# Driving, Dropouts, and Drive-Throughs: Mobility Restrictions and Teen Human Capital

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# Teens and Accessibility

Teens make decisions that impact lifetime human capital (e.g., school & work)

Automobiles are often necessary to access school, work, and leisure for US teens

- 76% of HS students drive some, 50% use an autos to commute to school

Teens driving is dangerous, leading to adoption of driving restrictions

- Once legal age to drive in US, auto mortality increases 44% (Huh & Reif '21)

Ex ante, difficult to sign or predict effects of driving restrictions

- All activities plausibly impacted by driving restrictions
- Activity choices interrelated because of limited time budget
- Many activities can be chosen, and they might be substitutes or complements

# This Paper

**Research questions**

1. Did graduated driver licensing (GDL) laws shift 16yo school & work behavior?
2. How can we distinguish:
   - **direct** effects of reduced accessibility to an activity from
   - **indirect** effects from substituting between activities?

**How we answer**

- Use DDD design to study effect of GDL on schoolgoing
- Provide reduced form evidence on potential explanations, like substitution to work or varying degree of license restrictions
- Estimate a mulitple discrete choice model to quantify indirect effects and "rationalize" unintended consequences

# Contributions & Summary

- First evidence of GDL effects on educational outcomes
  - DDD interacted policy research design (using compulsory schooling laws)
- Schooling for 16yo's *increases* by 1.1pp after GDL adoption if dropping out legal
  - Placebo test: no effect in states with compulsory attendance
  - Accessibility is a determinant of high school dropout, but...
- 16yo employment declines by 1.7-2.2pp
  - Better understanding employment decisions and how they relate to accessibility
- Multiple discrete choice model rationalizes unintended consequences
  - Reduced form $\rightarrow$ maybe school/work are substitutes?
  - Model: School & work are weak complements; effects *not* substitution from work
  - Reduced value of leisure is a more plausible explanation

# Related Literature

Non-educational policies impact HS dropout behavior Cohodes et al. ’16; Lovenheim, Reback, & Wedenoja ’16; Miller & Wherry ’18; Groves ’20; Kennedy ’20

GDL laws/driving age shifts teen outcomes Dee, Grabowski, & Morrisey ’05; Deza & Litwok ’16; Deza ’19; Argys, Mroz, & Pitts ’19; Huh & Reif ’21; Severen & van Benthem ’22

Effects of compulsory schooling laws Oreopoulos ’07; Anderson ’14

Teen employment; accessibility and LFP Argys, Mroz, & Pitts ’19; Amuedo-Dorantes, Arenas-Arroyo, & Sevilla ’20; Black, Kolesnikova, & Taylor ’14

Multiple discrete choice models, complementarity, policy eval Gentzkow ’07; Goolsbee & Petrin ’04; Li ’18

# Data

**GDL Laws:** IIHS (1995 and later) + historical data collection

- Same data as Severen & van Benthem (2021), but focus in on GDLs @ age 16

**Compulsory Schooling Laws:** Update Anderson (2014) to add 2009–2017

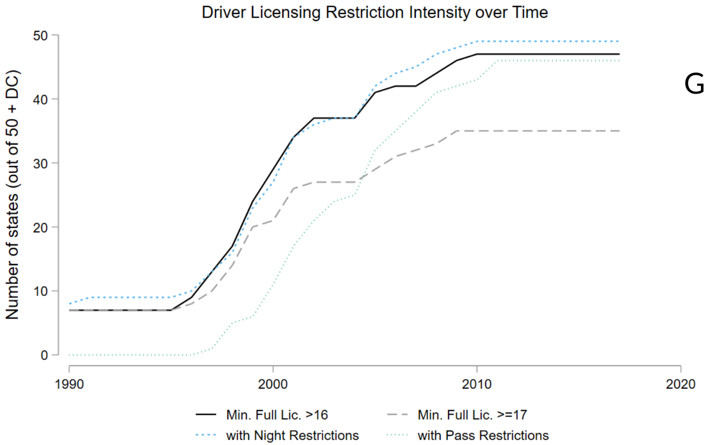
**CPS ASEC:** March sample each year 1990–2017, about 75k 16yo teens

- School and work status + demographics and household info

**NCES Common Core:** School district/grade-specific drop out data

**FARS:** Verify effect on driving using our design with fatalities as a proxy

# GDLs Over Time




GDL laws vary, but mainly:

- Increase min. age for full-privilege license
- Create 'restricted' intermediate license
- Sometimes increase all driving ages
- Biggest effect on 16yo's

