Food for Thought:

Understanding the Impact of Food Insecurity on Fertility Dynamics in the U.S.

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Abstract

This paper examines the relationship between food insecurity rates and fertility rates in the United States using panel data at the county level spanning from 2010 to 2017. Drawing upon health literature that highlights the disproportionate burden of food insecurity on women and its adverse effects on maternal and child health, I investigate the hypothesis that counties with lower rates of food insecurity exhibit lower fertility rates by employing an instrumental variable regression approach with two-way fixed effects. The two most notable findings are, first, that there is weak but suggestive evidence of a positive relationship between food insecurity and fertility at the national level and second, regional disparities can cause this relationship to turn negative. These findings underscore the significance of socioeconomic factors in shaping reproductive behaviors. Further research using alternative econometric techniques is warranted to investigate causal mechanisms in the observed relationship.

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American abundance isn't just a concept—it's a way of life. For over 100 years, the United States has stood as a world power, boasting ample wealth and resources from its free-market economy. Despite the consumerist culture and over-consumption stereotypes that plague the U.S., over 44 million Americans did not have enough to eat or did not have access to healthy food in 2023 (Rabbitt et al., 2022). How does this paradox between abundance and food insecurity persist within one of the wealthiest nations on earth?

The USDA defines food security as “access by all people at all times to enough food for an active, healthy life.” It is one of the most critical public health issues in the United States, hindering the prosperity of its people. Food insecurity in the U.S. and other developed countries poses a unique case: rather than being a direct result of civil conflict, crop failures, or inadequate infrastructure, Americans who are hungry simply don’t have enough money to buy food (The Global Giving Team, 2021). In addition to this, about 10% of the approximately 65,000 census tracts in the United States were classified as food deserts, regions where people have limited access to healthy and affordable food (Dutko et al., 2012).

Literature Review

Food insecurity bears many economic and social costs to American society such as productivity losses, education and social service expenses, lost economic potential, and decreases in community welfare. Without question, the facet of American life that faces the greatest burden of food insecurity costs is the healthcare sector. A 2019 study from Berkowitz et al. estimated that food insecurity costs the U.S. healthcare system an additional $53 billion annually by triggering chronic diseases and fueling emergency room visits, hospitalizations, and readmissions (Berkowitz et al., 2019). A more recent study from Palakshappa et al. found that food-insecure families in the U.S. paid an average of $2,500 more annually in healthcare costs than families with sufficient food (Palakshappa et al., 2023).

Unsurprisingly, the effects of food insecurity are not felt equally across different groups. Racial minorities, low-income people, and women disproportionately experience food insecurity. Even though national food insecurity rates fell substantially between 2010 and 2021, a recent study from Gunderson found that these more vulnerable groups saw smaller declines in food insecurity rates and were “left behind” (Gunderson, 2023). This is backed by a study from Flores-Lagunes et al. which found that Black households are more likely than white households to experience a greater intensity of food insecurity (Flores-Lagunes et al., 2018). Additionally, women living alone and single-mother households with children are more likely to be severely food insecure than nuclear family households (USDA, 2019). Women also experience exacerbated adverse health effects related to food insecurity. Their poor health can impact fertility, creating long-term repercussions on population dynamics and demographic trends. A study using data from California found that nutrition during pregnancy not only influences the current health condition of women and infants, but also plays an important role in the health condition of children and adults in the future (Braveman et al., 2010).

There is an extensive body of research to support the correlation between food insecurity and negative health outcomes for women. For this reason, I wanted to explore the relationship between food insecurity and fertility in the United States. In 2006, a study by Cook et al. found that U.S. households suffering from food insecurity are more likely to have children with poorer general health. One year later, Carmichael et al. found that food insecurity during pregnancy was associated with higher risks of birth defects in California. Analysis from Grilo et. al echoed these sentiments, stating that poor nutrition increased the risk for pregnancy complications such as gestational diabetes, preeclampsia, and fetal macrosomia, leading to worse birth outcomes including shorter gestations and lower birth weights (Grilo et al., 2015).

