Long-Term Own and Dynamic Complementarity Effects of the WIC Program

Anna Malinovskaya

Cornell University

am2883@cornell.edu

2023 ACS Data Users Conference

May 17, 2023

Outline

Background

- **Existing research focuses on the short-term effects of WIC**, such as birth outcomes, infant health, and dietary intake.
  - For example, Hoynes et al. (2011) study the roll-out of WIC in the 1970s and find that county-level exposure to WIC raised mean birth weight and reduced the fraction of low birth weight infants.
- There is **little research on cognitive & academic benefits of WIC**.
  - Jackson (2015) found that early WIC participation is associated with positive cognitive and academic benefits.
  - Kowaleski-Jones and Duncan (2000) found that prenatal WIC participation is associated with improved child temperament.
  - Chorniy et al. (2018) found that WIC participants have a lower incidence of ADHD and other common childhood mental health conditions as well as fewer grade repetitions.

Background

It is unclear to what extent existing research was able to identify a causal relationship between participation in the WIC program and the outcomes this research considered. The methods used in existing research on WIC include

- Comparing WIC participants to non-participants with plausibly similar characteristics, including using propensity-score matching and/or maternal fixed effect models (Joyce et al., 2005; Bitler and Currie, 2005; Khanani et al., 2010; Foster et al., 2010; Sonchak, 2016; Currie and Rajani, 2015; Gueorguieva et al., 2009; Lazariu-Bauer et al., 2004; Kowaleski-Jones and Duncan, 2002);
- Exploiting a policy change in Florida using a regression discontinuity approach (Figlio et al., 2009);
- Using an instrumental variable approach (Gai and Feng, 2012);
- Exploiting variation across counties and over time from WIC historical roll-out in the 1970s (Hoynes et al., 2011).

Background

This study is **different** in the following ways:

- It focuses on the long term effects of the program (measured around the time of high school graduation or after);
- It considers a range of outcomes (educational, socio-economic, etc.)
- It uses two very large samples with over 1 million observations each;
- It relies on two identification strategies with the goal of comparing the results obtained from these two alternative approaches.
- It considers how WIC might interact with other large scale public programs from different domains, such as Head Start and Food Stamps.

Identification

Identification Strategy I

In this approach, I follow Hoynes et al. (2011) and exploit variation across counties and over time from WIC historical roll-out in the 1970s.

$$y_{ict} = \alpha + \beta_1 \cdot WIC\_Treat_c \cdot Post_t + \beta_2 \cdot Z_{ct} + \beta_3 \cdot GT_{ct} + \mu_c + \nu_t + \gamma_{st} + \epsilon_{ict}$$

Identification Assumption

Whether the roll-out of WIC across counties and over time was indeed close to random is unknown. Hoynes et al. (2011) used various county characteristics to predict WIC adoption and found that variation in WIC adoption appears close to random, **given the county characteristics they considered**.

I do not observe *enrollment* in WIC in childhood; I only observe *exposure* to WIC in childhood, so I am estimating *intent-to-treat* effects, which is common in this strand of literature.

Empirical Approach

Outcomes y_{ict}

- high school drop-out;
- college enrollment;
- four-year college completion;
- income in adulthood;
- survival to 2020;
- economic self-sufficiency index as in Bailey et al. (2020);
- neighborhood quality index as in Bailey et al. (2020);
- physical ability & health index as in Bailey et al. (2020);
- human capital index as in Bailey et al. (2020);
- not incarcerated dummy as in Bailey et al (2020).

Controls Z_{ct}

- the percent of the county population in 1970 that lived in an urban area, on a farm, was black, was less than 5, was 65 or older, or was poor, and the log of the county population in 1970;
- community health centers (CHCs) grants
- county income, employment, and population;
- population of women ages 15-44 by county-year;
- rate of pregnancies and rate of teenage pregnancies;
- percent of premature births and percent of births with low birth weight;
- the percent of children born to unmarried mothers;
- average length of prenatal care;
- number of high schools per capita;
- the number of per capita doctors and short-term general hospitals;
- state-level unemployment, state-level real AFDC benefit standards, per capita AFDC caseloads;
- an indicator if the adult was conceived in a state and year with legalized abortion.

