

Business Outcomes in Advertising Powered by Machine Learning



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NCSolutions

BUSINESS OUTCOMES IN ADVERTISING POWERED BY MACHINE LEARNING

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*Better advertising
begins here.*

AI IS ALL THE BUZZ

A blue robotic hand on the left and a human hand on the right are positioned to form a heart shape with their fingers. The background is a solid blue color.

56% OF MARKETERS
WANT TO IMPROVE THEIR
CAMPAIGN MEASUREMENT
PERFORMANCE IN THE
NEXT 12 MONTHS

TODAY, WE WILL:

- Provide an overview of traditional and machine learning campaign measurement techniques
- Share how each traditional technique performed in a head-to-head comparison with machine learning
- Help you determine if you're accounting for all of the right variables



CAMPAIGN MEASUREMENT TECHNIQUES

TRADITIONAL

Household matching (Nearest-Neighbor)
Household matching (Propensity)
Inverse propensity weighting (IPW)

- Based on simple statistical models applied uniformly
- Simulates balanced test and control groups to estimate group-wise counterfactual



MACHINE LEARNING

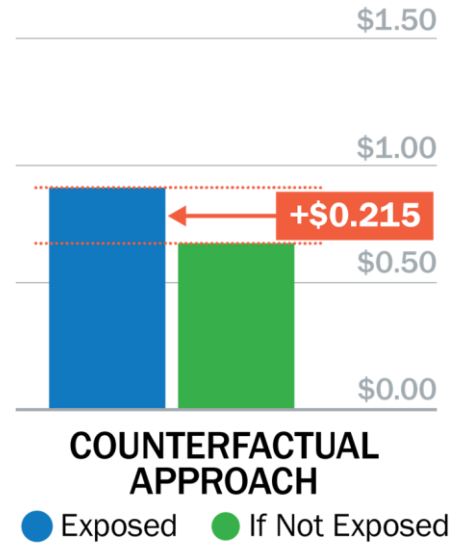
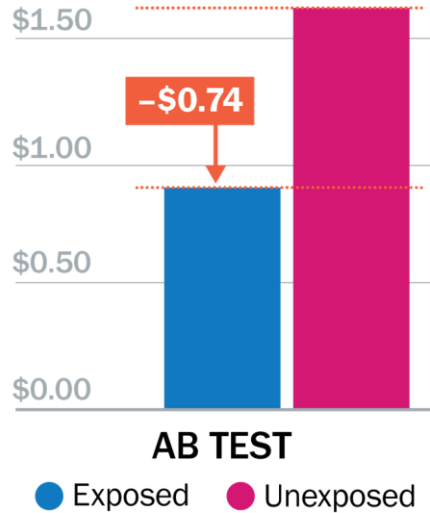
NCSolutions' Measurement Methodology

- Computationally robust for large, complex data sets
- Understands that data is not one-size-fits-all
- Estimates counterfactual for individual observations



WHY PREDICTIVE MODELING?

Simple A/B testing does not capture true effect



COUNTERFACTUAL uses a What-If MODEL to estimate true effect

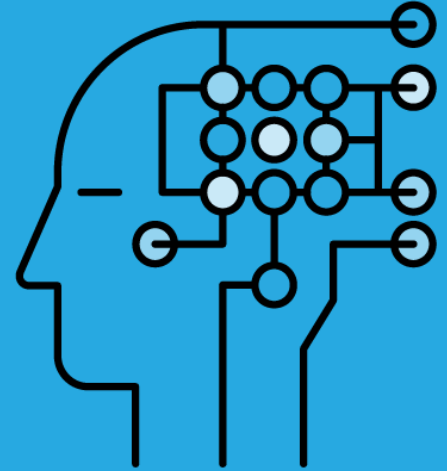
HOW DOES MACHINE LEARNING COMPARE TO TRADITIONAL METHODS?