While many researchers have examined the impact of food insecurity on pregnant women, few have looked at the possibility of food insecurity inducing fertility outcomes. One of the few studies that investigates a causal relationship is from DiClemente et al. which analyzed fertility preferences among Tanzanian women during times of food insecurity (DiClemente et al., 2021). The results indicated that women who experience household hunger had a preference to delay or avoid pregnancy. An adjacent study by Alam et al. found that the likelihood of pregnancies and childbirth was significantly lower and contraception use was significantly higher for Tanzanian households that experienced crop losses (Alam et al., 2017). Based on these results, I was curious how this relationship might fare in a drastically different part of the world.

Despite strong evidence that links food insecurity and fertility, there are various other interdependent influences. In 2020, Bijlsma et al. note that fertility rates in the UK are influenced by many external factors such as education, employment, and marriage. There are also more abstract influences on fertility that are harder to measure. Barrett et al. found that the desired family size of a household in Sub-Saharan Africa is positively related to the average family size in the community. This is evidence that fertility can not only be influenced by private desires, but societal mores as well. There is also a strong and pertinent income effect in this relationship. A 2016 study by Murthy found that low-income families are more likely to be food insecure, but they are also more likely to postpone medical care or underuse medicine because of budget constraints (Murthy, 2016). Because food insecurity and income are so closely correlated, it will be hard to differentiate which fertility effects are due to income and which are due to food insecurity. In my regression analysis, I will do my best to control for these factors to cipher out the specific effect of food insecurity on fertility.

Economics of the Problem

The health literature on food and fertility is fairly straightforward. Food security improves women's overall health and nutrition, making them better equipped to sustain a pregnancy to term. If babies are carried to term when a mother is unhealthy, this can lead to negative health outcomes for the child. Introducing economic theory entangles the conversation.

The baseline, neoclassical theory views fertility as a result of individual choice-making. Women will weigh the costs and benefits of having children, and continue to have them until the marginal benefit equals the marginal cost. In this theory, a high demand and low supply of food will induce women to stop having children they cannot feed, so long as they can control it. It will also prompt households to allocate scarce resources away from child-rearing activities, such as healthcare and education, and towards obtaining food. Additionally, because of the perceived impacts of giving birth while in poor health, this may also restrict women from choosing to have children while food insecure.

On the flip side, human capital theory suggests that fertility decisions are influenced by the trade-off between the quality and quantity of children. Especially in high-income families, parents may opt for fewer children, enabling them to invest more time and money per child. This will potentially increase each child's human capital and future earning potential. As parents see these returns on investment increase, they will continue to invest in their existing children, rather than having more. There are also strong income and education effects in this relationship. As one's income grows, the income effect predicts that people will begin to demand and consume more. This close link between income and food results in both variables having a similar impact on fertility choices. In the same vein, women with more education have a higher opportunity cost of bearing children in terms of lost income. In two-parent households, more educated women are better able to support themselves and have more bargaining power over family size, which is validated by the household bargaining model (Echevarria et al., 1999). These women also have more robust sex education surrounding pregnancy prevention and pregnancy risks. This link between education and fertility results in both variables having a similar relationship with food insecurity.

While there are competing economic theories on the relationship between food insecurity and fertility, I believe the latter theory is supported by the U.S. context due to the robust social safety nets that counteract the neoclassical theory. Women experiencing food insecurity and economic instability may choose to have more children as a form of social security or insurance against economic shocks. Social programs such as the Child Tax Credit and the Earned Income Tax Credit provide financial assistance to low and middle-income families with children. There are also programs like the Supplemental Nutrition Assistance Program (SNAP) and the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) that offer nutritional support for pregnant women, new mothers, and young children. Due to the existence of these programs, as well as human capital theory and education/income effects, I hypothesize a positive relationship, meaning U.S. counties with lower rates of food insecurity will induce lower rates of fertility.

Data Description

I am examining panel data with 6,126 observations of women ages 15-60 across U.S. counties from 2010-2017. The data for my independent variable of interest, food insecurity rate (FIR), comes from the non-profit organization Feeding America through their annual "Map the Meal Gap" study. Feeding America provides FIRs for every U.S. county, which they estimate based on household questionnaires, median income, unemployment, homeownership, and disability prevalence. The data for one of the instrumental variables, "cost per meal", also comes from Feeding America. This is calculated by adjusting the national average cost per meal by a relative food cost index to derive a county-level estimate.

