Car Seats as Contraception

A statistical analysis of JD Vance’s controversial claim

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Car Seats? Birth Rates?

Welcome, VP Vance!

“As my husband and I were discussing having children, he turned to me and said “what about the car seats though?” I said “you’re right, let’s just forget about it””

-TikTok user ktduncan33 in apparent sarcasm

Fertility Rates

- Fertility Rates in the United States decreased by 3% in 2023, from 2022, reaching a historic low.
- From 2014-2020, the rate has consistently decreased by 2% annually.
- Attributed to increased education and employment for women, rising costs, greater acceptance of smaller families
- But, car seats laws?

Car Seat Laws Decrease Birth Rates?

- **Car Seats as Contraception** - David Solomon (University of Washington) and Jordan Nickerson (Boston College)
- Economists
- Forthcoming since 2021
- No data or appendix attached
- Methodology raises questions

Car Seat Laws

Mandate History in CT

- 1982 - Connecticut enacted a child auto restraint law that required children younger than a year old to be in a federally approved seat.
- 1994 - Law was amended to require children 3 or younger to be in car seat
- 2005 - Children required to be in car seat until over 6 years
- 2017 - 7 years or younger

The Argument

Car Seats as Contraception

- When family have exactly two young children already in car seats
- Third child?
  - Bigger car is a significant cost
  - Minivans are ugly
    - “most practical options like minivans… have class and lifestyle connotations that may not appeal to everyone”

Conditions

- Not all families are affected by car seat mandates
- Effect only seen for third child births, so women need to have two exact children that are mandated to be in car seats
- Households with access to a car
- Households with an adult male present

Model

OLS regression

$$Birth_{i,j,t} = a + b_1 \cdot \text{TwoChildrenBothBound}_{i,j,t} + b_2 \cdot \text{County-Year-NumChildren}_{i,j,t}$$
$$+ b_3 \cdot \text{ChildAges}_{i,j,t} + b_4 \cdot \text{County-Race}_{i,j} + b_5 \cdot \text{Year-Race}_{i,t} + b_6 \cdot \text{County-Income}_{i,j}$$
$$+ b_7 \cdot \text{Year-Income}_{i,t} + b_8 \cdot \text{County-Education}_{i,j} + b_9 \cdot \text{Year-Education}_{i,t}$$
$$+ b_{10} \cdot \text{County-MalePresent}_{i,j} + b_{11} \cdot \text{Year-MalePresent}_{i,t} + e_{i,j,t}$$

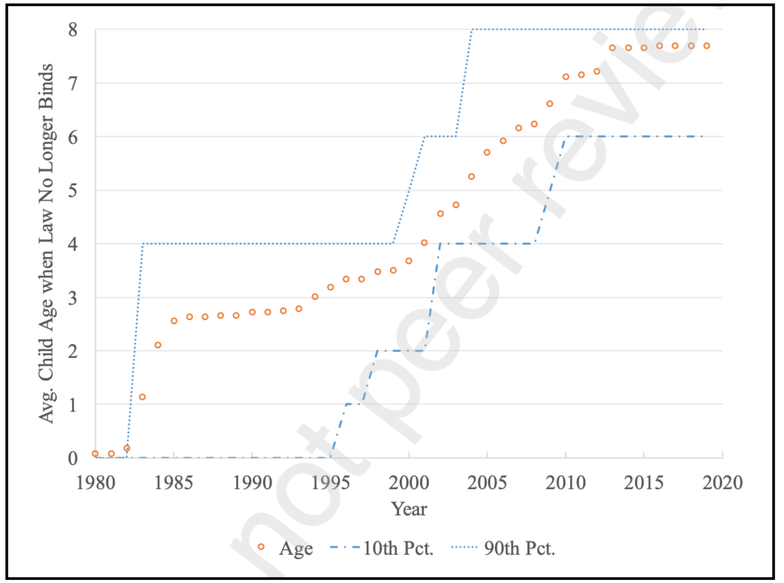
for woman i in state j and year t

- Measures how much of an effect TwoChildrenBothBound has on probability of a woman giving birth
- Model is soaking up differences across core demographics, isolating the seat-law effect from everything else that might drive fertility