MEASURES:

- 1. ACCURACY:** percent of experiments where the method was closest to the true effect
- 2. VALIDITY:** percent of experiments where the true effect was in the 80% confidence interval
- 3. POWER:** average width of the confidence interval

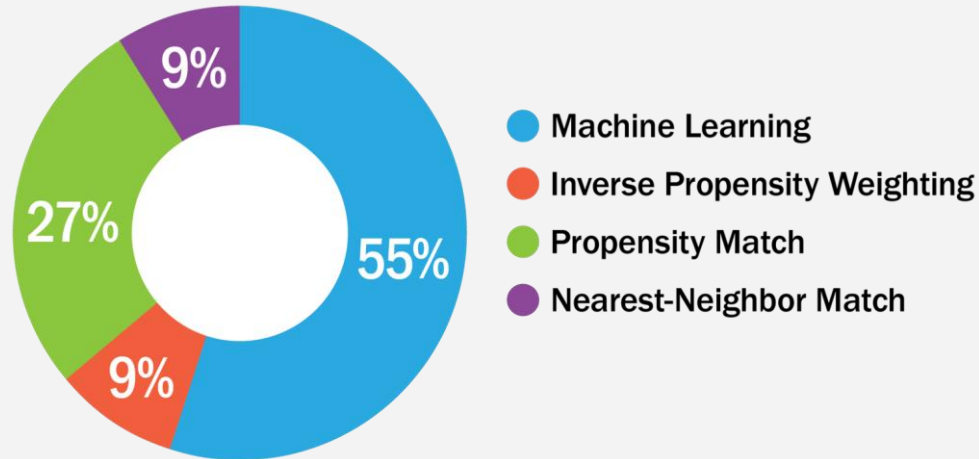
APPROACH:

- 11 experiments
 - Real observational input data across CPG departments
 - Simulated brand purchase with a known true effect



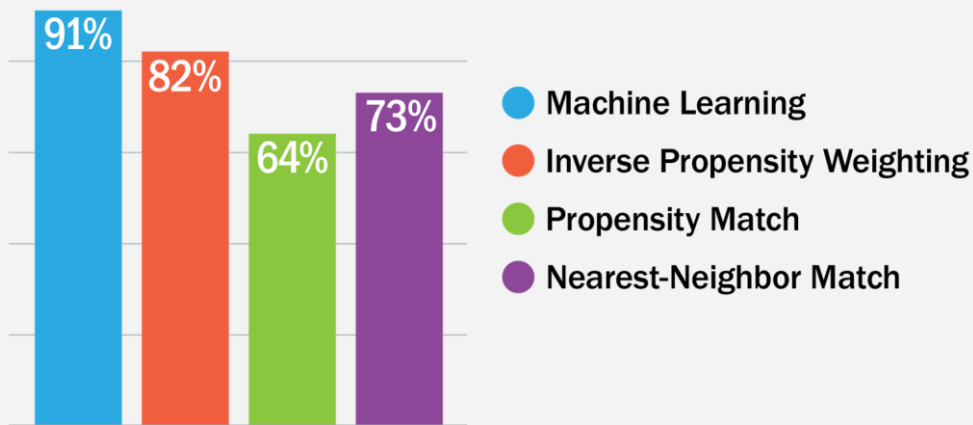
MACHINE LEARNING OUTPERFORMS ON ACCURACY