The data for my dependent variable of interest, fertility, comes from the American Community Survey (ACS), conducted by the United States Census Bureau. All estimates are at the county-level and look at the 15-50 year old age range among women. The ACS provided one-year estimates for the total female population, as well as the female population who gave birth. With these values, I generated the fertility outcome variable: the percentage of women who gave birth in the past year. I used the same generation method to find various demographic percentages among these women such as the percentage of women who are married, foreign-born, employed, living below 100% of the poverty level, and among seven different age groups. These were all used as controls in my regression. Data for the other two instrumental variables also comes from the ACS, which looks at the number of cars per household. Per the US Census, all this data is collected in survey form from a random sample of addresses in each state.

When checking for robustness in my results, I also controlled for the number of abortions per county. This data comes from the Guttmacher Institute which provides abortion estimates for each US state. I disaggregated these state-level values by generating proportions based on similar related county-factors such as population and fertility.

Table 1

Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
FIR	6126	13.99	3.628	3.4	28.3
fertility	6126	5.446	1.524	.85	16.002
poverty	6126	18.039	7.023	1.639	54.439
married	6126	46.536	6.589	21.771	68.387
labor	6126	72.459	6.103	41.513	99.395
foreign	6126	10.993	9.025	.285	55.284

The FIR exhibits a sample mean of approximately 14% with a standard deviation of roughly 3.6, indicating notable variability in FIRs across counties. The range of FIR spans from a minimum of 3.4 to a maximum of 28.3, highlighting the diversity in outcomes observed within the dataset. Similarly, the poverty rate displays a sample mean of about 18% with a standard deviation of 7.023, reflecting substantial variation in poverty levels among counties. The fertility rate exhibits a mean of 5.4% with a standard deviation of about 1.5 indicating minimal variability in fertility across counties. These descriptive statistics provide valuable insights into the distribution of my variables of interest, laying the groundwork for subsequent empirical analyses.

Table 2

FIR Sample Average Comparisons

	Food Insecurity Rate		
	Below Average	Above Average	Total
N	3,178 (51.9%)	2,948 (48.1%)	6,126 (100.0%)
fertility	5.304 (1.423)	5.598 (1.611)	5.446 (1.524)
poverty	14.259 (5.478)	22.114 (6.176)	18.039 (7.023)
married	48.501 (5.578)	44.417 (6.930)	46.536 (6.589)
labor	73.972 (5.872)	70.829 (5.926)	72.459 (6.103)
foreign	11.498 (9.481)	10.449 (8.475)	10.993 (9.025)

Table 2 splits the counties into two groups: above and below the sample average FIR of roughly 14%. The below-average group holds about 52% of the sample observations while the above average holds about 48%. This symmetry suggests there are not large outliers on either end that significantly drag the average up or down. The values for the subsequent variables indicate the mean and standard deviation for the given group. Across the board, it is evident that the cluster of counties below the FIR average has a lower average fertility and poverty rate with higher rates of marriage and labor force participation. This relationship is consistent with the theory of income effect, since income and fertility have a positive correlation and food insecurity is closely correlated with income.

Table 3

Poverty Rate Sample Average Comparisons

	Poverty Rate		
	Below Average	Above Average	Total
N	3,199 (52.2%)	2,927 (47.8%)	6,126 (100.0%)
FIR	12.008 (2.809)	16.156 (3.154)	13.990 (3.628)
fertility	5.350 (1.441)	5.550 (1.603)	5.446 (1.524)
married	49.237 (5.624)	43.584 (6.294)	46.536 (6.589)
labor	73.788 (5.324)	71.007 (6.554)	72.459 (6.103)
foreign	11.690 (9.232)	10.232 (8.733)	10.993 (9.025)

Table 3 uses the same method but instead splits the groups by the sample average poverty rate of about 18%. Displayed is the mean of each group with the standard deviation in parenthesis. Similarly to Table 2, the two groups have a fairly even split of observations, suggesting there are no large outliers related to poverty. On average, the counties clustered below the poverty rate average experience lower rates of fertility and food insecurity with higher rates of marriage and labor force participation. Given the income effect, the raw data statistics are unsurprising.

