathbb{E}(Y \mid A, B) = 1 + a_1^* + a_2^* + b_2^* + a_1^* b_2^* + 2a_2^* b_2^* + 3a_2^* b_1^*$$

- Interaction effect for $(a_2, b_2) >$ Interaction effect for (a_1, b_2)
- Another equivalent model with the baseline condition (a_0, b_1) :

$$\mathbb{E}(Y \mid A, B) = 1 + a_1^* + 4a_2^* + b_2^* + a_1^*b_2^* - a_2^*b_2^* - 3a_2^*b_0^*$$

- Interaction effect for $(a_2, b_2) <$ Interaction effect for (a_1, b_2)
- Interaction effect for (a_2, b_1) is zero under the second model
- All interaction effects with at least one baseline value are zero

The Contributions of the Paper

- Standard treatment interaction effects suffer from the lack of order and interval invariance to the choice of baseline condition
- Propose the marginal treatment interaction effect that is invariant
- Derive the identification condition and estimation strategy for this new quantity
- Generalize these results to the K-way causal interaction
- Illustrate the methods with the immigration survey experiment

Two-way Causal Interaction

• Two factorial treatments:

$$A \in \mathcal{A} = \{a_0, a_1, \dots, a_{D_A-1}\}$$
$$B \in \mathcal{B} = \{b_0, b_1, \dots, b_{D_B-1}\}$$

• Assumption: Full factorial design

Randomization of treatment assignment

$$\{Y(a_{\ell}, b_m)\}_{a_{\ell} \in \mathcal{A}, b_m \in \mathcal{B}} \perp \{A, B\}$$

Non-zero probability for all treatment combination

$$\Pr(A = a_{\ell}, B = b_m) > 0 \text{ for all } a_{\ell} \in \mathcal{A} \text{ and } b_m \in \mathcal{B}$$

- Fractional factorial design not allowed
 - Use a small non-zero assignment probability
 - Pocus on a subsample
 - Ombine treatments