ACCURACY: PERCENT OF SCENARIOS WITH CLOSEST ESTIMATE



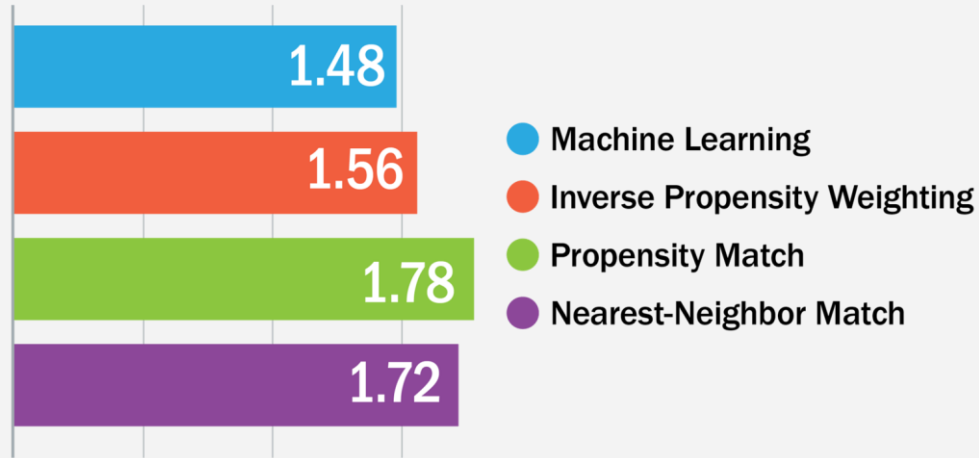
MACHINE LEARNING GIVES VALID ESTIMATES MOST OFTEN

VALIDITY: PERCENT OF SCENARIOS WITH TRUE EFFECT IN CONFIDENCE INTERVAL



MACHINE LEARNING IS MORE STATISTICALLY POWERFUL

POWER: AVERAGE WIDTH OF CONFIDENCE INTERVAL



ML vs. RCTs

In tightly controlled experiments, randomized controlled trials (RCTs) are considered very accurate.

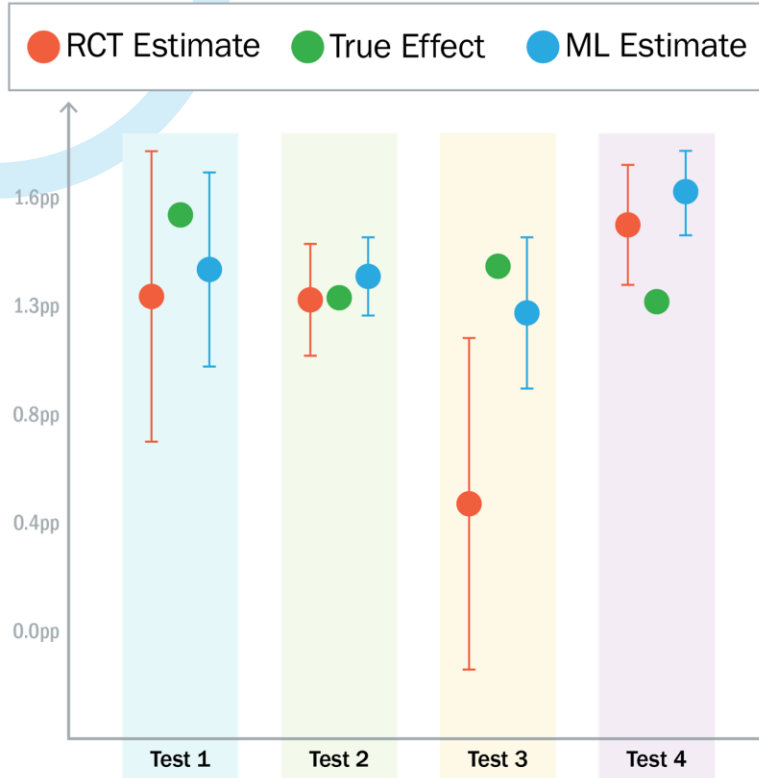
(These are costly, and not always feasible)

APPROACH:

- Ran both RCT & ML analysis
- 4 technicians created test-control groups on real, limited data
 - Given 250,000 HH, not all needed to be used
- Applied the same outcome function to each, depending on a larger set of variables