"First stage" decline of 16yo traffic fatalities by 27% (cf. Dee, Grabowski, & Morrisey '05)

FARS

# Research Design

Triple-difference interacted-policy design on 16yo outcomes

- Compare teens across states before and after GDL adoption
- Compare states with binding compulsory schooling (CS) laws to those without
- Focus on binary measure of minimum full privilege license $>$ 16yo

TWFE estimator (probit b/c only 3.8% of sample, robust to LPM):

$$NotInSchool_{ist} = \beta_1 GDL_{st} + \beta_2 CS_{st} + \beta_3 GDL_{st} * CS_{st} + X_i'\nu + Z_{st}'\mu + D_s + D_t + \epsilon_{ist}$$

| | |
|---|---|
| $\beta_1$ | Effect of GDL without binding CS law (placebo = 0) |
| $\beta_2$ | Effect CS law without binding GDL |
| $\beta_3$ | Marginal effect of GDL with binding CS law |
| $\beta_1 + \beta_3$ | Total effect of GDL under binding CS law |

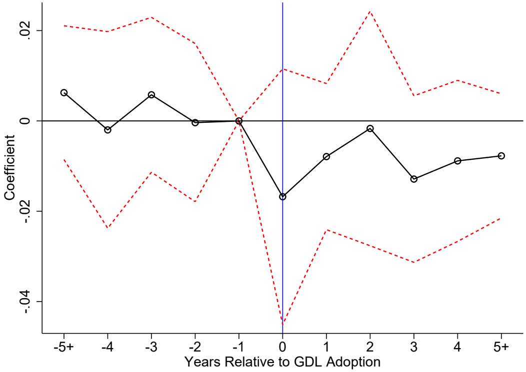
# Effect of GDLs on Education

## Marginal effects from TWFE-style probit

| | Not In School = 1 | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Min. Unres. Driving Age $>16$ $(\beta_1)$ | 0.0022 | 0.0014 | 0.0030 | 0.0013 |
| | (0.0042) | (0.0039) | (0.0049) | (0.0040) |
| School-Leaving Age $\leq 16$ $(\beta_2)$ | 0.0197*** | 0.0182*** | | |
| | (0.0048) | (0.0047) | | |
| Min. Unres. Driving Age $>16$ $\times$ School-Leaving Age $\leq 16$ $(\beta_3)$ | -0.0129*** | -0.0119** | -0.0191*** | -0.0115** |
| | (0.0048) | (0.0048) | (0.0071) | (0.0054) |
| **Effect of GDL if School-Leaving Age $\leq$ 16** $(\beta_1 + \beta_3)$ | -0.0107** | -0.0105** | -0.0161** | -0.0102** |
| | (0.0050) | (0.0049) | (0.0076) | (0.0051) |
| School-Leaving Age | As Observed | | Never Switchers Only | Fixed in Yr. of GDL Change |
| Controls | - | Y | Y | Y |
| Obs | 75,196 | 75,196 | 46,567 | 75,196 |

- Substantial **negative** effect of GDLs with legal school-leaving
- Reduced access $\rightarrow$ more schooling...
- GDLs reinforce CS laws
- ID & Robustness
  - “placebo” test $\beta_1 \approx 0$
  - LPM very similar
  - Robust to diff CS timing assignment

# Event Study & Robustness




Borusyak et al. ('21) imputation estimator

| | Not In School = 1 | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| **Effect of GDL if School-Leaving Age $\leq$ 16** | -0.0109** (0.0047) | -0.0111** (0.0045) | -0.0113** (0.0046) |
| Exclude Always Treated | Y | Y | Y |
| Exclude Never Treated | - | - | Y |
| Controls | - | Y | Y |
| Obs | 50,729 | 50,729 | 46,853 |

- Using $GDL \times CS$ as treatment

- No evidence of pre-trends $\rightarrow$ supports parallel trends
- ATE estimate robust to dynamic/heterogeneous treatment effects
- Validate GDL effect in separate NCES (district-level) dropout rate data ▸ NCES

# Heterogeneity

Use variation in GDL intensity: Effect of totally banning 16yo driving?

