Substantive insights from an income-based intervention to reduce poverty

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Outline

- Background
- Objectives
- Methodological challenges/insights
- Substantive challenges/insights
- Conclusions

Causal effects of SES indicators

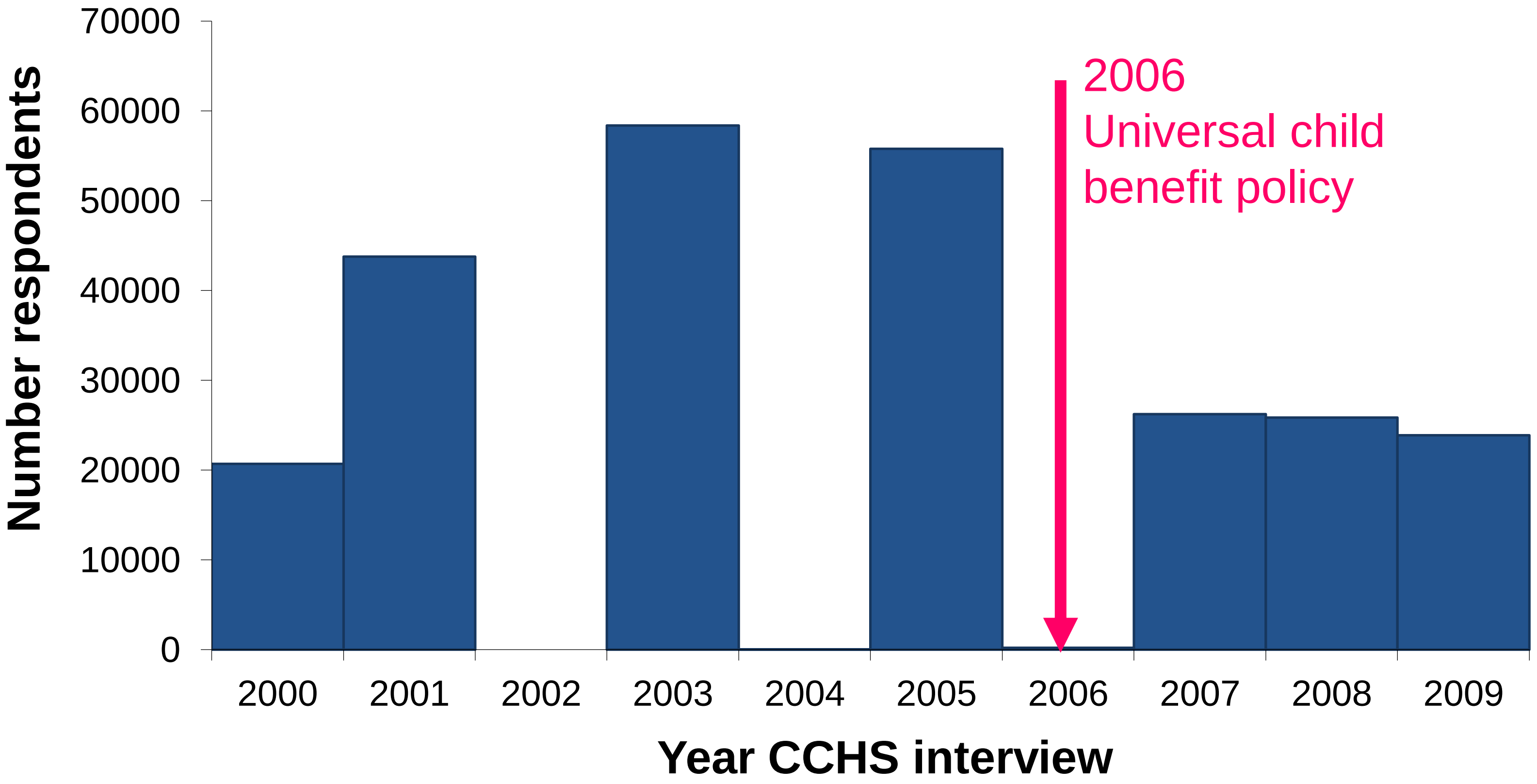
- **Socio-economic status (SES) affects health**
- **Isolating the causal effect of any single SES indicator**
  - Is difficult because SES indicators cluster in individuals
  - Is very important because it could guide interventions
- **Policies that affect only one indicator (e.g. income) can be used to isolate the causal effect of that indicator**

Universal Child Care Benefit Policy

- Canadian income-based federal policy
- Implemented July 2006
- $100 (taxable) monthly for each child aged < 6
- All families with children < 6 eligible (universal)

Canadian Community Health Survey

- Pan-Canadian cross-sectional survey (Statistics Canada)
- Respondents age ≥ 12



Canadian Community Health Survey

Data appropriate

- Income
- Number children age < 6 (eligible for policy)
- Socio-demographic characteristics respondent/household
- Potential outcomes
  - Food insecurity
  - Health behaviors
  - Self-reported health indicators

Canadian Community Health Survey

Data appropriate

- Income
- Number children age < 6 (eligible for policy)
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- Potential outcomes
  - Food insecurity
  - Health behaviors
  - Self-reported health indicators

- Completeness of data (optional modules)?
- Are they likely to be immediately affected by small changes in income?

Objectives

1. To estimate the causal effect of income supplementation on health using an exogenous income-based policy

2. To identify whether the policy itself has an impact on health outcomes
   - → **Food insecurity**
   - → Self-perceived stress, Migraine/headache diagnosed by doctor, BMI, Energy expenditure score

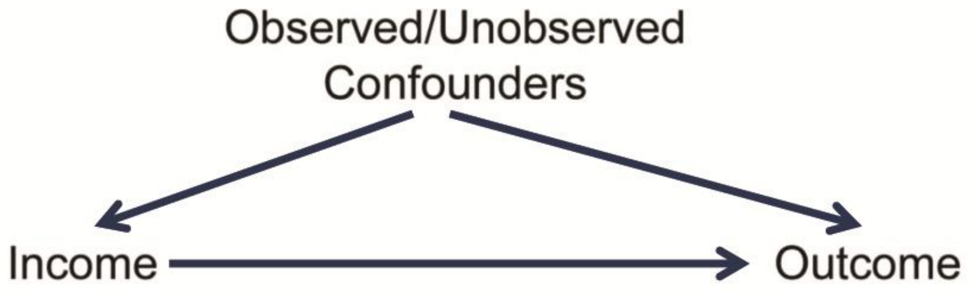
3. To identify the threshold income level at which the policy impacts health

Methodological insights

Taking advantage of exogenous Policy

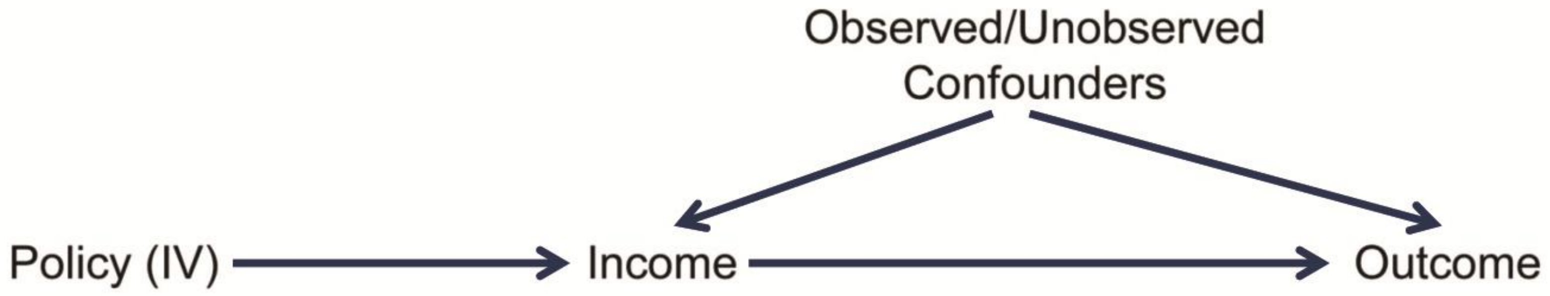
Instrumental variable (IV) approach

- Removes bias due to unobserved confounding



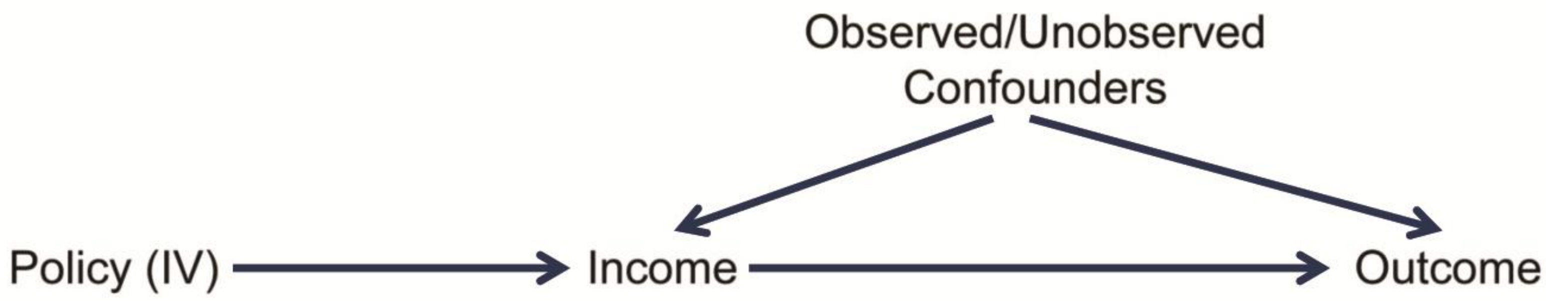
Instrumental variable (IV) approach

- Removes bias due to unobserved confounding



Instrumental variable (IV) approach

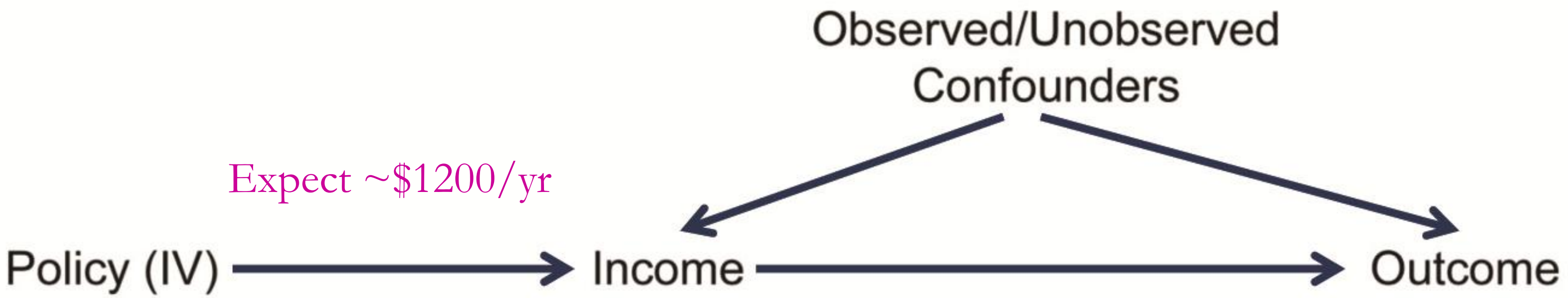
- **Removes bias due to unobserved confounding**