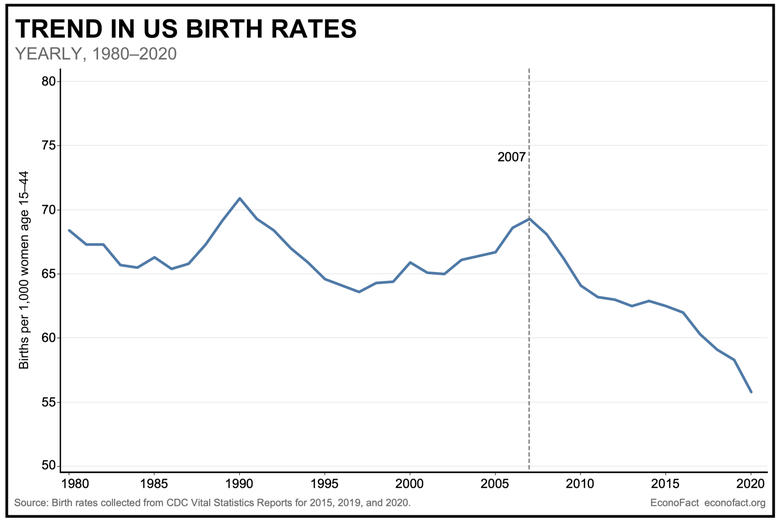
Model Strengths

- National-level data with a variety of age cutoffs
- Addresses usual suspects that might drive fertility
  - County x Year x Number of Children
    - Local economy, culture, specific policy changes
  - Child Ages
    - Having two young children vs having two older children
    - Can still have different twoChildrenBothBound values because of differing car seat law across time and state

Distribution of Car Seat Laws Over Time



Source: “Car Seats as Contraception”



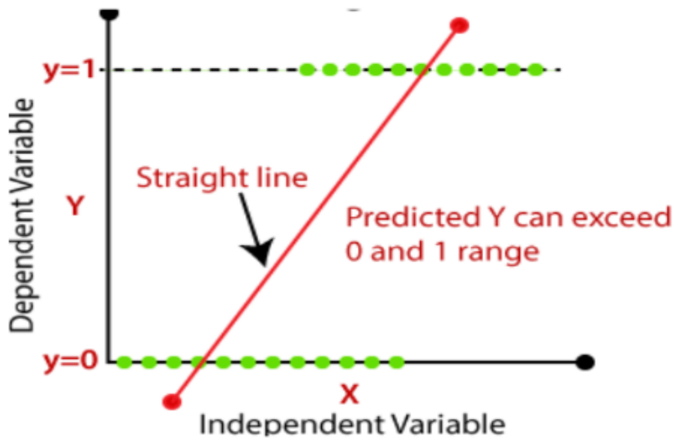
Source: CDC

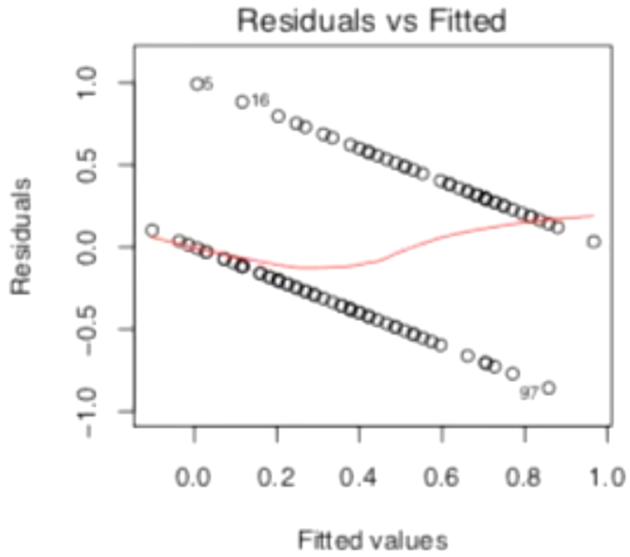
Model Weaknesses

- OLS regression on a binary outcome could be problematic
- No explanation as to why this model was chosen
  - Model wasn’t checked
  - No assumptions
- Not necessarily a problem, but it could be. This is a complicated model

OLS concerns

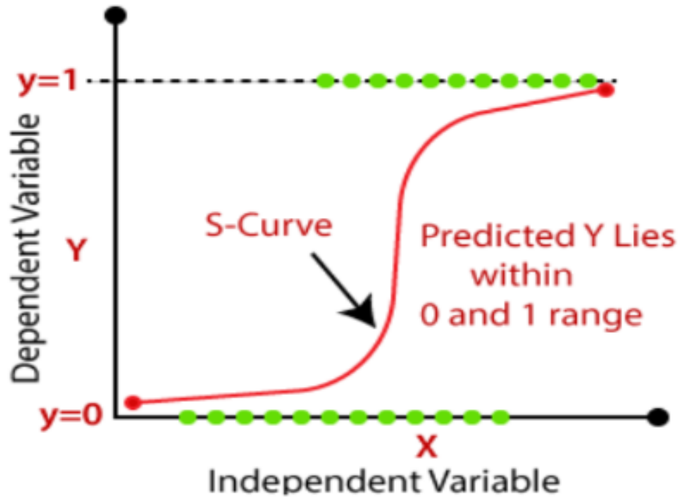
- Predicts continuous outcome, can fall outside predicted values of [0, 1]
- Violates homoscedasticity assumption
  - Authors address heterscedasticity by using two-way clustered, robust standard errors
- Residuals non-normal