- 16yo GDL driving $\rightarrow$ 16yo ban on driving: $NotInSchool \uparrow$ 1%
- Fully reverses primary effect

$\Rightarrow$ Evidence of a **direct effect** of reduced access; but only if regulations are very stringent

Not much heterogeneity on demographics

- Similar effects across sex, family income, and by race
- Somewhat larger effect in "urban" areas (central cities of large MSAs)
    - May be driven by poor compliance to CS laws

# Alternative Activities – Work

Increased schooling despite reduced access suggests strong **indirect** effects

Look at work outcomes (LFP)

(see also Argys, Mroz, & Pitts '19)

- 23.3% of 16yo in LF
- Sizable negative effect of reduced access from GDLs (bigger in LPM)
- Small placebo ($\beta_1$) again suggests some sort of substitution

| | In Labor Force = 1 | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Min. Unres. Driving Age $>16$ $(\beta_1)$ | -0.0033 | -0.0024 | -0.0113 | 0.0010 |
| | (0.0102) | (0.0116) | (0.0145) | (0.0105) |
| School-Leaving Age $\leq 16$ $(\beta_2)$ | 0.0244 | 0.0183 | | |
| | (0.0160) | (0.0168) | | |
| Min. Unres. Driving Age $>16$ $\times$ School-Leaving Age $\leq 16$ $(\beta_3)$ | -0.0138 | -0.0149 | -0.0195 | -0.0211 |
| | (0.0130) | (0.0141) | (0.0199) | (0.0129) |
| **Marginal Effect of GDL if School-Leaving Age $\leq$ 16** $(\beta_1 + \beta_3)$ | -0.0171* | -0.0173* | -0.0308** | -0.0202* |
| | (0.0100) | (0.0101) | (0.0140) | (0.0108) |
| School-Leaving Age | As Observed | | Never Switchers Only | Fixed in Yr. of GDL Change |
| Controls | - | Y | Y | Y |
| Obs | 75,196 | 75,196 | 46,567 | 75,196 |

# Interpreting Effects

This looks like substitution from work to school... but is it?

- Teens can do many other activities; GDL/CS laws shown to impact:
  - Crime, pregnancy, risky behaviors
- Access to these other activities likely reduced due to GDL

Leisure (and other activities) generally hard to observe

- Time use data is very incomplete, especially before 2000
- Data on other activities is sparse at best
- Still might not reveal substitution patterns

How to proceed?

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How to proceed?

**Add additional structure!**

# Model Intro

Adapt *multiple discrete choice* model from IO (Gentzkow '07) to school/work choice:

$$\text{Agents (16yo teens) choose} \begin{cases} (0,0) & \text{No activities = `Leisure'} \\ (1,0) & \text{Work only} \\ (0,1) & \text{School only} \\ (1,1) & \text{Both activities} \end{cases}$$

- Idiosyncratic preference for each activity, arbitrary (parametric) correlation
- Estimate complementarity/substitutability between school and work
- Retain DDD-like design to estimate causal effects w/in model

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Use estimated model for *effect decomposition*:

- **Direct:** Change in outcome $k$ if GDL only shifts the utility of $k$
- **Indirect:** Change in outcome $k$ if GDL shifts utilities of other activities (-$k$)
- **Total:** Direct + Indirect (overall change in outcomes)

# Multiple Discrete Choice

Indirect utility of (Work, School) for 16-year old $i$:

$$
\begin{aligned}
V_i(0,0) &= 0 \\
V_i(1,0) &= \alpha^A + \gamma^A GDL^A_{st} + x'_{ist}\lambda^A + z'_{st}\pi^A + f^A(s,\xi) + \delta^A_t + e^A_i \\
V_i(0,1) &= \alpha^B + \gamma^B GDL^B_{st} + x'_{ist}\lambda^B + z'_{st}\pi^B + f^B(s,\xi) + \delta^B_t + e^B_i \\
V_i(1,1) &= V_i(1,0) + V_i(0,1) + \Gamma + \gamma^\Gamma GDL^\Gamma_{st}
\end{aligned}
$$

- $\Gamma$: compl./subs.
- $\gamma^k$: utility effect of GDL on $k$
- $\mathbf{e}_i = [e^A_i \;\; e^B_i]'$ is idiosyncratic utility
- Normalize to neither activity

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- $\Gamma$: compl./subs.
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- $\mathbf{e}_i = [e_i^A \ \ e_i^B]'$ is idiosyncratic utility
- Normalize to neither activity

## Assumption (1)

*Idiosyncratic preferences are independent and are distributed bivariate normal:* $\mathbf{e}_i \sim N(0,\Omega)$, *where*

$$\Omega = \begin{pmatrix} 1 & \rho\sigma \\ \cdot & \sigma^2 \end{pmatrix}.$$

# Model Identification

## Assumption (2)

*Exclusion Restrictions: Components of $z$ may shift the utility of at most one of $A$ or $B$. Specifically,*

$$\pi^{A'} = \left[\pi^A_{UR}, \pi^A_{MW}, 0, 0\right]$$
$$\pi^{B'} = \left[0, 0, \pi^B_{CS}, \pi^B_{GDL\times CS}\right].$$