Figure 1

Scatterplot

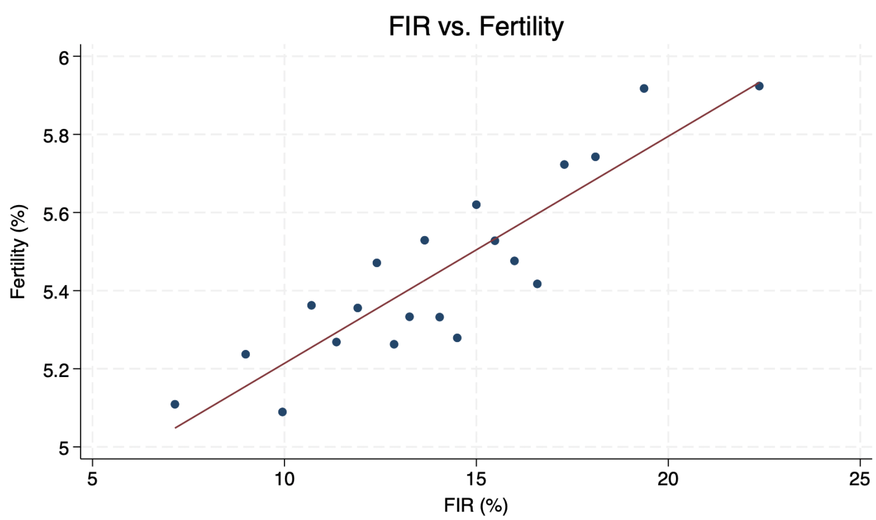

Figure 2

Scatterplot

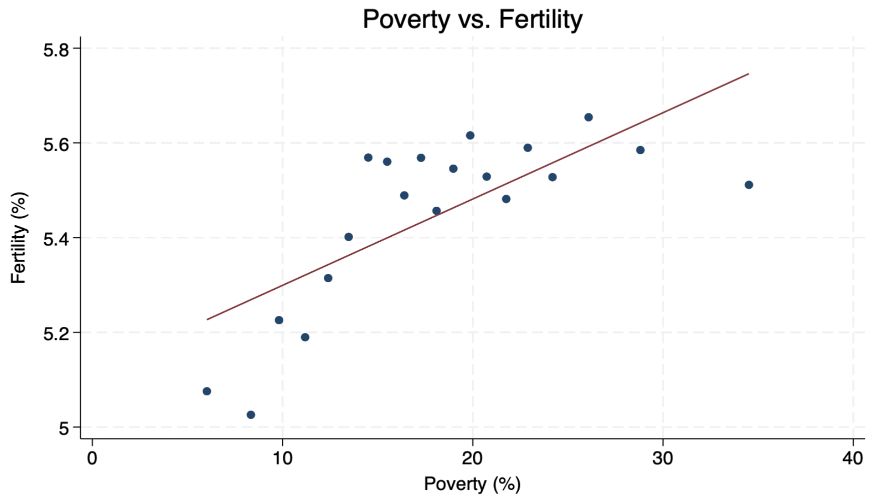

Figure 1 visualizes the trend in the raw data between food insecurity and fertility. In order to reduce clutter and better conceptualize the relationship, I created a bin scatterplot. This method groups the counties into equal-sized bins based on the x-axis variable, using the mean in each bin to create a scatterplot of data points. Figure 1 reveals a distinct positive linear trend between food insecurity and fertility. A similar relationship is also evident in Figure 2 which details poverty and fertility. Both figures further solidify the income effect theory.