Controls GT_{ct}

- measures of real annual county per capita income and government transfers, including cash public assistance benefits, medical spending, and cash retirement and disability payments;
- an indicator variable for the Food Stamp Program (FSP).

Data

Main data on outcomes

- Decennial Census 2000
- American Community Survey [ACS] 2005-2020
- Social Security Administration's Numident File

It is linking to the Numident File that allows me to determine county of birth for individuals observed in Census 2000 or in ACS 2005-2020.

Other data

Current Population Survey (CPS), Survey of Income & Program Participation (SIPP), a dataset on WIC historical roll-out, and a range of datasets with control variables.

Preliminary Results

Preliminary results from the first identification strategy

	Outcome		
	HS completion	college enrollment	college completion
	Sample: Decennial Census 2000		
Post_treatment	+***	+***	+
Post_treatment * female	-**	-***	+**
Post_treatment * non-white	-***	-***	-***
Post_treatment * nonwhite * female	+	+	+
N	1,297,000	1,297,000	1,297,000
	Sample: ACS 2005-2019		
Post_treatment	+***	+***	+
Post_treatment * female	-**	-***	+***
Post_treatment * non-white	-***	-***	-***
Post_treatment * nonwhite * female	+	+	+
N	2,064,000	2,064,000	2,064,000

Note: The model on which these preliminary results are based did not include some of the additional controls that were added later (in particular, it excludes controls that were not used in Hoynes et al., 2011 as those were added at a later stage).

Next Steps

1. **Identification strategy II: Regression discontinuity design**
2. **Linking adults to their mothers in CPS / SIPP**
   - So that I can zoom in on the population most likely eligible for WIC at birth
3. **Robustness checks**
   - Migration in childhood
   - Controlling for the effects of the Oil Price Shock, China's imports competition, and NAFTA
4. **Program interactions**
   - WIC and state-level court-mandated school quality reforms
   - WIC and Head Start
   - WIC and SNAP
   - Medicaid and SNAP
   - and others

Next Steps: Regression discontinuity design

- I use the archival information available to me from the *Affirmative Action Plan* developed by officials from the state of Texas.
- In this Action Plan, they ranked Texas counties *in terms of their priority for WIC funding* and explained their methodology in detail.
- Each year, counties were then awarded WIC funding according to their rank until annual WIC funding for the state was exhausted.

That is, the historical **roll-out of WIC was not exogenous in Texas**. It is unknown, however, whether officials in any other state followed a similar approach.

- In the first RD analysis, I use their rankings in an RD design for the state of Texas only and compare the results obtained for Texas from identification strategy I.
- In the second RD analysis, I make the assumption that all states behaved like Texas, extend Texas officials' methodology to compute county ranking for all other states, and estimate an RD model for the entire US.

Next Steps: Regression discontinuity design

Texas state officials **used the following variables to construct an index** to rank counties:

- averaged infant mortality rates
- number of infant deaths per 1000 live births
- percentage of families below the Poverty Level
- percentage of children under six years of age, in families below the Poverty Level
- number of women of child-bearing age, 15-44 years, in 1000s
- number of migrants in 1000s, if over 500 in the county.

I construct their index and **estimate the following model**:

$$WIC_{icbt} = \theta + \alpha_c + \nu_b + \delta_t + b \cdot X_{cb} + Z_{c70} \cdot b_\nu + \beta \cdot Index\_centd_{cb} + \rho \cdot Index\_above\_cutoff_{cb} + \epsilon_{icbt}$$

$$Y_{icbt} = \theta + \alpha_c + \nu_b + \delta_t + b \cdot X_{cb} + Z_{c70} \cdot b_\nu + \beta \cdot Index\_centd_{cb} + \rho \cdot \widehat{WIC}_{icbt} \cdot Post_b + e_{icbt}$$