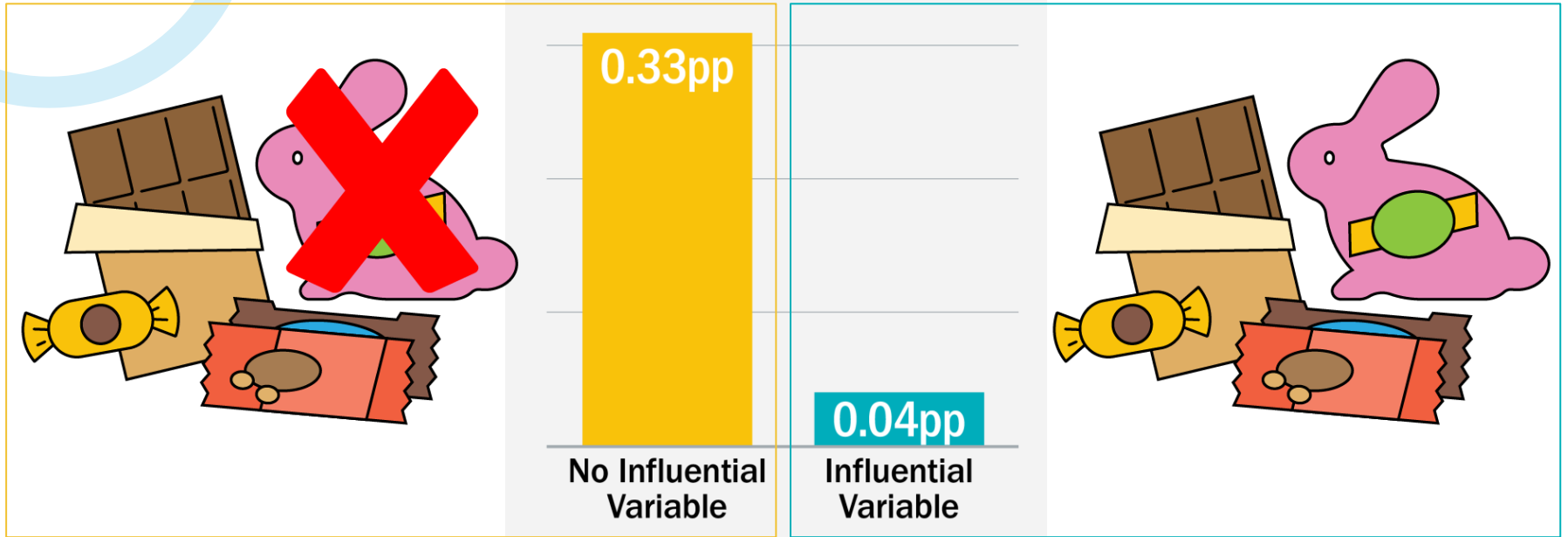


HEAD TO HEAD: ML VS. RCT



- Both ML and RCT are **ACCURATE**
- Both methods are generally **VALID**
- ML is **MORE POWERFUL**
- Test 3 had very small control group relative to the total population
 - Control = 12,864
 - Test = 24,000
 - RCT **ACCURACY** requires large test AND control populations

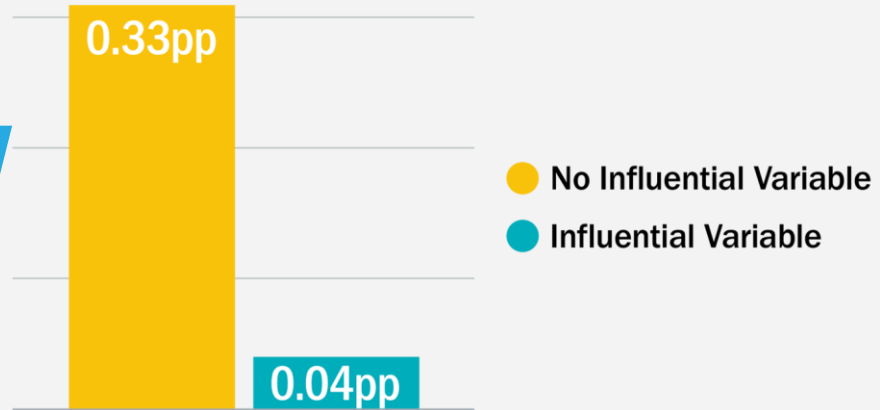
HOPPING INTO INSIGHTS



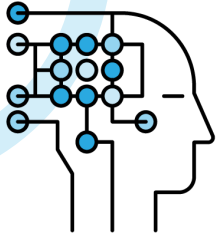
ACCOUNTING FOR ALL OF THE RIGHT VARIABLES