Figure 3

Histogram and Density Plot by Year

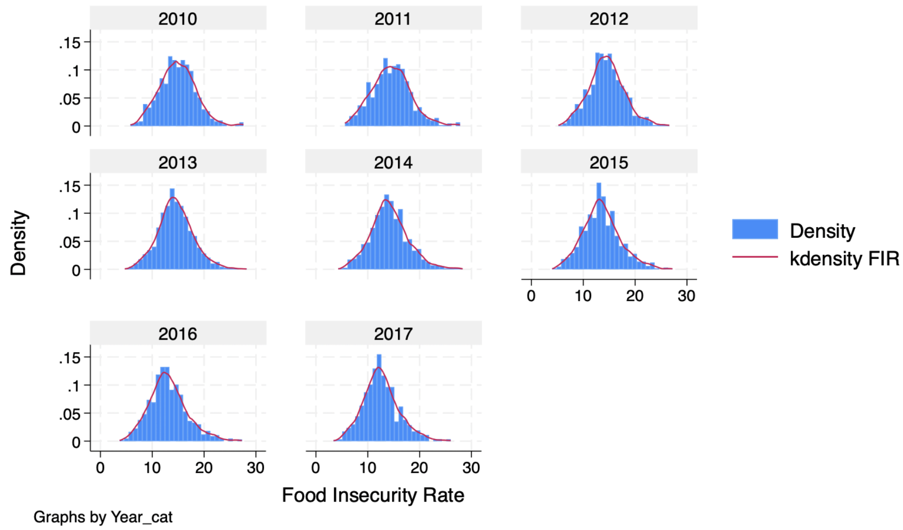

Figure 4

Histogram and Density Plot by Year

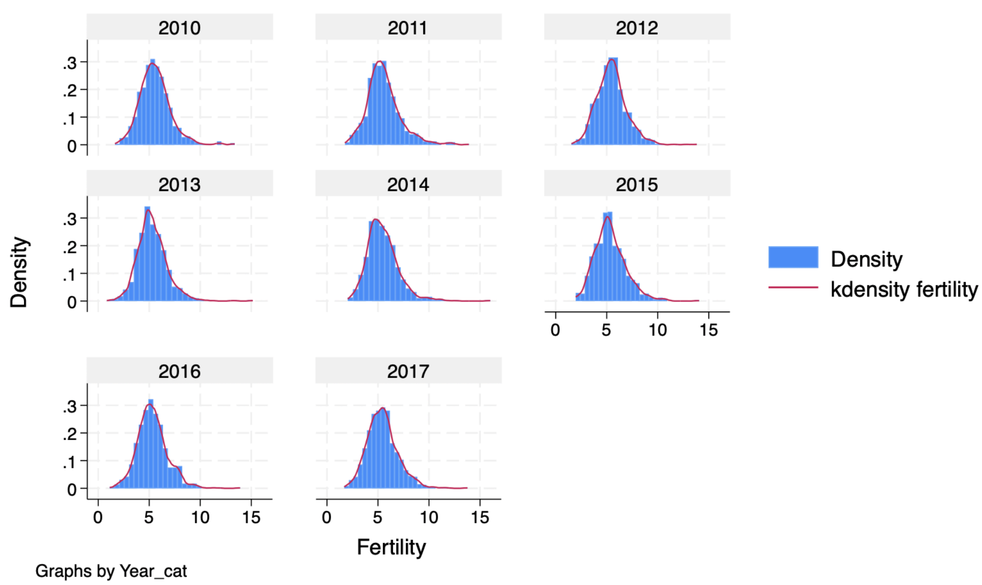

Figure 3, pictured above, combines a histogram and density plot of FIRs for every year. FIRs for each year are normally distributed with means of around 12-14%. This signifies that no single year is drastically skewing the FIR total sample mean. Figure 4 exhibits the same visualizations for fertility across each year. Fertility rates for each year are slightly skewed to the right with sizable tails. This suggests that every year, there are consistently a few outlier counties that have very high fertility rates of around 10-15%. Both figures demonstrate that there is uniformity across the years of interest when it comes to my independent and dependent variables. These observed patterns are less likely to be spurious or driven solely by anomalies in specific years. Having this consistency across time for both variables will strengthen my empirical exploration of a causal relationship.

Empirical Strategy

My regression will attempt to discern a causal relationship between food insecurity and fertility. I am using an instrumental variable (IV) regression with the two-stage least squares technique. The instruments are cost per meal in USD, number of households that do not own a vehicle, and number of households that own one vehicle. Stage one will use my instruments to predict the independent variable. This predicted value is then used in stage two analysis instead of the original values.