Next Steps: Linking adults to their mothers in CPS/SIPP & Robustness Checks

- **Linking adults to their mothers in CPS/SIPP**
  - After performing this linkage, I use a measure of mother's education to estimate my regressions separately by mothers' level of educational attainment.
- **Robustness checks**
  - The last birth cohort – individuals born in 1979 – could have been affected *in-utero* by the 1979 oil price shock, which could in turn bias the results downward for this cohort. I use triple DID and compare individuals who were *in-utero* or born before the inflation peak in January of 1979 with those born or *in-utero* in the 2nd trimester in January – February of 1979.
  - Individuals in my sample were born in 1974, 1975, 1978, and 1979. The 1978-1979 birth cohort finished high school in 1996-1997, soon after the passage of NAFTA in 1994. Previous work has found that NAFTA had employment and education effects on some counties (Lee, 2021; Benguria, 2020). To control for NAFTA possibly confounding WIC effects, I repeat my analysis at the commuting zone level and control for the local average tariff variable that measures each commuting zone's exposure to the NAFTA shock based on the commuting zone's industry composition prior to the passage of NAFTA.

Next Steps: Linking adults to their mothers in CPS/SIPP & Robustness Checks

- **Robustness checks** *(continued)*
  - Another potential concern is the expansion of China's imports to the US during 1990-2007, which was found by Autor et al. (2013) to raise unemployment and the use of disability and other transfer benefits, while also lowering labor-force participation and wages. To control for this potentially confounding factor, I construct a measure of potential exposure to import competition from China at the commuting zone level following the approach taken by Autor et al. (2013).
  - To minimize potential lack of compliance with treatment stemming from the possibility of families moving across counties during an individual's first 5 years of life, I repeat my analysis separately for individuals who at the time of the survey resided in their county of birth and all others. Additionally, I explore, similarly to Bailey et al. (2020), whether exposure to WIC is associated with moving to a different county. It might be that moving to a different county (with higher socio-economic indicators) is one of the mechanisms for the long-term positive effects of WIC.

Next steps: Program interactions

The motivation for studying program interactions is **to understand the smaller effect of WIC for non-whites**. Bailey et al. (2020) studied the long-term effect of Food Stamps on individuals' human capital outcomes and also found smaller effects for non-whites. One of their suggested mechanisms is complementarity between nutrition and school quality combined with the lower quality of schools for blacks at that time.

To test the mechanism suggested by Bailey et al. (2020), I examine interaction effects

- between WIC and Head Start;
- between WIC and school quality reforms;
- between WIC, Head Start, and school quality reforms;
- between WIC and SNAP;
- between SNAP and Head Start;
- between SNAP and school quality;
- between SNAP, Head Start, and school quality;
- between WIC, SNAP, Head Start, and school quality;
- between Medicaid and the programs above except for WIC.

Appendix

The components of the **economic self-sufficiency index** include (following Bailey et al., 2020): in labor force; worked last year; weeks worked last year; usual hours worked per week; labor income; other income not from public sources; income-to-poverty ratio; reverse coded income from welfare, supplemental security, and other government source.

The components of the **neighborhood quality index** include (following Bailey et al., 2020): value of home; gross rent; home or apartment ownership; residence with single and not multiple families; income-to-poverty ratio in census tract of residence; reverse-coded teen pregnancy in tract, reverse-coded share of single-headship in census tract; reverse-coded share of poor children in tract; share of home ownership in census tract of residence; median house price index in census tract of residence; median gross rent in census tract of residence; and county absolute mobility score using estimates from Chetty et al. 2014.

The components of the **physical ability & health index** include (following Bailey et al., 2020): no work disability; no ambulatory difficulty; no cognitive difficulty; no independent living difficulty; no vision or hearing difficulty; no self-care difficulty.

The components of the **human capital index** include (following Bailey et al., 2020): educational outcome variables plus years of schooling completed, professional degree obtained dummy, and professional occupation dummy.