- **3 main IV assumptions**
  1. The IV is associated with the exposure
  2. The IV affects the outcome only through its effect on exposure
  3. The IV-outcome association is not confounded

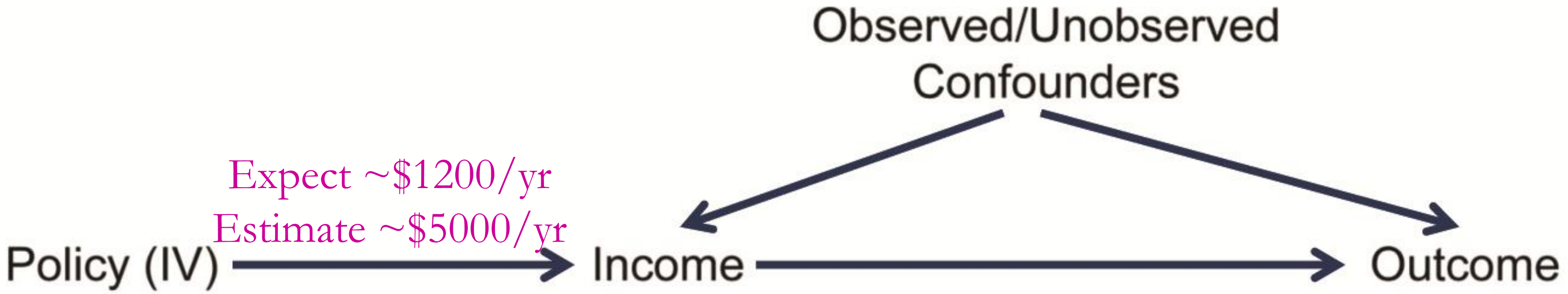
Instrumental variable approach

- Assumption that policy increases the income among the eligible



Instrumental variable approach

- Assumption that policy increases the income among the eligible



Instrumental variable approach

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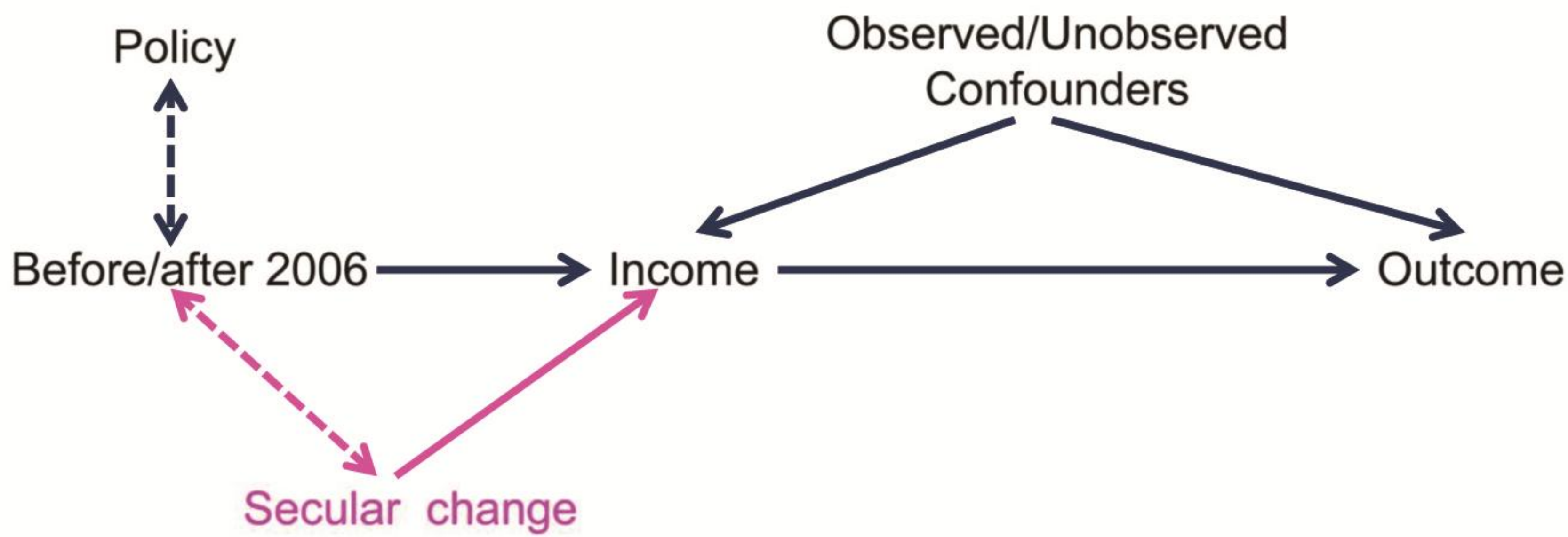
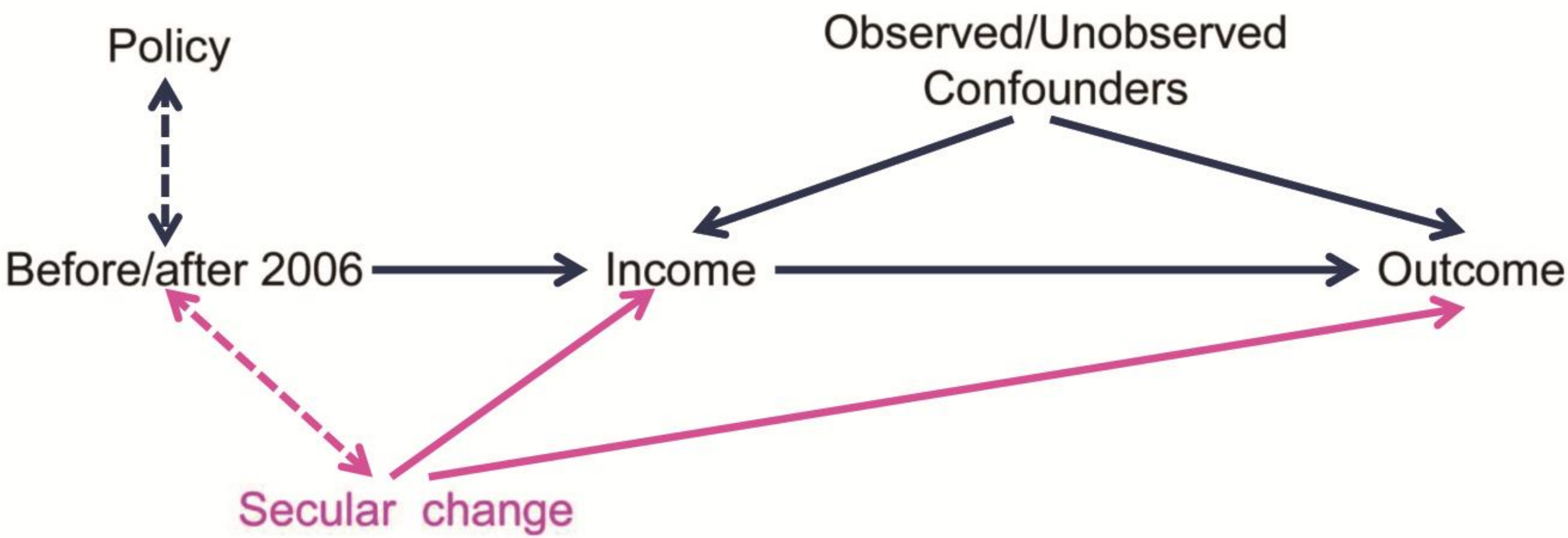
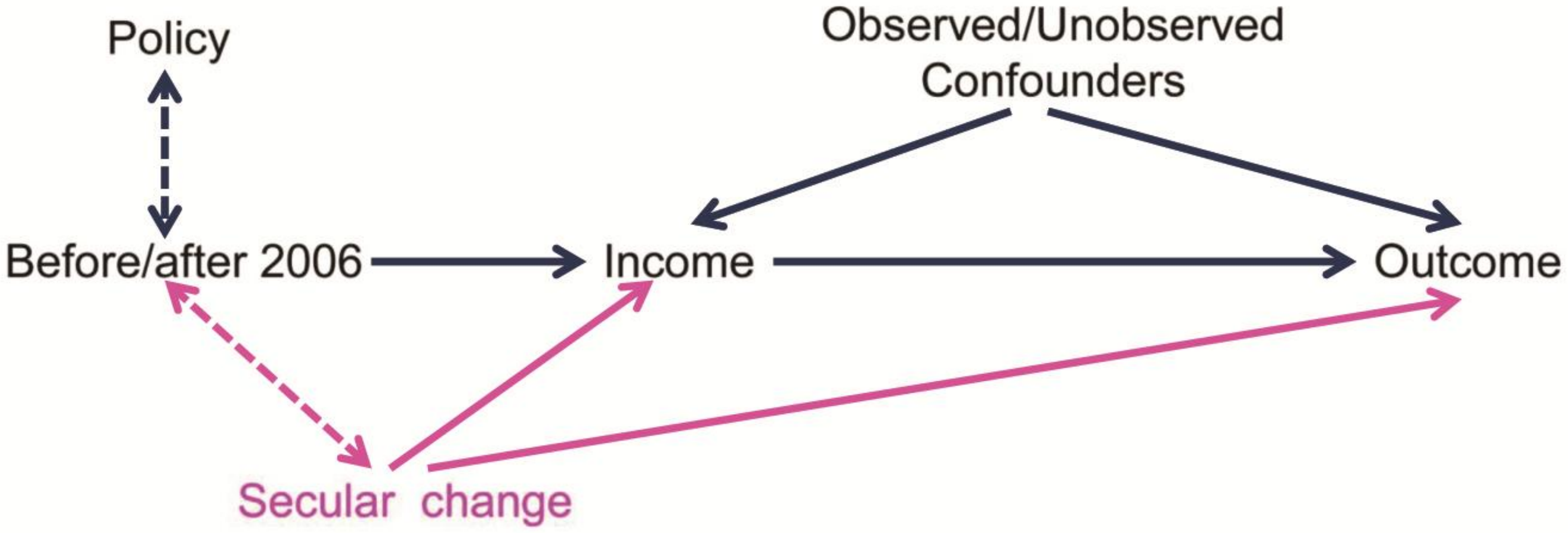