I am employing two-way fixed effects in hopes of curbing the impact of unobserved confounding variables that are constant across counties and time periods. This will be especially helpful to parse out the noise regarding how sentiments towards women and childbirth differ across time and communities. Rather than using robust standard errors, I am using VCE clustering which gathers my data into 823 clusters by county. Since the within-county observations are likely to be correlated, this method will allow for a more efficient estimation of standard errors by explicitly modeling the covariance structure within clusters.

First Stage IV:

$$FIR_{it} = \pi_0 + \pi_1 CostPerMeal_{it} + \pi_2 noVehicle_{it} + \pi_3 oneVehicle_{it} + \pi_4 (LMD * FIR)_{it} + \pi_5 Poverty_{it} + \pi_6 Married_{it} + \pi_7 Labor_{it} + \pi_8 Foreign_{it} + \pi_9 Age15to19_{it} + \pi_{10} Age20to24 + \pi_{11} Age25to29_{it} + \pi_{12} Age30to34 + \pi_{13} Age35to39 + \pi_{14} Age40to44_{it} + \pi_{15} Age45to50_{it} + \alpha_i + \gamma_t + u_{it}$$

The three instruments will be used to predict food insecurity values that will then be regressed with fertility. Cost per meal acts as a conduit to food prices and inflation over the observed years. It is directly related to the affordability of food, as higher costs will increase food insecurity. The issue here is that there is not much variation in meal prices across counties, making it hard to discern a statistically significant relationship between cost per meal and food insecurity, despite its relevance.

Vehicle and transportation access is another variable that is commonly used to evaluate food insecurity in economic research (Ploeg et al., 2015). Affordable and nutritious food options may be located in areas that are further away or less accessible by other modes of transportation. Despite their strong relevance, they are ultimately weak instruments due to the existing pathways of connection to fertility. Therefore, I cannot say for certain that vehicle ownership is uncorrelated with fertility. These shortcomings will be discussed later in the paper. While I have established these three instruments are weak in their own regard, I will still implement them in hopes of mitigating some endogeneity and improving the bias of my estimators.

Second Stage IV:

$$Fertility_{it} = \beta_0 + \widehat{\beta_1} FIR_{it} + \beta_2 (LMD * FIR)_{it} + \beta_3 Poverty_{it} + \beta_4 Married_{it} + \beta_5 Labor_{it} + \beta_6 Foreign_{it} + \beta_7 Age15to19_{it} + \beta_8 Age20to24_{it} + \beta_9 Age25to29_{it} + \beta_{10} Age30to34_{it} + \beta_{11} Age35to39_{it} + \beta_{12} Age40to44_{it} + \beta_{13} Age45to50_{it} + \eta_i + \theta_t + u_{it}$$

My final regression is intended to obtain consistent evidence of a causal relationship between my variables of interest. Ideally, this will help me draw reliable conclusions related to public health and the American economy.

Results

Table 4

OLS Regression Results

VARIABLES	*(1) No Lag* fertility	*(2) With Lag* fertility
L.FIR		0.0659**
		(0.0332)
FIR	0.0376*	0.000201
	(0.0221)	(0.0367)
Constant	4.149*	4.331
	(2.223)	(2.929)
Observations	6,125	5,158
R-squared	0.372	0.393

Note. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. Controls and TWFE added

The first OLS regression finds weak but suggestive evidence of a positive relationship between FIR and fertility. It estimates that a 10 percentage point increase in food insecurity rate is associated with a roughly 0.38 percentage point increase in fertility rate. Using the sample average as an example, this is reflected as a fertility rate increase from 5% to 5.38%. However, because fertility choices are made roughly nine months before birth, I suspect we might see a stronger effect using a one-year lag on food insecurity rates. This means that food insecurity in

2010 is actually impacting fertility in 2011. In the second OLS regression, I lagged the independent variable and found an increase in its effect on the dependent variable. Due to the unbalanced nature of the panel, approximately 1,000 counties were dropped. Now, a 10 percentage point increase in food insecurity is associated with a roughly 0.7 percentage point increase in fertility rate. These results are more trustworthy, with an increased significance of 5%. The lagged model also exhibits a slightly higher R-squared compared to the model without a lag. While these values are less important for economic interpretation and determining causality, this increase could indicate that the lag improves the overall explanatory power of the model.