- State Unemp. Rate and Min. Wage only impact utility of work
- CS laws only impact utility of school

## Assumption (3)

*Correlated Random Effects: The state-specific unobserved effects $f^k(s,\xi)$ for $k \in \{A, B\}$ are correlated with $GDL_{st}$, $x_{ist}$, and $z_{st}$ in the following manner:*

$$f^A(s,\xi) = \xi^k_1 \overline{GDL}_s + \overline{x}'_s \xi^k_2 + \overline{z}'_s \xi^k_3,$$

*where $\bar{\cdot}_s$ indicates an average across observations in state $s$.*

- Like fixed effects but friendlier to optimization methods
- Mundlak '78 shows equivalence in linear settings

# Estimation

- We show that the model is compatible with a GHK simulator (**Lemma 1**)
- Estimate via maximum simulated likelihood in a few steps
- Total of 104 parameters estimated, focus on:

| | | |
|---|---|---|
| $\rho$ | -0.469 | *Correlation between work/school pref* |
| $\Gamma$ | 0.012 | *School/work are weak complements* |
| $\gamma^A$ | -0.027 | *Utility impact of GDL on work* |
| $\gamma^B + \pi^B_{CS \times GDL}$ | 0.004 | *Utility impact of GDL on school (note $\sigma$ is small)* |
| $\gamma^\Gamma$ | -0.002 | *Change in complementarity due to GDL* |

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- Model fit is good, matches observed choice 62% of the time
- Effects are consistent with reduced form results:

| | Neither | Work | School |
|---|---|---|---|
| **Total effect of GDL** | -1.06pp | -0.83pp | 1.31pp |

# Renormalization

Total effects seem reasonable, but...

- Utility effect of GDL on school $\gamma^B$ is positive!

$\Rightarrow$ We normalized against the neither option

From choice data, $\gamma^k$ are only identified *relative* to the effect on neither option

Want to renormalize to be explicit about utility effect of GDLs on neither option:

- Renormalization cannot be identified from choice data
- It will not impact estimates of total effects
- But it will impact decomposition in direct and indirect effects

# Renormalization

Use auxiliary parameter $\tilde{\gamma}^0$ to renormalize model:

$$V_i(0,0) = \tilde{\gamma}^0 GDL_{st}^0 \tag{1}$$
$$V_i(1,0) = \alpha^A + (\gamma^A + \tilde{\gamma}^0)GDL_{st}^A + x'_{ist}\lambda^A + z'_{st}\pi^A + f^A(s,\xi) + \delta_t^A + e_i^A \tag{2}$$
$$V_i(0,1) = \alpha^B + (\gamma^B + \tilde{\gamma}^0)GDL_{st}^B + x'_{ist}\lambda^B + z'_{st}\pi^B + f^B(s,\xi) + \delta_t^B + e_i^B \tag{3}$$
$$V_i(1,1) = V_i(1,0) + V_i(0,1) + \Gamma + (\gamma^\Gamma - \tilde{\gamma}^0)GDL_{st}^\Gamma. \tag{4}$$

Recall, $\tilde{\gamma}^0$ is *not* identified from choice data and does not impact total effects, but

- Additional assumptions may be reasonable...

# Renormalization - Set Identification

Set identify $\gamma^0 \in \mathcal{G}$ such that:

- Utility effects of GDL are weakly negative (gives an upper bound for $\gamma^0 < 0$)
- Direct effect on schooling $\leq$ Direct effect on work in magnitude

# Renormalization - Set Identification

Set identify $\gamma^0 \in \mathcal{G}$ such that:

- Utility effects of GDL are weakly negative (gives an upper bound for $\gamma^0 < 0$)
- Direct effect on schooling $\leq$ Direct effect on work in magnitude

## Assumption (4)

*Let $\tilde{\gamma}^0$ be such that the indirect utility impact of GDL laws on neither, work, and school are weakly negative ($\tilde{\gamma}^0 \leq 0$, $\gamma^A + \tilde{\gamma}^0 \leq 0$, and $\gamma^B + \pi^B_{CS\times GDL} + \tilde{\gamma}^0 \leq 0$) and that the direct effect on schooling is no larger in magnitude than the direct effect on work $\left(|\theta^B_{\text{Dir}}| \leq |\theta^A_{\text{Dir}}|\right)$.*

$$\mathcal{G} = \left\{\tilde{\gamma}^0 : \left(|\theta^A_{\text{Dir}}(\tilde{\gamma}^0)| < |\theta^B_{\text{Dir}}(\tilde{\gamma}^0)|\right) \wedge \left(\tilde{\gamma}^0 \leq \min\{0, -\gamma^A, -(\gamma^B + \pi^B_{CS\times GDL}\}\right)\right\}$$