Instrumental variable approach

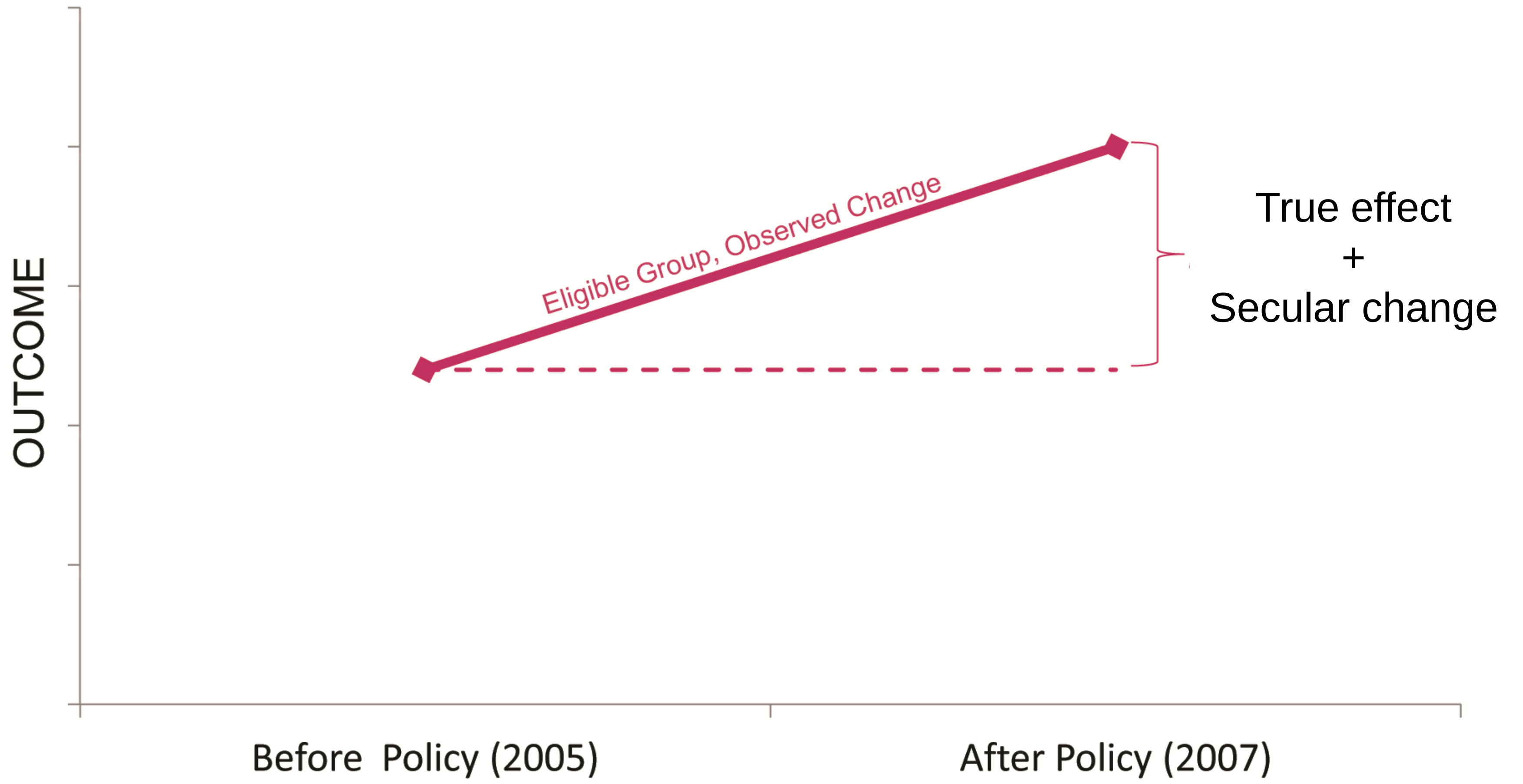


Instrumental variable approach

- IV assumptions are violated!



Difference-in-difference (DID) approach



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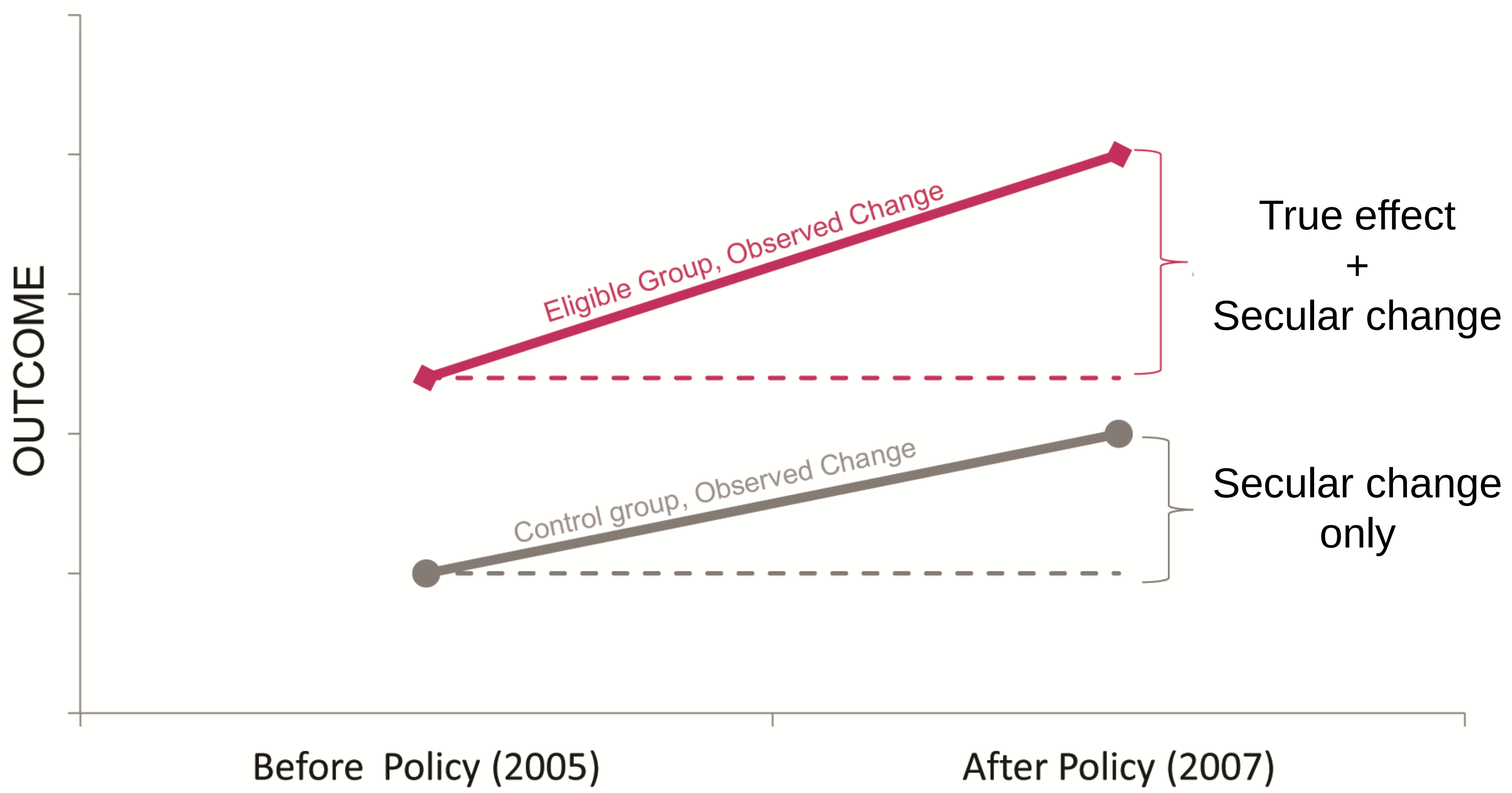

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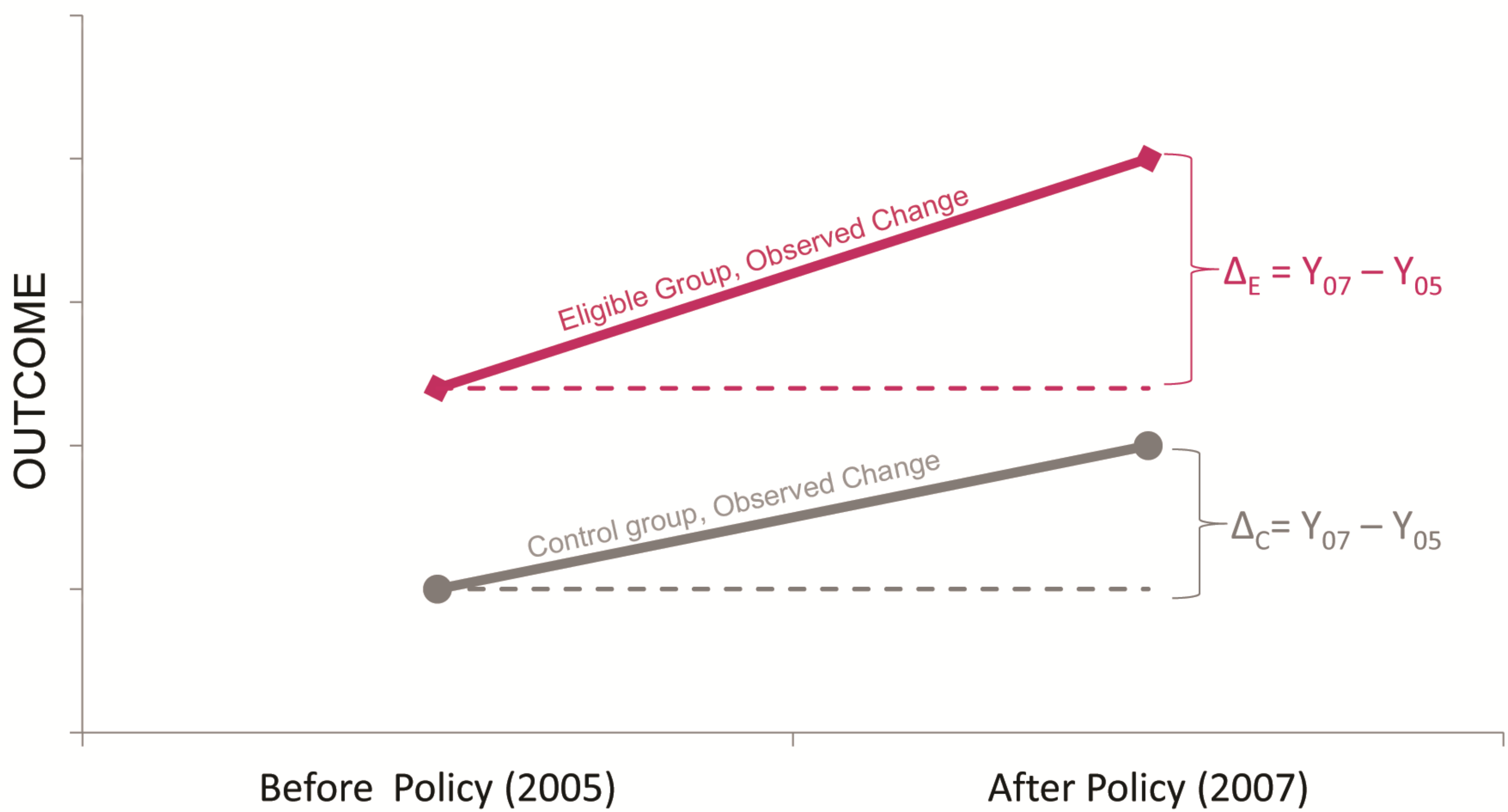