There is still an acute concern about the feedback loop between the independent and dependent variables. While varying levels of food insecurity can influence reproductive decisions, fertility rates can also strain available resources, which may lead women to delay or limit childbearing. This endogeneity makes it challenging to establish a clear causal relationship between the two variables. In an attempt to battle some of this endogeneity, I ran an instrumental variable regression.

Table 5

IV Regression Results

	(3) No lag	*(4) With lag*
VARIABLES	fertility	fertility
L.FIR		-0.906
		(0.886)
FIR	0.415*	0.804
	(0.238)	(0.732)
Constant	0.419	4.640
	(3.188)	(2.890)
Observations	6,125	5,158
Number of FIPS	823	798

Note. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Controls and TWFE added

The addition of instruments induced a substantial change in coefficient estimates for regressions 3 and 4. No-vehicle households and one-vehicle households were significant at the 1% level, while cost per meal had a statistically insignificant coefficient. Regressions 3 and 4 have F statistics of about 261 and 280 respectively, far above the threshold for a strong IV (see Appendix A). The magnitude of the F stat indicates greater overall explanatory power of the instruments and provides evidence against the null hypothesis. Knowing that the instruments performed moderately well and substantially impacted coefficient estimates, I assert that these instruments untangled some of the biased estimates and unreliable statistical inferences that were present in my OLS regressions. However, in the IV process, the lagged model lost all significance. Regression 3 finds that a 10 percentage point increase in food insecurity is associated with a 4.15 percentage point increase in fertility rate.

Despite weak but suggestive evidence of a positive relationship, I was still doubting these results. Due to the substantial variation in governmental policies and regulations enacted at the state and local levels, I have trouble believing that a relationship holds uniformly across the entire country. To further investigate this, I looked into the region-specific effects of food insecurity by creating a dummy interaction variable for the Lower Mississippi Delta (LMD) region. This area consists of various counties surrounding the Mississippi River in the southern United States (National Park Service, 2024). It is also home to some of the strictest abortion laws and the highest food insecurity rates in the nation. I was curious to see how this combination of socioeconomic factors would influence the relationship between my variables of interest.

Table 6

IV Regression with LMD Dummy Interaction

VARIABLES	(5) fertility
FIR	0.416*
	(0.237)
LMD	-0.411*
	(0.220)
Constant	0.592
	(3.123)
Observations	6,125
Number of FIPS	823

Note. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Controls and TWFE added

Table 6 details the final regression results which continue to find weak but suggestive evidence of a positive relationship between FIR and fertility. The FIR coefficient effectively stays the same, finding that a 1 percentage point increase in food insecurity is associated with a 0.411 percentage point increase in fertility rate. These results may seem negligible, but they have significant real-world impact. In 2017, the average population of women ages 15-50 in a county was about 75,000, excluding extreme outliers. Assuming the average fertility rate of about 5%, the results of this regression indicate an additional 308 women giving birth in a year from just a 1 percentage point increase in FIR.

The addition of the LMD dummy interaction extracts the relationship between FIR and fertility in this specific region. Both coefficients are similar in magnitude, but the LMD variable indicates a negative relationship, with fertility decreasing by 0.408 percentage points for every 1 percentage point increase in FIR. These results paint an interesting picture of regional differences across the United States. The coefficient sign flip makes it clear that not all regions operate with the same positive relationship between FIR and fertility that is seen at the national level.

While these results technically hold significance, there is still a 10% chance that the observed relationship between FIR and fertility is due to random sampling variability rather than a true relationship in the population. The 10% significance level is not very stringent, but it still suggests that the observed relationship is likely to be meaningful. In order to check for robustness in my results, I implemented a few tests. I began by logging three control variables and my results came out effectively the same (see Appendix Table B1). I also added a control for abortions per county which also did not largely impact my results (see Appendix Table B2).