# Decomposition Results

Under reasonable assumptions:

- GDLs greatly reduce utility of neither-work-nor-school
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| Effect of GDL Laws on: | Neither | | Work | | School | |
|---|---|---|---|---|---|---|
| | Effect | % of Total | Effect | % of Total | Effect | % of Total |
| **Total effect** | -1.06pp | | -0.83pp | | 1.31pp | |
| **A. Upper-bound renormalization** $\tilde{\gamma}^0 = \min\{0, -\gamma^A, -(\gamma^B + \pi^B_{CS\times GDL})\}$. | | | | | | |
| Direct | -1.13pp | 106.7% | -0.88pp | 106.6% | 0pp | 0.0% |
| Indirect | 0.07pp | | 0.05pp | | 1.31pp | |
| *via Neither* | - | | 0.01pp | -1.2% | 1.13pp | 86.1% |
| *via Other activities* | 0.07pp | -6.7% | 0.04pp | -5.4% | 0.18pp | 13.9% |
| **B. Lower-bound renormalization** $\tilde{\gamma}^0 : \theta^A_{\text{Dir}} = \theta^B_{\text{Dir}}$. | | | | | | |
| Direct | -1.56pp | 146.8% | -0.93pp | 112.8% | -0.93pp | -71.3% |
| Indirect | 0.50pp | | 0.11pp | | 2.24pp | |
| *via Neither* | - | | 0.01pp | -1.7% | 1.78pp | 136.0% |
| *via Other activities* | 0.50pp | -46.8% | 0.09pp | -11.1% | 0.46pp | 35.3% |

# Conclusions

- GDLs substantially shift 16yo activities in potentially long-lasting ways
- Policy interactions matter:
  - GDL increases schooling by 1.1pp when dropping out is permitted
  - Effect direction suggest indirect/substitute activities important
- There are also substantial effects on work
  - 16yo work declines by 1.7pp when dropping out is permitted
- Looks like substitution, but is it? Use multiple discrete choice:
  - School-work estimated to be weak complements
  - Reduced value of latent (neither-work-nor-school) activities appear to drive effects

Thank you!

Extra Slides... Are you sure you want to go there?

# FARS "First-Stage" Results

- Policies substantially reduce 16yo fatalities ▸ Return

| | Accidents per 1,000 | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Minimum Unrestricted Driving Age | -0.032*** | | |
| | (0.011) | | |
| Min. Unres. Driving Age $>$ 16 (year t+2) | | | -0.013 |
| | | | (0.018) |
| Min. Unres. Driving Age $>$ 16 (year t+1) | | | 0.009 |
| | | | (0.014) |
| Min. Unres. Driving Age $>$ 16 | | -0.070*** | -0.022 |
| | | (0.016) | (0.015) |
| Min. Unres. Driving Age $>$ 16 (year t-1) | | | -0.038*** |
| | | | (0.012) |
| Min. Unres. Driving Age $>$ 16 (year t-2) | | | -0.018 |
| | | | (0.015) |
| Mean Outcome | | 0.259 | |
| Obs | 1,400 | 1,400 | 1,200 |

# NCES Results

- Permits inclusion of school-district fixed effects, but less data coverage
- DD design because harder to identify ages (only see grades); DDD still works

| | Dropout Rate Grades 9-12 | Dropout Rate Grades 9-12 | Dropout Rate Grades 9-12 | Dropout Rate Grade 9 | Dropout Rate Grade 10 | Dropout Rate Grade 11 | Dropout Rate Grade 12 |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Min. Unres. Driving Age | -0.0042*** | | | | | | |
| | (0.0011) | | | | | | |
| Min. Unres. Driving Age $>$16 | | -0.0032* | -0.0046** | -0.0036 | -0.0050** | -0.0058** | -0.0047* |
| | | (0.0017) | (0.0021) | (0.0024) | (0.0021) | (0.0025) | (0.0026) |
| Years in Sample | 1994-2009 | 1994-2009 | 1994-2001 | 1994-2001 | 1994-2001 | 1994-2001 | 1994-2001 |
| Mean Dropout Rate | 0.034 | 0.034 | 0.036 | 0.026 | 0.035 | 0.041 | 0.042 |
| Obs | 114,043 | 114,043 | 44,735 | 44,166 | 44,246 | 44,366 | 44,623 |

Return