ROBUST DATA IS CRITICAL FOR ANY MEASUREMENT TECHNIQUE TO BE SUCCESSFUL WITH MORE ACCURACY

IMPACT OF LEAVING OUT AN INFLUENTIAL VARIABLE



TAKEAWAYS & BEST PRACTICES



MACHINE LEARNING IS A PROVEN APPROACH TO MEASURE ROI

- Accurate, valid and powerful
- Reliable and a great alternative to RCTs



MACHINE LEARNING BENEFITS:

- Versatile, agile and applies the right models
- Faster and offers more precision and granularity
- Supports smaller brands and smaller campaigns



QUESTIONS TO ASK:

- Is the data robust and informative for the questions you are asking?
- Are the sample populations large enough?
- Are the methodologies provably accurate, valid and powerful?
- Are your sales lift results driving and informing your strategic decisions?

THANK YOU!

CONNECT WITH US:

Learn how NCS Next Gen machine learning measurement can help your outcomes:

- Faster Results
- Flexible
- Actionable
- Precise Insights

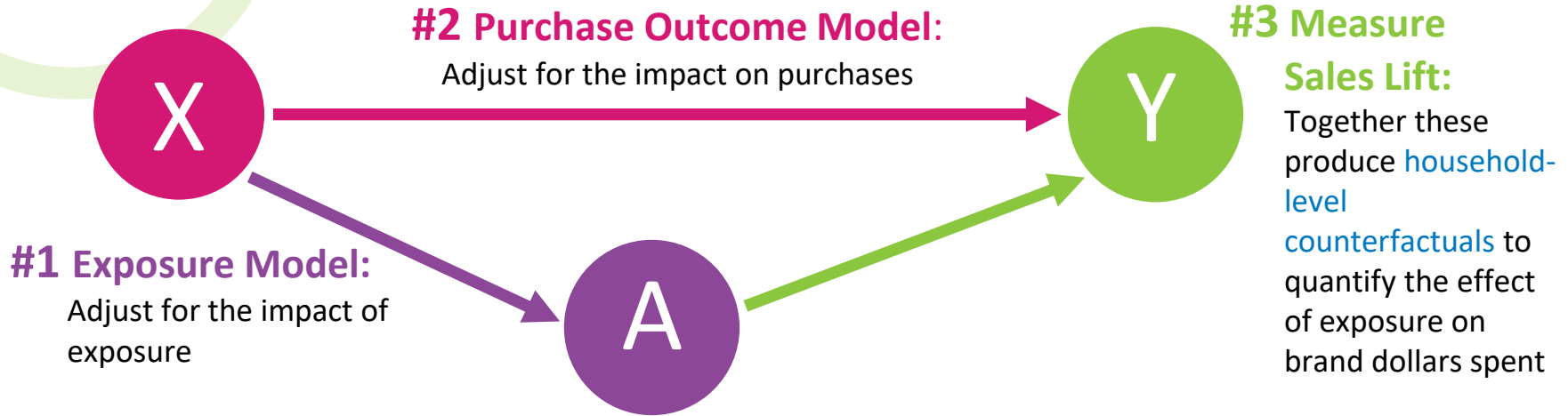


SCAN ME



APPENDIX

MACHINE LEARNING NEXT GEN CAUSAL FRAMEWORK: POWERED BY SUPERLEARNERS



X = Variables (i.e., HH demos, previous category and brand buying, etc.)

A = Ad Exposure (i.e., Targeting)

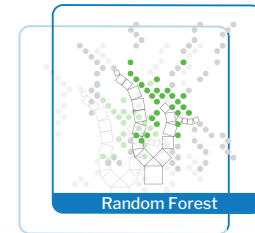
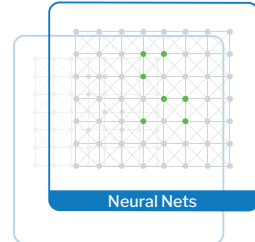
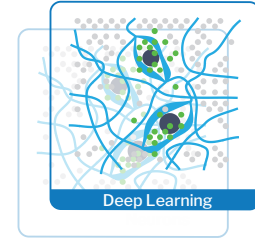
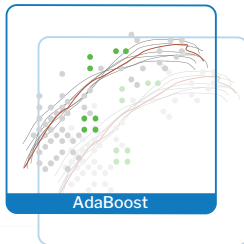
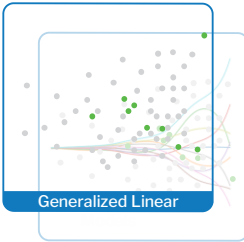
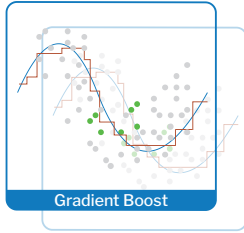
Y = Outcomes (i.e., Brand Dollars Spent)