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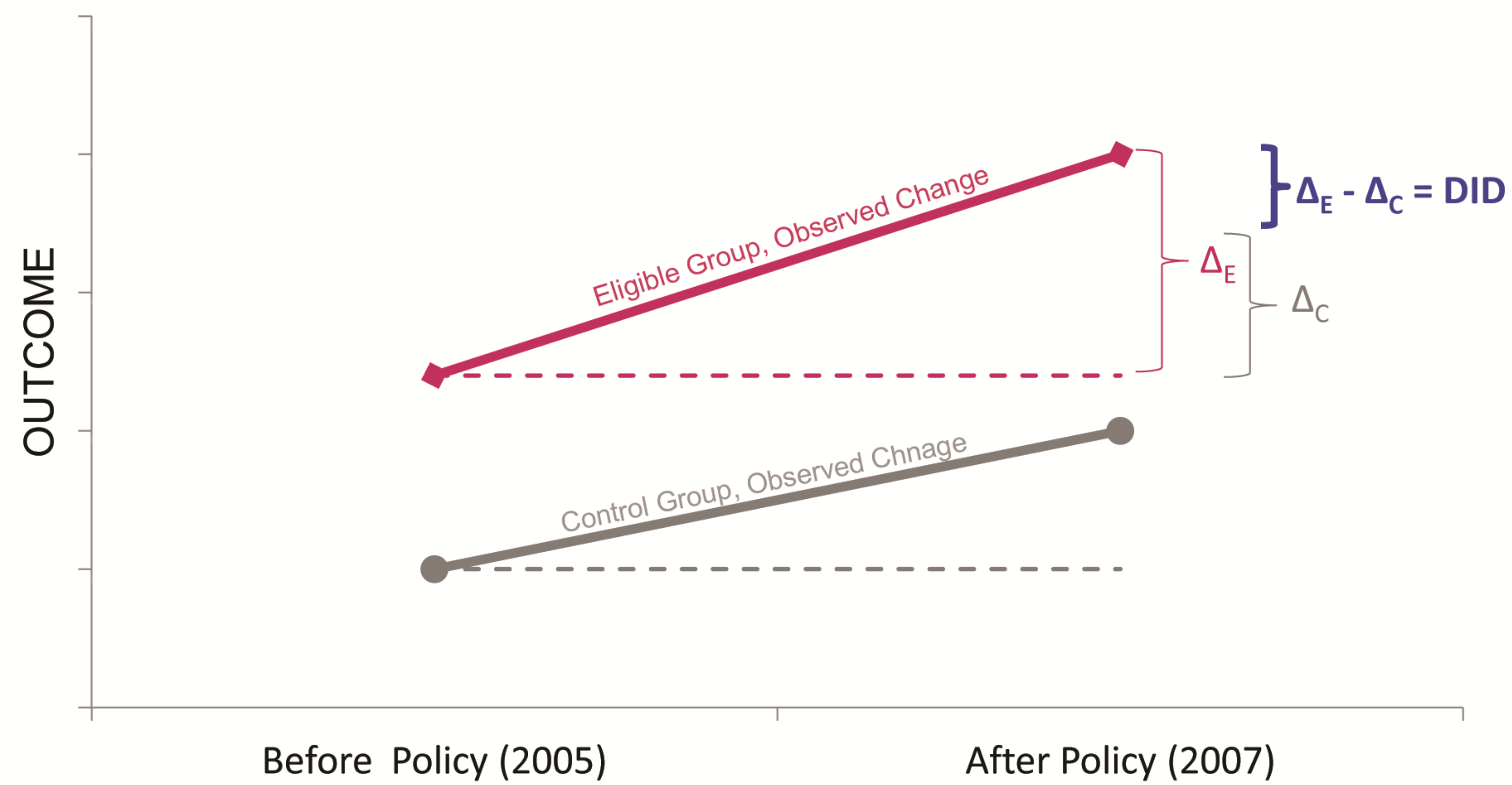

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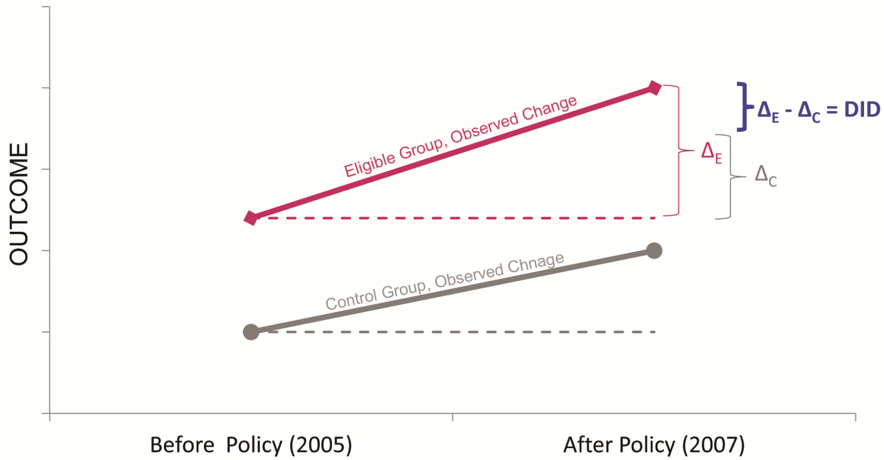
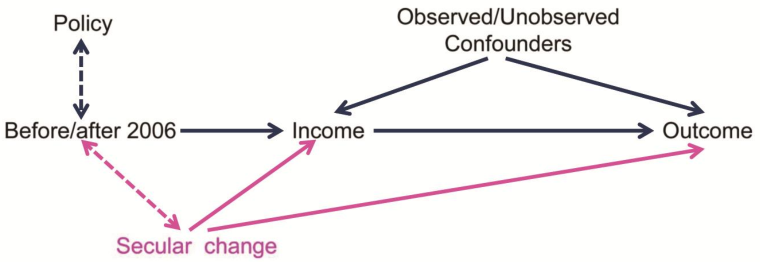


- **DID main assumption**
  - Control group captures secular change in outcome

Using exogenous policy: IV or DID?

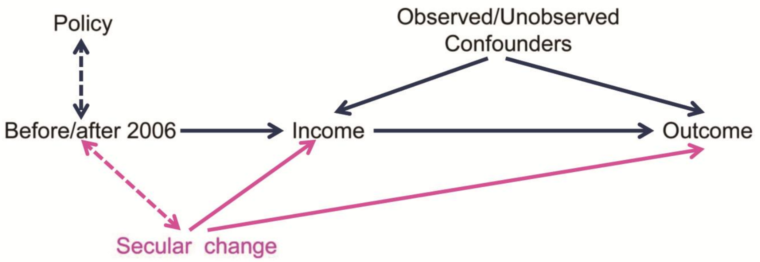


What do we estimate?

- **Difference-in-difference**
  - → effect of policy on outcome (intention to treat)
  - → $\hat{\beta}_{DID} = \text{ITT}$
  - → effect income biased toward null if not everyone gets the money

- **Instrumental variable**
  - → effect of income on outcome
  - → ITT effect rescaled $\hat{\beta}_{IV} = \frac{\text{ITT}}{\textit{Compliance}}$
  - → applies only to those who actually get the money ("compliers")

Using exogenous policy: IV or DID?



- Sources of bias
  - Unobserved confounding
    - ✓ DID/ ✓ IV
  - Secular trends
    - ✓ DID / ✗ IV
  - Non-compliance with policy (ITT biased)
    - ✗ DID / ✓ IV

Decision: IV or DID?

Scenarios		General solution
Non-Compliance	Secular Trends	
+	-	Use IV
-	+	Use DID
+	+	???

Decisions our application

Scenarios		Decision for our empirical data
Non-Compliance	Secular Trends	
+	-	Use IV
?	+	Use DID
?	+	???

Decisions our application

Scenarios		Decision for our empirical data
Non-Compliance	Secular Trends	
+	-	Use IV
- Compliance with Universal Child Care Benefit almost perfect (> 90% receive it automatically)	+	Use DID
+	+	???

Decisions our application

Scenarios		Decision for our empirical data
Non-Compliance	Secular Trends	
+	-	Use IV
-	+	Use DID
+	+	???

Decisions our application

Scenarios		Decision for our empirical data
Non-Compliance	Secular Trends	
+	-	Use IV
-	+	**Use DID** • Same interpretation DID/ IV $\hat{\beta}_{IV} = \frac{\text{ITT}}{\textit{Compliance}} = \beta_{DID} / 1 = \beta_{DID}$
+	+	???