Benefits of Logistic Regression

- Models the probability of events given one or more independent variables
- Output will always be binary
- $$f(x) = \frac{1}{1 + e^{-(\beta_1 x + \beta_0)}}$$
- No linear relationship needed between x and y
  - Only linearity between x and log odds of y
- Errors don’t have to be normal
- Homoscedasticity not required



Data

- Car seat mandate data from every state
- Household-level data, American Community Survey (ACS)
  - Yearly random sample of 3.5 million addresses
  - Raw data are rows of each person in a household with selected variables about that person

SERIAL NO	AGE	SEX	RACE	HHINCOME	RELP
15932	67	1	White	150070	0
15932	64	2	White	150070	1
23347	42	1	Asian	59300	0
23347	38	2	Asian	59300	1
23347	4	1	Asian	59300	2

Final Sample

1. ACS data from 2000-2017
2. Filter out group quarters and households with in-laws and only keep households with at least one woman
3. Each observation corresponds to one woman in a household
4. Link demographics with number and ages of children
5. Using ages, they reconstruct a panel of each woman's birth history
6. Restrict to only women aged 18-35

69.7 million observations

SERIAL NO	Age	# of previous children	Panel Year	Year	Two Children Both Bound	Birth
26222	18	0	1994	2006	0	0
26222	24	0	2000	2006	0	1
26222	30	1	2006	2006	0	0
57230	28	0	2011	2014	0	1
57230	29	1	2012	2014	0	1
57230	30	2	2013	2014	1	0

Results

Car Seat Constraint Reduces Births

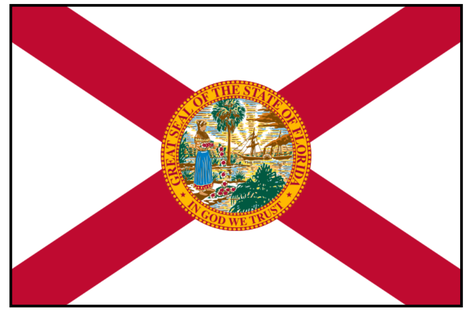
Panel A - Baseline Effect of Car Seat Mandates on Third Child Births						
Dep. Variable: 1(Birth Year)	(1)	(2)	(3)	(4)	(5)	(6)
Two Children, Both Bound	-0.422***	-0.554***	-0.620***	-0.737***	-0.587***	-0.732***
	(-2.79)	(-4.09)	(-4.80)	(-5.44)	(-4.76)	(-5.69)
County-Year-#Children, Child Ages	Y	Y	Y	Y	Y	Y
Base Char. F.E.	N	Y	Y	Year	County	County, Year
Ex-Post Char. F.E.	N	N	Y	Year	County	County, Year
Observations	69,691,299	69,691,299	69,691,299	69,691,299	69,691,279	69,691,279
R-squared	0.045	0.048	0.063	0.066	0.065	0.068

- After controlling for all variables, women who have exactly two children who both fall under the car seat law for that year, her probability of giving birth drops by 0.732 percentage points
- Baseline birth rate in sample - 8.4%. This is an 8% to 9% relative reduction

Replication Sample: CT & FL

Smaller Scale

- Two very different car seat histories
  - CT raised its car seat age from 3 -> 6 in 2005
  - FL kept the age at 3 until 2015, then moved to 5
- Variation in car seat law history
- Only used 2006-2017 data



Key differences vs authors' model

- Only 2 states (authors used all 50 + DC)
- ChildAges redone into three buckets vs. thousands of exact-age combos
- CountyxYearx#kids gone vs huge interaction set
- Over-specification risk: thousands of dummies -> `lm()` never converges
  - Unknown software or estimation tricks (no appendix)

Why *not* panel data?