WHAT IS A SUPERLEARNER?

Step 1: Builds many different models

Step 2: Narrows them down based on a loss function

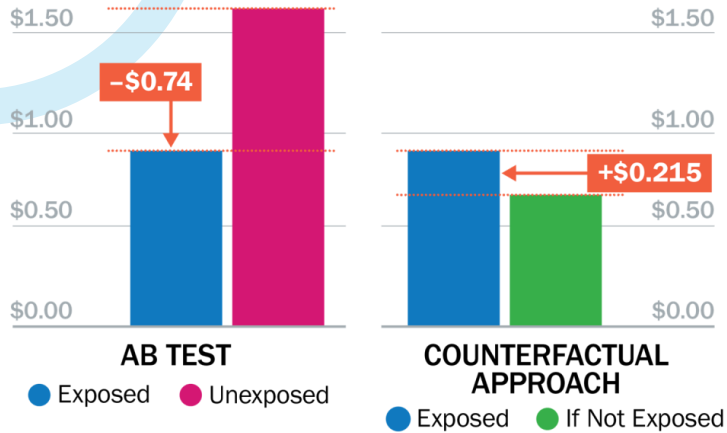
Step 3: Combines them into one ensemble model



SuperLearner - Built with Robust Statistics

● HH with Lift

WHY PREDICTIVE VARIABLES?



Exposed?	Real Brand X \$	Brand X \$ (if unexposed)
Yes	\$1.19	\$1.00
No	\$2.25	—
No	\$1.00	—
Yes	\$0.59	\$0.35

SAMPLE OUTCOME FUNCTION

```
def prob(banner, pce, income, disc, hhsize, femage, gender, poc, csqty, catquart, popre, exposed):  
    if pce == 1:  
        if banner == 60:  
            p0 = 0.005*income**0.5 + 0.15*disc*popre/4 + 0.2*gender + 0.1*poc + 0.05*hhsize - 0.1*((femage-2)**2-0.5)  
                + 0.08*exposed*(1-0.1*hhsize+0.3*gender+0.2*poc)  
        elif banner == 19:  
            p0 = 0.007*income**0.5 + 0.02*disc + 0.2*gender - 0.05*poc + 0.3*hhsize*popre/7 - 0.03*((femage-2)**2-0.5)  
                + 0.1*exposed*(1+0.05*hhsize+0.3*gender+0.1*poc)  
        else:  
            p0 = 0.005*income**0.5 + 0.08*disc*hhsize/6 + 0.2*gender + 0.07*hhsize - 0.07*((femage-3)**2-0.5) + 0.03*popre  
                + 0.07*exposed*(1+0.05*hhsize+0.3*gender+0.1*poc*catquart/4)  
    elif pce == 0:  
        if banner == 60:  
            p0 = -0.3 + 0.001*income**0.5 + 0.1*disc + 0.05*hhsize - 0.01*popre/10 + 0.01*poc + 0.06*exposed*(1-0.1*hhsize)  
        elif banner == 39:  
            p0 = -0.3 + 0.01*np.log(np.max([income,1])) + 0.1*gender + 0.1*disc*hhsize + 0.05*poc - 0.03*femage  
                + 0.06*exposed*(1+0.05*hhsize+0.2*gender+0.5*disc)  
        else:  
            p0 = -0.3 + 0.005*popre/10 + 0.01*income**0.25 + 0.1*gender*(1+0.5*disc) + 0.12*hhsize - 0.1*((femage-2)**2-0.5)
```