Methodological contribution

Scenarios		Our take
Non-Compliance	Secular Trends	
+	+	??? • We propose a model that combines DID and IV →Conventional IV model $\hat{\beta}_{IV} = \frac{\text{ITT}}{\textit{Compliance}} = \frac{\hat{\beta}_{OLS(IV \to Y)}}{\hat{\beta}_{OLS\ (IV \to X)}}$ → Proposed DID IV model $\hat{\beta}_{DID\text{-}IV} = \frac{\hat{\beta}_{DID(IV \to Y)}}{\hat{\beta}_{DID\ (IV \to X)}}$ →Corresponding 2-stage least squares model

Substantive insights

The Universal Child Care Benefit Policy

Study population

- **DID model** (> 95% compliance)
  - **Eligible Group**
    - Receives Universal Child Care Benefit income supplement
    - Families with children < 6
  - **Control Group**
    - Must capture the secular trends that affect the eligible
    - Families with children aged 6-11, but no children < 6
- **Identified in Canadian Community Health Survey**

Study population

Inclusion criteria

- Child ≤ 12 in household (22% of initial sample)
- Children live with at least one parent
- Household income < 200,000

Sample size

- ~61,000 for income outcome
- ~ 32,500 for food insecurity outcome

(only provinces without any missing data cycle: NS, QC, AB, BC, NW, Nunavut)

Statistical analyses

Difference-in-Difference OLS model

$$E(Y) = \beta_0 + \beta_1 \times \text{Eligible} + \Sigma\beta_{2i} \times \text{DummyYr}_i + \beta_3 \times \text{Eligible} \times \text{Period} + \beta_{jk} \times \text{Cov}_k$$

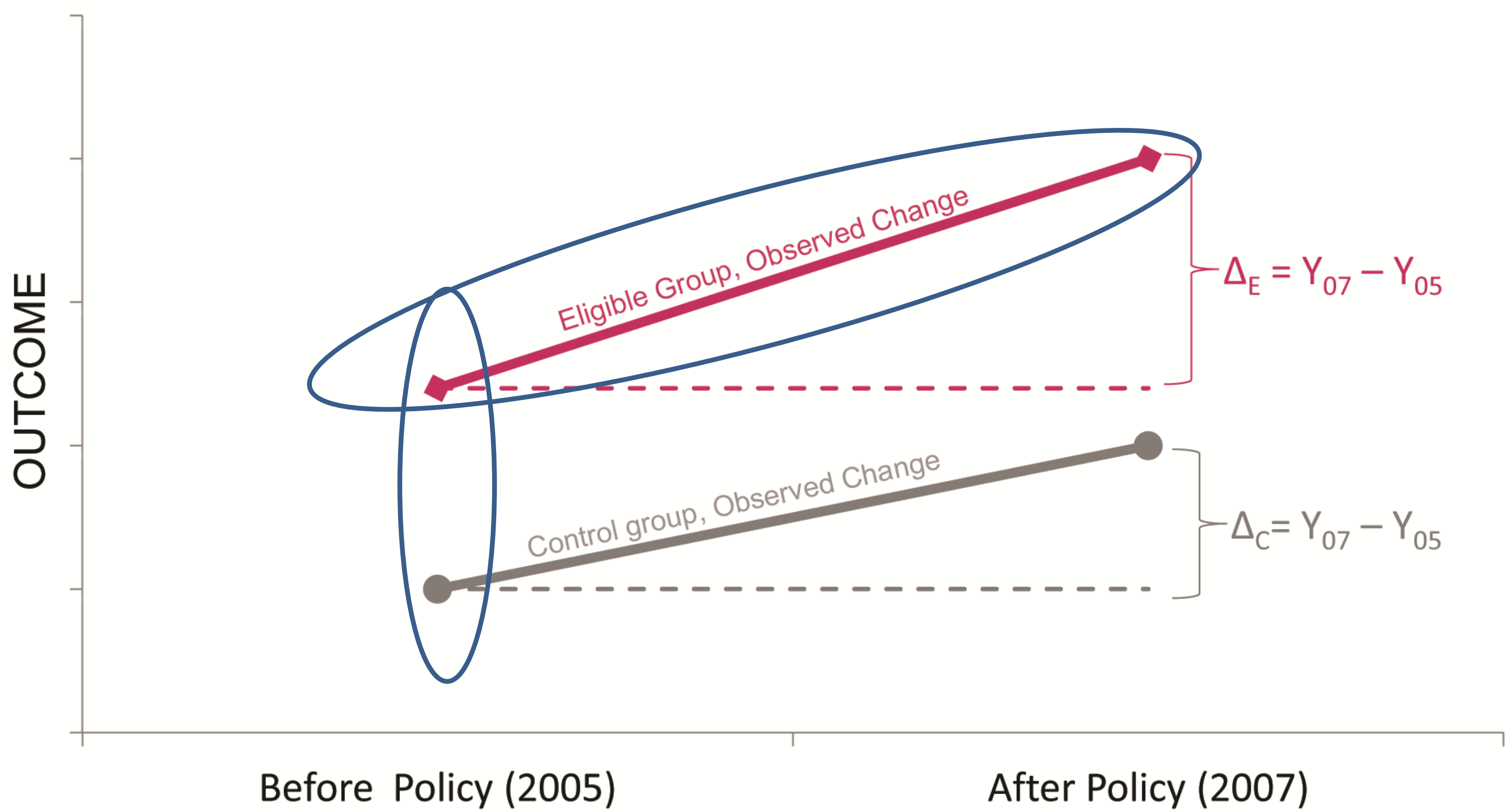
DID RD

Main assumption

- Secular trends in eligible vs. controls do not change over time

Results weighted for sampling probabilities

Difference-in-difference (DID) approach



Descriptive statistics

Covariates		Eligible group	
		Before 2006 policy	After 2006 policy
Respondent	age (mean)	32	32
	male (%)	48	48
	university ed. (%)	**22**	**27**
	immigrant (%)	24	26
	white (%)	**80**	**76**
	married/common law (%)	83	83
	employed (%)	78	79
Household	urban (%)	82	83
	highest ed. university (%)	**32**	**37**
	size (mean)	4	4
	single parent (%)	8	9

Descriptive statistics

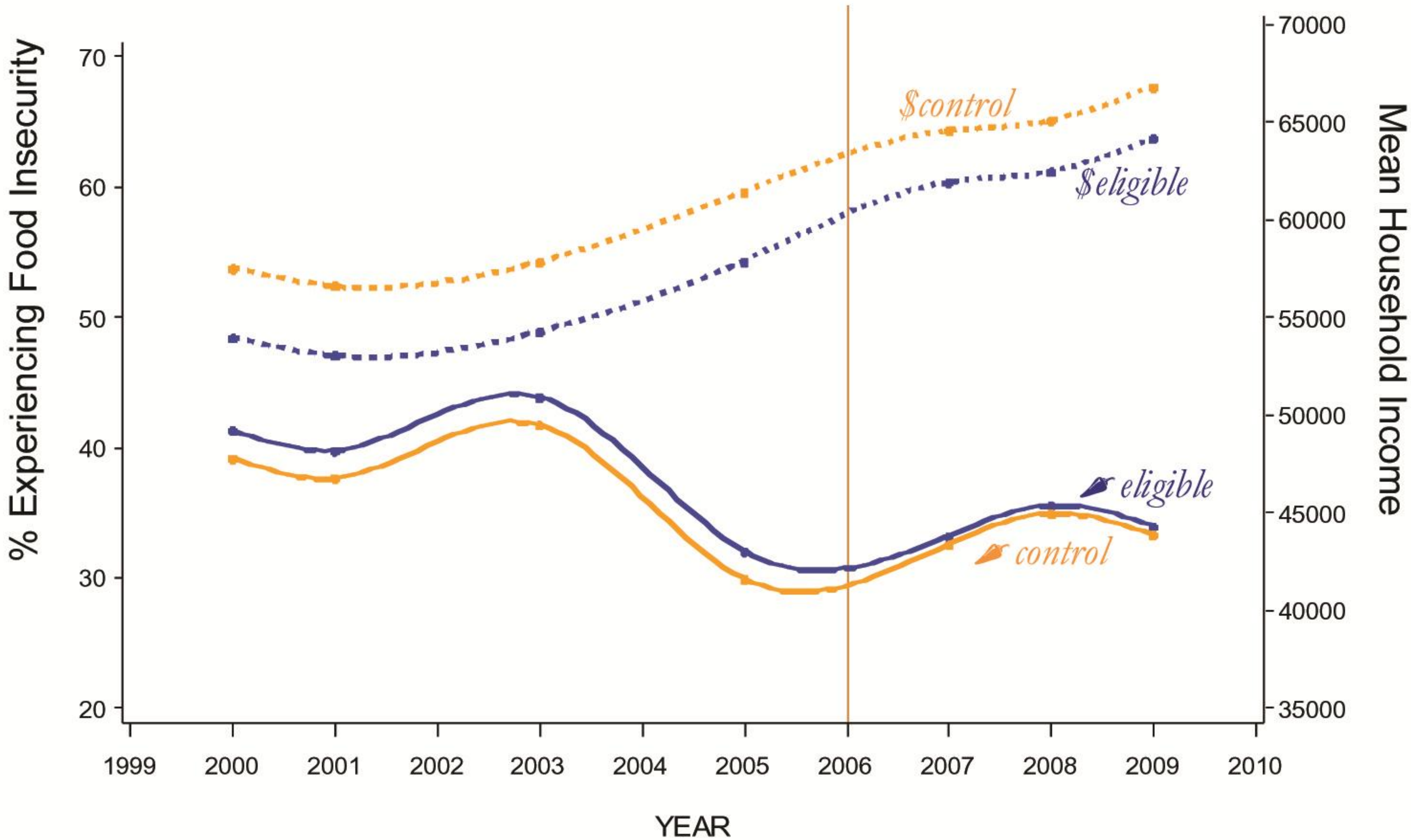
Covariates		Before 2006 policy	
		Eligible group	Control group
Respondent	age (mean)	32	32
	male (%)	48	47
	university ed. (%)	**22**	**14**
	immigrant (%)	**24**	**19**
	white (%)	80	83
	married/common law (%)	**83**	**62**
	employed (%)	**78**	**83**
Household	urban (%)	82	80
	highest ed. university (%)	**32**	**27**
	size (mean)	4	4
	single parent (%)	**8**	**14**

Change in economic indicators

Country/Province	Before 2006 policy	After 2006 policy
bank rate (mean)	4.2	2.9
% unemployment (mean)	7.4	6.8
Consumer Price Index (mean)	100.1	114.0