- Cross-section only: each woman appears once in the year that they were surveyed
- Still ~ 135K observations
- No need to do extra modeling
- Simplifies interpretation and still measures effect
- Inferences on key variable remain strong: standard errors small, effect sizes stable

Model Used

$$\begin{aligned} Birth = a + b_1 \cdot \text{TwoChildrenBothBound} + b_2 \cdot \text{ChildAges} \\ + b_3 \cdot \text{Race} + b_4 \cdot \text{Income} + b_5 \cdot \text{Year} \\ + b_6 \cdot \text{Education} + b_7 \cdot \text{Age} \\ + b_8 \cdot \text{MalePresent} + b_9 \cdot \text{State} + e \end{aligned}$$

- Going to fit an OLS model and a logistic model
- Model is leaner

Results

```
Coefficients:
                          Estimate Std. Error z value Pr(>|z|)
(Intercept)              19.426618   5.456599   3.560 0.000371 ***
twoChildrenBothBound      0.003872   0.076918   0.050 0.959849
STFL                     -0.141131   0.026184  -5.390 7.05e-08 ***
YEAR                     -0.011074   0.002714  -4.080 4.50e-05 ***
ageCombo0-2               0.474288   0.029643  16.000  < 2e-16 ***
ageCombo0-2,0-2          -0.826216   0.184694  -4.473 7.70e-06 ***
ageCombo0-2,0-2,0-2      -9.493541  39.832096  -0.238 0.811618
ageCombo0-2,0-2,3-5      -1.470631   0.384592  -3.824 0.000131 ***
ageCombo0-2,0-2,6+       -1.048843   0.419426  -2.501 0.012396 *
ageCombo0-2,3-5          -0.355386   0.071135  -4.996 5.85e-07 ***
ageCombo0-2,3-5,3-5      -0.173377   0.170028  -1.020 0.307873
ageCombo0-2,3-5,6+       -0.466685   0.105145  -4.439 9.06e-06 ***
ageCombo0-2,6+           -0.311937   0.070998  -4.394 1.11e-05 ***
ageCombo0-2,6+,6+        -0.438071   0.117598  -3.725 0.000195 ***
ageCombo3-5               0.989560   0.029872  33.126  < 2e-16 ***
ageCombo3-5,3-5           0.244476   0.080146   3.050 0.002286 **
ageCombo3-5,3-5,3-5       0.229978   0.360835   0.637 0.523897
ageCombo3-5,3-5,6+        0.099091   0.123545   0.802 0.422514
ageCombo3-5,6+           -0.110084   0.046632  -2.361 0.018240 *
ageCombo3-5,6+,6+        -0.445373   0.085235  -5.225 1.74e-07 ***
ageCombo4+               -0.261750   0.067281  -3.890 0.000100 ***
ageCombo6+                0.290805   0.039006   7.455 8.97e-14 ***
ageCombo6+,6+            -0.525724   0.054841  -9.586  < 2e-16 ***
ageCombo6+,6+,6+         -0.895587   0.104432  -8.576  < 2e-16 ***
RaceBlack                 0.437748   0.052476   8.342  < 2e-16 ***
RaceOther                 0.181333   0.057896   3.132 0.001736 **
RaceWhite                 0.176545   0.046017   3.837 0.000125 ***
Age                      -0.010608   0.002546  -4.167 3.09e-05 ***
EducationC               -0.108674   0.023094  -4.706 2.53e-06 ***
EducationM                0.077045   0.030293   2.543 0.010981 *
income_quintile2         -0.339737   0.032136 -10.572  < 2e-16 ***
income_quintile3         -0.497860   0.033202 -14.995  < 2e-16 ***
income_quintile4         -0.496557   0.034177 -14.529  < 2e-16 ***
income_quintile5         -0.276217   0.035623  -7.754 8.91e-15 ***
male_present1             1.462353   0.029673  49.283  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Logistic Model Output