Limitations

Despite weakly significant results, a myriad of limitations prevent these results from being internally valid. As previously noted, all three instruments are correlated with the independent variable of interest, making them relevant candidates for an IV regression. However, the cost per meal instrument was ultimately statistically insignificant, despite boasting stronger evidence of exogeneity. On the other hand, the two instruments for vehicle access both had statistical significance, but still violated the exclusion restriction assumption due to the pathways between vehicle ownership and fertility. To put this into context, owning a car can expand one's access to birth control and maternal care and therefore influence fertility decisions. This direct relationship makes it impossible to discern the causal effect of the endogenous variable because the instrument is capturing variation in fertility that is not due to FIR. Due to the weakness of the instruments, these results are still plagued with bias as a result of existing reverse causality.

In addition to endogeneity, there is a sizable amount of omitted variable bias, which occurs when influential variables are left out of the analysis. A few examples of omitted variables that also impact fertility are educational attainment, religious beliefs, abortion clinics, and other health factors. Failing to account for these variables limits the interpretation of my results as casual. In order to improve the robustness, future research should aim to incorporate a more comprehensive set of control variables.

The residual vs. fitted plot of my final regression revealed some interesting findings (see Appendix C). The residual trend is downward sloping, with data points clustered along the line. Based on this trend in residuals, the conditional mean of the error term given the independent variable is not zero, violating the first Gauss-Markov condition. Ideally, the error term should capture random fluctuations or noise that cannot be explained by the independent variables included in the model. However, this residual trend indicates that there is omitted variable bias in the model. Another plausible explanation is that once I controlled for other factors, it revealed that the true relationship between food insecurity and fertility is non-linear.

It is also imperative to acknowledge the potential existence of sampling error that comes with using survey data. While the ACS is employed nationwide, it does not mandate a response. Due to the sensitivity surrounding health, some women may not feel comfortable reporting on their fertility. The direction in which this bias may affect my results is ambiguous, but the bias itself remains present. Additionally, there is a threat of estimation error in the data from Feeding America. As per their technical report, data was first analyzed at the state level before these coefficient estimates were used with the same variables for every county. Due to the nature of empirical work, the measurement of these food insecurity estimates may be imprecise. The Technical Report also encourages users to exercise caution when comparing estimates over time, especially when differences are small since they may not be statistically different. That being said, the magnitude of those changes may be relatively large and potentially meaningful.

Conclusion

In conclusion, these findings reveal a weak but suggestive positive relationship between food insecurity and fertility at the national level. This is consistent with my hypothesis which draws on health literature and economic theories of human capital and income effects. However, the inclusion of the LMD dummy variable uncovers regional disparities. More importantly, it begins to highlight the significance of socioeconomic factors in shaping reproductive behaviors. Further research should look to expand upon these region-specific effects.

This paper attempts to contribute to the ongoing discourse surrounding public health and social welfare policies. My research underscores the importance of addressing food insecurity as a critical public health issue and women's issue. Policies aimed at reducing food insecurity not only alleviate economic hardship, but also have the potential to influence reproductive health outcomes among women. It is also critical to introduce the idea of race into this study, as food and healthcare access varies greatly among racial groups. By further exploring these dynamics, research like this can help to inform evidence-based policies that will improve the well-being of American women and their communities.

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Appendix A

Table A. F Tests

Regression 3	Regression 4	Regression 5
F(22, 822) = 227.63 Prob > F = 0.0000	F(21, 797) = 280.42 Prob > F = 0.0000	F (22, 822) = 227.63 Prob > F = 0.0000

Appendix B

Table B1. Regression with logged variables

VARIABLES	(1) fertility
FIR	0.399*
	(0.239)
LMD	-0.394*
	(0.222)
Constant	-5.990*
	(3.575)
Observations	6,125
Number of FIPS	823

Table B2. Regression with abortion control

VARIABLES	(1) fertility
FIR	0.404*
	(0.238)
LMD	-0.406*
	(0.219)
Constant	0.440
	(3.099)
Observations	6,125
Number of FIPS	823

Appendix C

Figure C1. RVF Plot