Adjusted trends in mean household income vs. % food insecurity

Presented for standard mean population



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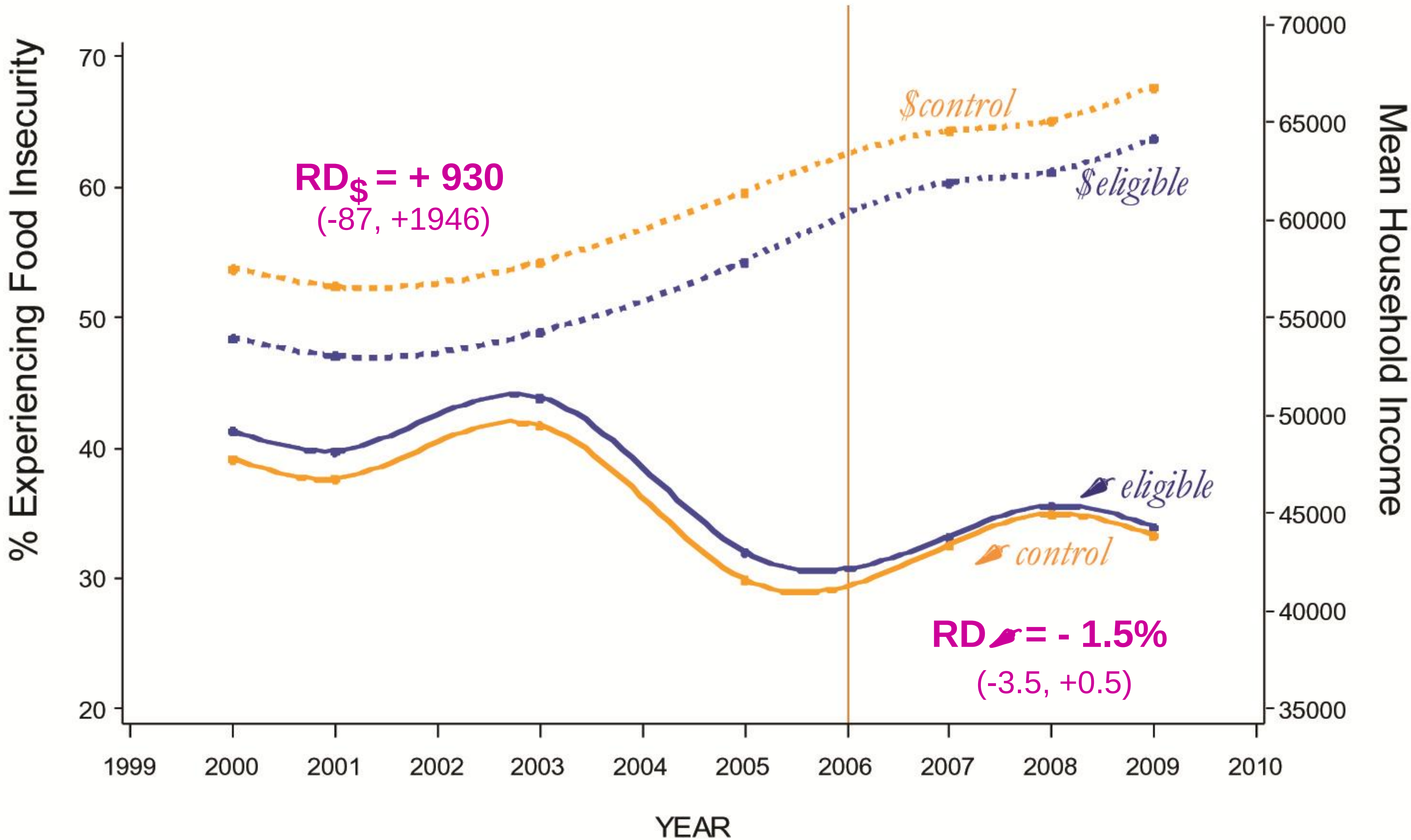

Subgroup analyses food insecurity

Study population		Sample size regression
Full		32,640
Baseline income	Below median*	13,334
	Above median*	19,306
Type family	Single parent	4,923
	Couple	27,245
Age respondent	12-24	2,534
	25+	30,106

**$15,000 per household member*

Subgroup analyses food insecurity

Study population		Sample size regression	% food insecurity
Full		32,640	**14.3%**
Baseline income	**Below median***	13,334	**27.3%**
	Above median*	19,306	**5.4%**
Type family	**Single parent**	4,923	**29.1%**
	Couple	27,245	**11.7%**
Age respondent	**12-24**	2,534	**24.4%**
	25+	30,106	**13.5%**

**$15,000 per household member*

Subgroup analyses food insecurity

Study population		Sample size regression	% food insecurity	DID RD (95% CI)
Full		32,640	14.3%	**-1.5%** (-3.5, +0.5)
Baseline income	**Below median***	13,334	27.3%	**-0.2%** (-5.1, +4.7)
	Above median*	19,306	5.4%	**-1.1%** (-2.6, +0.3)
Type family	**Single parent**	4,923	29.1%	**-2.9%** (-10.2, +4.9)
	Couple	27,245	11.7%	**-2.0%** (-4.1, +0.02)
Age respondent	**12-24**	2,534	24.4%	**-11.1%** (-20.8, -1.5)
	25+	30,106	13.5%	**-0.6%** (-2.6, +1.3)

**$15,000 per household member*

Limitations

- **Controls may not remove all bias due to secular trends**
  - Groups could be more comparable if possible to compare 6 vs 7 years olds
- **Small samples result in imprecise estimates**
  - >75% of sample lost when restricting to families with children aged 6 -12
  - Stratified analyses further reduce the samples
- **Gaps in data collection**
  - Limit the choice of outcomes
  - Further reduce the samples

Conclusions

- **We detected a signal that the Universal Child Care Benefit income supplement reduces food insecurity, especially for those aged 12-24**

- **To facilitate causal SES research using IV/DID models**
  - Randomize space-time variation when implementing policies
  - Commission an ongoing survey that accommodates the requirements of IV/ DID models (e.g. oversample low SES)
  - Make data readily available to researchers

Acknowledgements

Collaborators

- Dr. Jay Kaufman (McGill University)
- Dr. Maria Glymour (Harvard University)
- Dr. Eric Tchetgen Tchetgen (Harvard University)

Data

- Statistics Canada (Mme Danielle Forrest)

Financial Support

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Summary methodological insights

- **Secular trends in exposure/outcomes require a difference-in-difference model**

- **When compliance with policy almost perfect, the DID model estimates both**
  - ITT effect of policy *(per policy change in outcome)*
  - IV effect of income *(per dollar change in outcome)*

Summary substantive insights

- We detected a signal that the Universal Child Care Benefit income supplement reduces food insecurity, especially those aged 12-24
- A threshold for income could not be identified due to a low number of households in each low income bracket (e.g. $5000 increments)

Sensitivity to DID model choice

Study group	Food Insecurity Outcome (binary)	
	RD_{Policy} (95% CI)	OR_{Policy} (95% CI)
Full sample	**-1.5%** (-3.5, +0.5)	**0.85** (0.71, 1.01)
Income below median	**-0.2%** (-5.1, +4.7)	**1.01** (0.82, 1.26)
Income above median	**-1.1%** (-2.6, +0.3)	**0.53** (0.38, 0.75)
Age respondent 12-24	**-11.1%** (-20.8, -1.5)	**0.52** (0.30, 0.92)
Age respondent 25+	**-0.6%** (-2.6, +1.3)	**0.87** (0.71, 1.05)
Single parent	**-2.9%** (-10.2, +4.9)	**0.97** (0.65, 1.43)
Couple parent	**-2.0%** (-4.1, +0.02)	**0.88** (0.72, 1.08)

Statistical analyses

- **DID that incorporates all years before/after the policy**

$$E(Y) = \beta_0 + \beta_1 \times \text{Eligible} + \Sigma\beta_{2i} \times \text{DummyYr}_i + \underbrace{\beta_3}_{RD_{DID}} \times \text{Exposed} + \beta_{jk} \times \text{Cov}_k$$

- **Model assumptions**
  - Effect policy does not change over time
  - Compliance with policy remains >95% in all years post-policy
  - Secular trends in eligible vs. controls do not change over time
- **Results weighted for sampling probabilities**

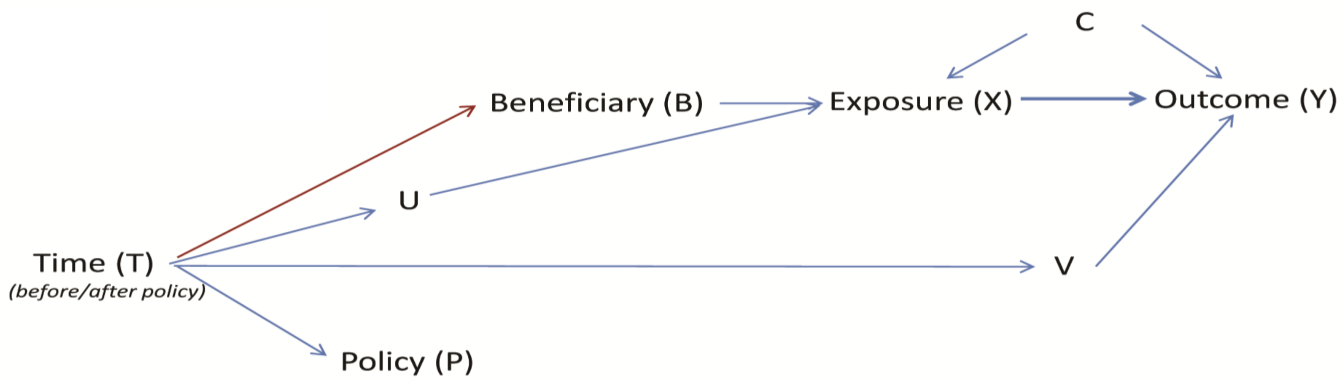
Sensitivity to DID model choice

Outcome	DID Model 1 FI = Eligible +YearDummies + Exposed		DID Model 2 FI = Eligible+YearDummies+Eligible×YearDummies	
	RD_{Policy} (95% CI)	OR_{Policy} (95% CI)	RD_{Policy} (95% CI)	OR_{Policy} (95% CI)
Income (continuous)	**+969** (-59, +1996)	**-**	**+1231** (-550, +3012)	**-**
Food insecurity (binary)	**-1.4%** (-3.4, +0.6)	**0.87** (0.86,0.87)	**-0.7** % (-3.3, +1.9)	**0.85** (0.83,0.87)