```
Coefficients:
                          Estimate Std. Error t value Pr(>|t|)
(Intercept)               1.9471906  0.4642593   4.194 2.74e-05 ***
twoChildrenBothBound     -0.0004897  0.0064926  -0.075 0.939877
STFL                     -0.0128433  0.0023166  -5.544 2.96e-08 ***
YEAR                     -0.0009349  0.0002309  -4.049 5.15e-05 ***
ageCombo0-2               0.0520588  0.0030276  17.195  < 2e-16 ***
ageCombo0-2,0-2          -0.0604653  0.0127336  -4.748 2.05e-06 ***
ageCombo0-2,0-2,0-2      -0.1162086  0.0596832  -1.947 0.051526 .
ageCombo0-2,0-2,3-5      -0.0836958  0.0185355  -4.515 6.32e-06 ***
ageCombo0-2,0-2,6+       -0.0683838  0.0247533  -2.763 0.005735 **
ageCombo0-2,3-5          -0.0325609  0.0058031  -5.611 2.02e-08 ***
ageCombo0-2,3-5,3-5      -0.0177467  0.0143764  -1.234 0.217045
ageCombo0-2,3-5,6+       -0.0388627  0.0078100  -4.976 6.50e-07 ***
ageCombo0-2,6+           -0.0274363  0.0055410  -4.952 7.37e-07 ***
ageCombo0-2,6+,6+        -0.0356488  0.0086983  -4.098 4.16e-05 ***
ageCombo3-5               0.1225199  0.0033166  36.941  < 2e-16 ***
ageCombo3-5,3-5           0.0226850  0.0076015   2.984 0.002843 **
ageCombo3-5,3-5,3-5       0.0203245  0.0347178   0.585 0.558266
ageCombo3-5,3-5,6+        0.0076022  0.0112959   0.673 0.500945
ageCombo3-5,6+           -0.0117374  0.0038871  -3.020 0.002532 **
ageCombo3-5,6+,6+        -0.0346508  0.0061745  -5.612 2.00e-08 ***
ageCombo4+               -0.0220435  0.0052249  -4.219 2.46e-05 ***
ageCombo6+                0.0237752  0.0034466   6.898 5.29e-12 ***
ageCombo6+,6+            -0.0371178  0.0038267  -9.700  < 2e-16 ***
ageCombo6+,6+,6+         -0.0532740  0.0060844  -8.756  < 2e-16 ***
RaceBlack                 0.0345088  0.0044619   7.734 1.05e-14 ***
RaceOther                 0.0163703  0.0049434   3.312 0.000928 ***
RaceWhite                 0.0157367  0.0039472   3.987 6.70e-05 ***
Age                      -0.0007733  0.0002129  -3.632 0.000281 ***
EducationC               -0.0080801  0.0019357  -4.174 2.99e-05 ***
EducationM                0.0093827  0.0026752   3.507 0.000453 ***
income_quintile2         -0.0227441  0.0025675  -8.858  < 2e-16 ***
income_quintile3         -0.0366941  0.0027204 -13.489  < 2e-16 ***
income_quintile4         -0.0394927  0.0029160 -13.544  < 2e-16 ***
income_quintile5         -0.0187645  0.0031706  -5.918 3.26e-09 ***
male_present1             0.0996956  0.0020110  49.575  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

OLS Model Output

Logistic Model Sanity Check

- As one unit in year increases, odds of giving birth decreases by 1.1%, all else constant
- As age increases, odds of giving birth decreases by 1.1%
- Women with only a HS diploma or less have 10% higher odds
- The lowest income quintile shows the highest odds of birth by far

	Estimate	Odds-Ratio	Std. Error	P-value
twoChildrenBothBound	0.0039	1.004	5.46	0.96
Year	-0.011	0.989	0.003	0.000
ST-FL	-0.1411	0.87	0.03	0.000
Age	-0.011	0.989	0.003	0.000
Educ C	-0.11	0.9	0.023	0.000
Income Quintile 3	-0.5	0.61	0.033	0.000
Income Quintile 5	-0.28	0.76	0.036	0.000

Kids' Ages effects

- Having 1 kid, 0-2, increases odds of birth by 61%, compared to if she had none, all else constant
- Having 2, on the other hand, decreases odds by 57%
- Having three very young children isn't a significant coefficient
- Having one kid aged 3-5 increases odds of birth by 2.69
- Having 4+ kids of any age decreases odds by 33%, compared to none

Kids' Ages	Estimate	Odds-Ratio	Std. Error	P-value
0-2	0.47	1.6	0.03	0.000
0-2, 0-2	-0.83	0.43	0.18	0.000
0-2,0-2,0-2	-9.49	0.000	39.8	0.8
0-2, 0-2, 3-5	-1.47	0.23	0.38	0.0001
3-5	0.989	2.69	0.03	0.000
3-5, 3-5	0.24	1.27	0.08	0.002
4+ kids	-0.26	0.77	0.067	0.0001

Discussion - CT/FL Replication

twoChildrenBothBound significance

- OLS - p-value = 0.7, logistic - p-value = 0.8
- How parents space their kids remains single largest predictor

- Despite our results, we unfortunately didn’t replicate the analysis 1:1
  - Having access to their raw data and knowing the specifics of how they crafted their model would be useful
  - Chance they applied subtle data clean up or fixed effect trick

Implications

- How did a single OLS headline number travel from a dense academic model to a sound-bite in the Senate?
- What standard should we hold public figures to - especially when they’re quoting nuanced statistical research to millions of people?

Thank you!