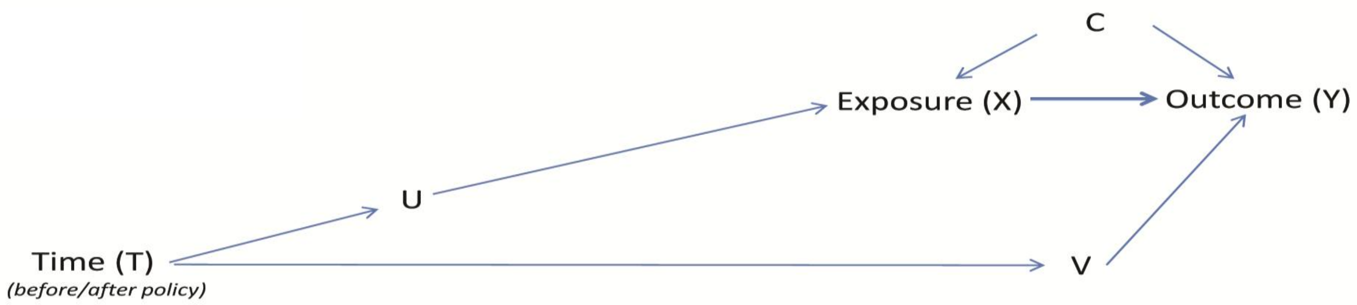
Difference-in-difference (DID) approach

- Estimate secular trends in a control population and subtract them from the effect of time among eligible

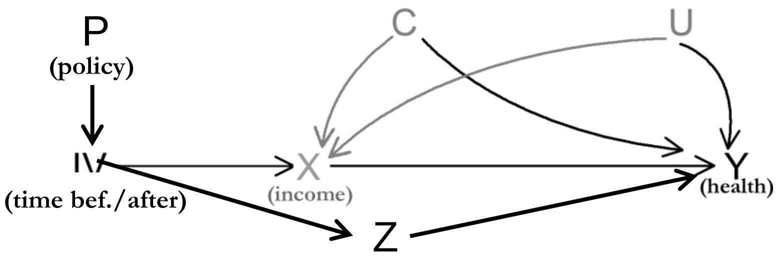
Eligible population



Control population



DID vs. IV: what do we estimate?



- **IV model** $\hat{\beta}_{IV} = \dfrac{\text{ITT}}{\textit{Compliance}}$
  - Removes bias due to U (unobserved confounding)
    due to ITT (non-compliance)
  - Does not remove bias due to Z (secular trends)

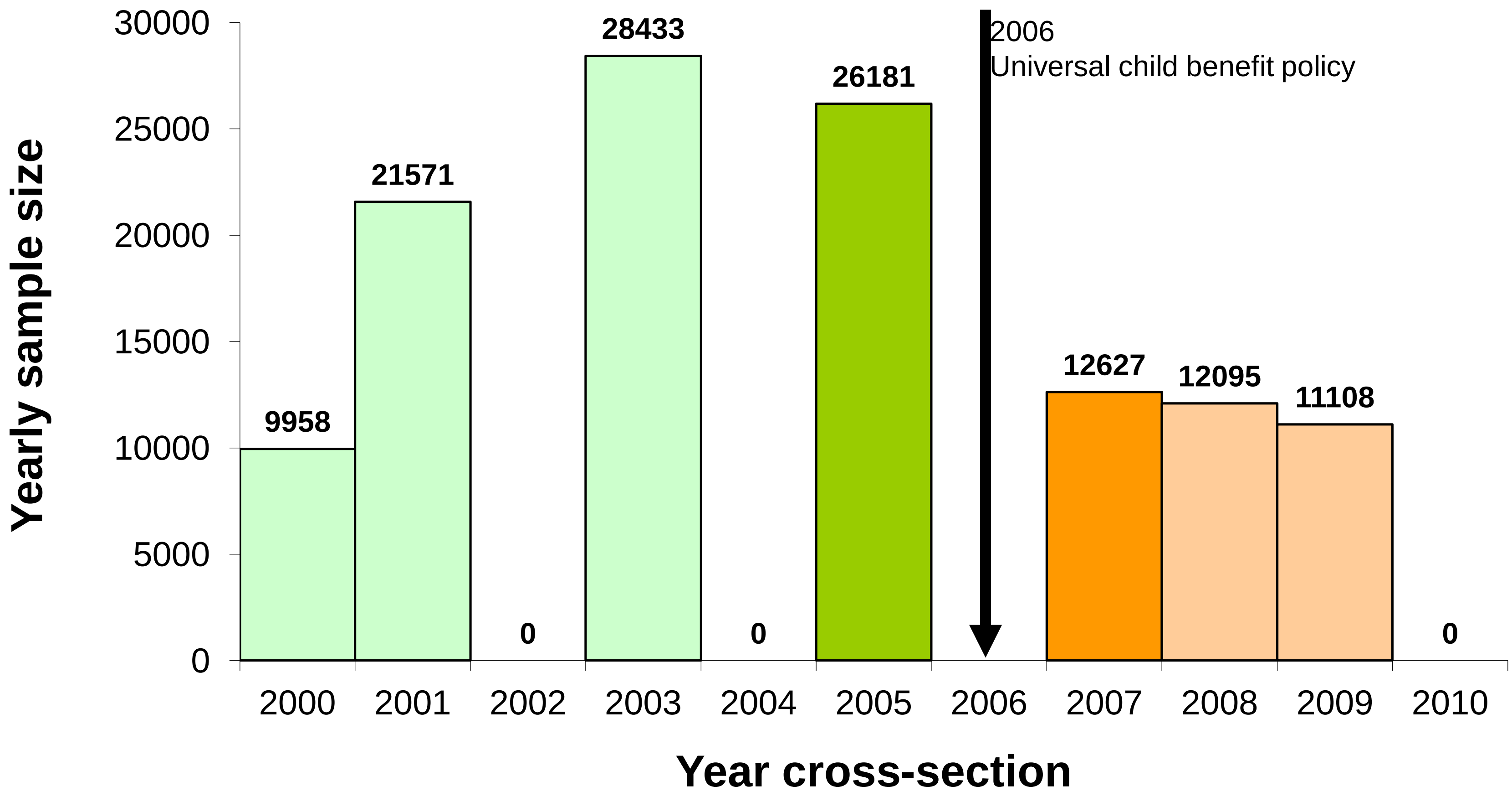
- **DID model** $\hat{\beta}_{DID} = \text{ITT}$
  - Removes bias due to U (unobserved confounding)
    due to Z (secular trends)
  - Does not remove bias due to ITT (non-compliance)

Statistical analyses

- **Basic DID model uses only 2 years**
  - $E(Y) = \beta_0 + \beta_1 {}^*Eligible + \beta_2 {}^*Yr07vs05 + \boldsymbol{\beta_3 {}^*Eligible {}^*Yr07vs05} + \beta_{4i} {}^*Cov_i$

- **Replaced with 2 alternative DID that use all years available**
  - $E(Y) = \beta_0 + \beta_1 {}^*Eligible + \Sigma\beta_{2i} {}^*DummyYr_i + \boldsymbol{\beta_3 {}^*Exposed} + \beta_{4i} {}^*Cov_i$
    - → Eligible subjects in years after Policy are classified as “Exposed”
    - → $\beta_3 \leftrightarrow$ interaction Eligible * before/after Period
  - $E(Y) = \beta_0 + \beta_1 {}^*Eligible + \Sigma\beta_{2i} {}^*DummyYr_i + \Sigma\beta_{3i} {}^*DummyYr_i {}^*Eligible + \beta_{4i} {}^*Cov_i$
    - → If Yr05 is used as a reference then DID estimate = $\boldsymbol{\beta_3}_{yr\,07}$
  - Uses all years without assuming a functional form for the effect of time
  - Linear models (for binary outcomes we compare linear vs. logistic models)

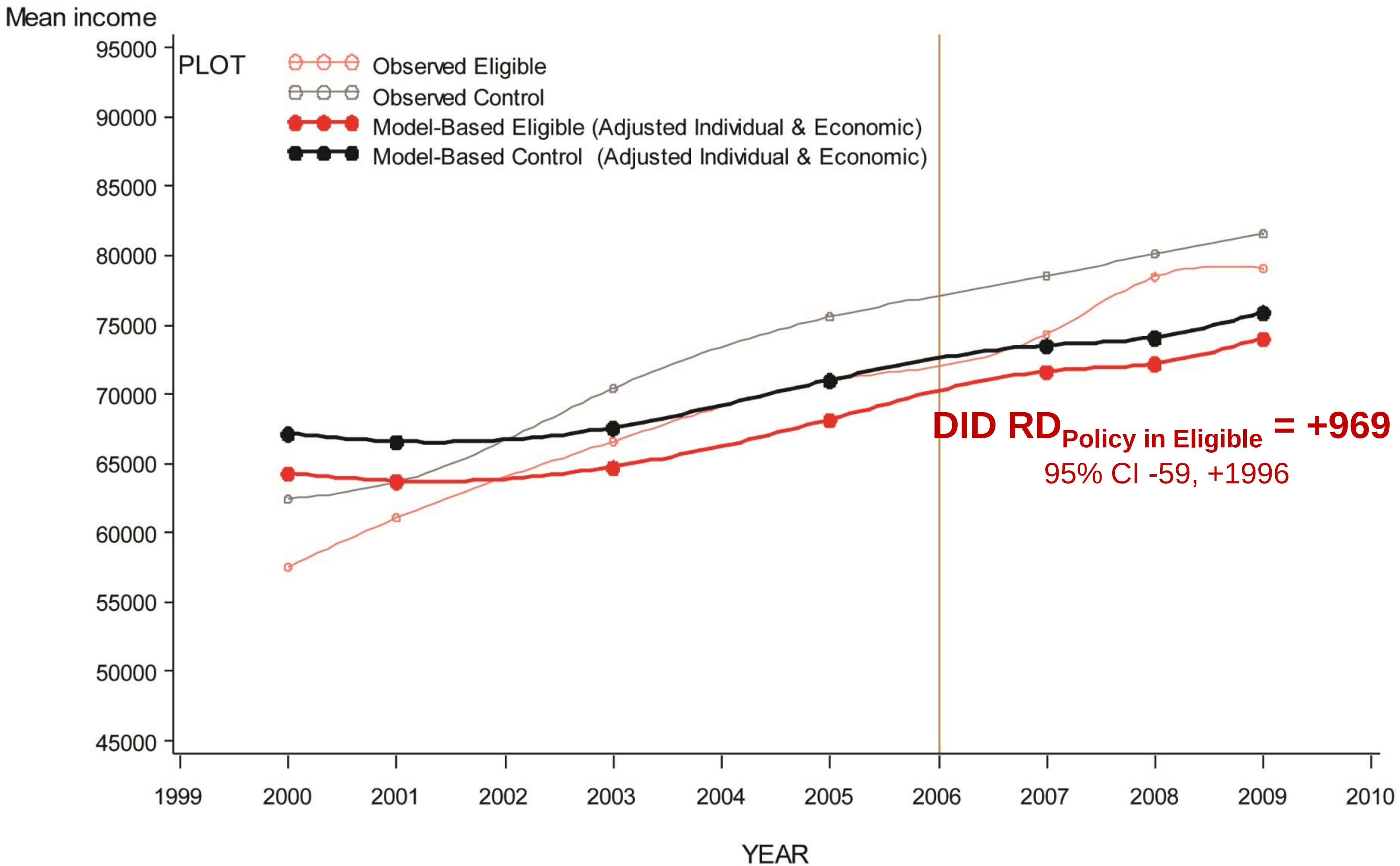
Study Population



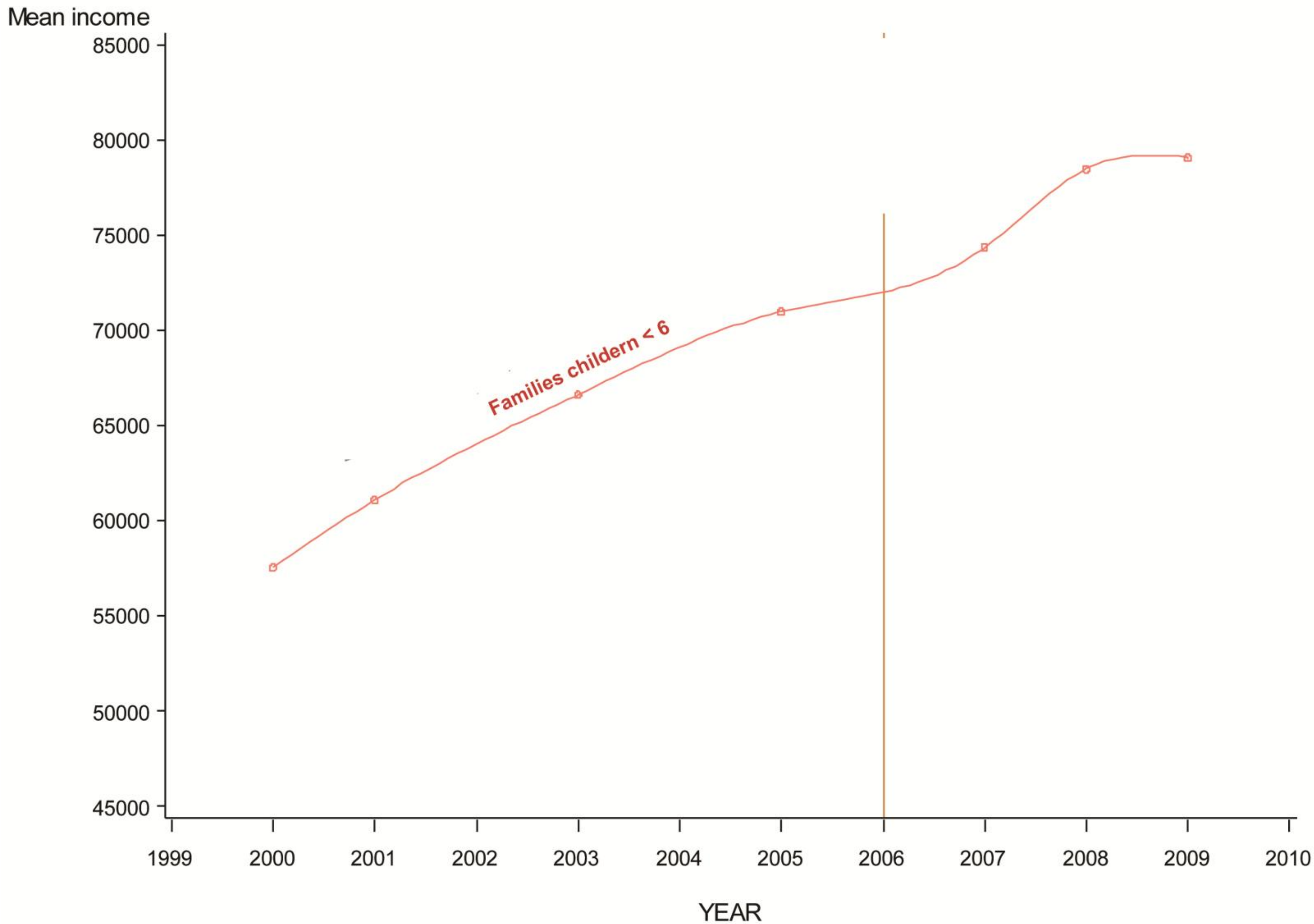
Adjustment variables

- **Socio-demographic characteristics for respondent/household**
  - → Age, sex
  - → Education respondent / household
  - → Household type /size
  - → Marital status
  - → Cultural /racial roots
  - → Residence (urban/rural, province)
  - → Immigration
  - → Baseline household income (for health outcomes)
- **Time variation in economic indicators at country/province level**
  - → Bank rate
  - → Consumer price index
  - → Unemployment rate
  - → Financial market indicators

Income outcome



Observed trends income



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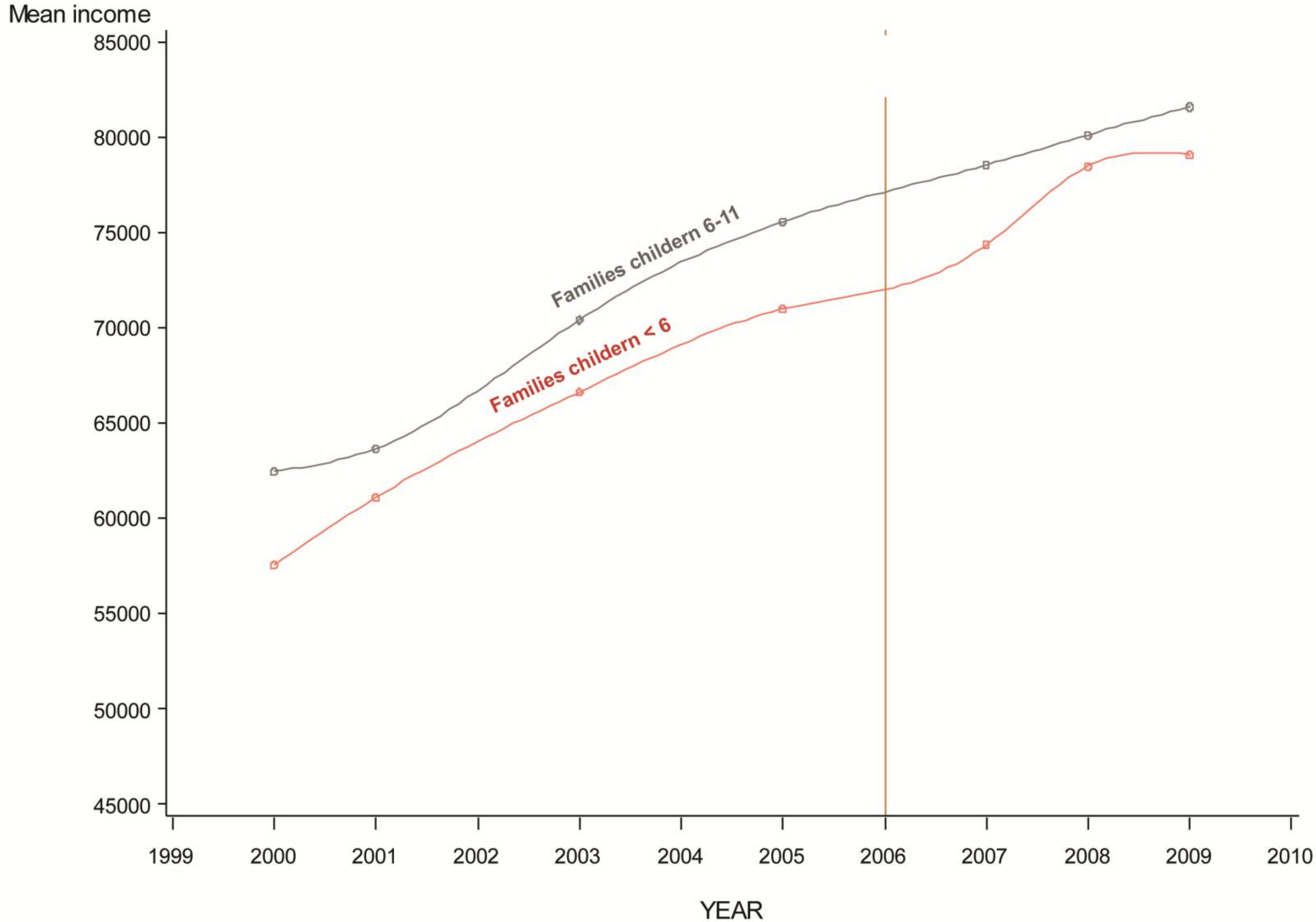

Description study population

Covariates		Before policy (Yrs 2000,2001,2003, 2005)		After policy (Yrs 2007,2008,2009)	
		Eligible	**Control**	**Eligible**	**Control**
Respondent	age (mean)	32	32	32	32
	male (%)	48	47	48	45
	university ed (%)	**22**	**14**	27	18
	immigrant (%)	**24**	**19**	26	23
	white (%)	80	83	76	78
	married/common law (%)	**83**	**62**	83	59
	employed (%)	**78**	**83**	79	83
Household	urban (%)	82	80	83	81
	highest ed university (%)	**32**	**27**	37	32
	size (mean)	4	4	4	4
	single parent (%)	**8**	**14**	9	16
Country	bank rate (mean)	4.2		2.9	
	% unemployment (mean)	7.4		6.8	
	Consumer Price Index (mean)	100.1		114.0	