Journal of Applied Economics and Policy

VOLUME THIRTY-FOUR, NUMBER 1 **Winter 2025**

Articles

A Publication of the

KENTUCKY ECONOMIC ASSOCIATION

Journal of Applied Economics and Policy

VOLUME THIRTY-FOUR, NUMBER 1 *Winter 2025*

A Publication of the

KENTUCKY ECONOMIC ASSOCIATION

Journal of Applied Economics and Policy

The *Journal of Applied Economics and Policy* (formerly the *Kentucky Journal of Economics and Business*) is published by the Kentucky Economic Association. All members of the Association receive the *Journal* electronically as a privilege of membership. All views expressed are those of the contributors and not those of the Kentucky Economic Association.

The *Journal of Applied Economics and Policy* accepts submissions from all JEL classifications; however, special attention is paid to manuscripts focusing on issues relating to Kentucky and the surrounding region.

Information and the online submission process can be found at journalofappliedeconomicsandpolicy.org/. The submission fee is $20.00 and may be paid via Pay Pal using a credit card or by check made payable to the *Journal of Applied Economics and Policy*. Correspondence regarding articles submitted for publication in the *Journal*:

Maria Apostolova-Mihaylova, Editor
Journal of Applied Economics and Policy
maria.apostolova@centre.edu
Centre College
600 West Walnut Street
Danville, KY 40422

The **Kentucky Economic Association** facilitates greater communication among state researchers from academia, government, and business, and promotes the sharing and discussion of research by economists and public policy analysts working on issues relevant to the Commonwealth. To these purposes the association holds an annual conference and publishes the *Journal of Applied Economics and Policy*. The Kentucky Economic Association's website is found at kentuckyeconomicassociation.org.

Communications related to membership, business matters, and change of address in the Kentucky Economic Association should be sent to Thomas Jones, Office of State Budget Director, thomasa.jones@ky.gov.

Kentucky Economic Association Roll of Presidents

James W. Martin	1975-76
Ray Ware	1976-77
Stephen Lile	1977-78
Dannie Harrison	1978-79
James McCabe	1979-80
Bernard Davis	1980-81
Frank Slensick	1981-82
Lawrence K. Lynch	1982-83
Clyde Bates	1983-84
Richard Sims	1984-85
Frank Spreng	1985-86
William Baldwin	1986-87
Richard Crowe	1987-88
Richard Thalheimer	1988-89
Lou Noyd	1989-90
Gilbert Mathis	1990-91
Claude Vaughn	1991-92
L. Randolph McGee	1992-93
Paul Coomes	1993-94
James R. Ramsey	1994-95
Ginny Wilson	1995-96
Bruce Sauer	1996-97
James Payne	1997-98
Mark Berger	1998-99
Martin Milkman	1999-00
Catherine Carey	2000-01
Manoj Shanker	2001-02
David Eaton	2002-03
Alan Bartley	2003-04
John T. Jones	2004-05
Brian Strow	2005-06
Tom Creahan	2006-07
Talina Matthews	2007-08
Chris Phillips	2008-09
Ali Ahmadi	2009-10
John Garen	2010-11
Bob Houston	2011-12
Nancy Lumpkin	2012-13
Halil D. Kaya	2013-14
Rohnn Sanderson	2014-15
Abdul Turay	2015-16
Chris Bollinger	2016-17
Alex Lebedinsky	2017-18

John Perry	2018-19
Joshua Pinkston	2019-20
Volker Grzimek	2020-21
Rohnn Sanderson	2021-22
Abdullah Al Bahrani	2022-23
Alexandria Halmbacher	2023-24
Lilly Rice	2024-25

Kentucky Economic Association Roll of Distinguished Economists

James Martin	1975
William Herzel	1976
Marlon Gillium	1977
Don Soule	1978
Clifton Lowry	1979
Paul Tanner	1980
Damon Harrison	1981
Charles Haywood	1982
Charles Hultman	1983
James Thompson	1984
Lawrence Lynch	1985
Stephen Lile	1986
Roy Bahi	1990
Juanita Kreps	1991
Ray Marshall	1992
Paul McCracken	1993
Benjamin Friedman	1994
Alan Randall	1995
Gerald Lynch	1996
Ronald Jones	1997
Price Fishback	1998
James Ramsey	1999
Kerry Back	2000
Eugene Steurle	2002
Margaret Walls	2003
Merl Hackbart	2004
Donald Kenkel	2005
W. Kip Viscusi	2006
Ralph d'Arge	2007
John Whitehead	2008
Glenn Blomquist	2009
Jeffrey Lacker	2010

Amitabh Chandra	
James J. Heckman	2012
Jerry R. Skees	2013
Paul A. Coomes	2014
La Vaughn M. Henry	2015
Eugenia F. Toma	2016
Kathryn H. Anderson	2017
Frank O'Connor	2018
David Wildasin	2019
John Garen	2020
Cathy Carey	2021
Frank Scott	2022
Todd Stinebrickner	2023
Bruce Johnson	2024

Review Board of the *Journal of Applied Economics and Policy*

Coincident Economic Activity Indexes for Metropolitan and Micropolitan Areas in Kentucky

Christopher Biolsi*

Abstract

I construct coincident economic activity indexes for each of the metropolitan and micropolitan areas in Kentucky. Using them, I apply empirical exercises to analyze local business cycles in the state. Local recessions are asynchronous with respect to national recessions, although they all do experience recessions during the major downturns of this century. Larger metropolitan statistical areas (with more educated and less poor populations) correlate significantly with both national and statewide indexes, though the micropolitan statistical areas do not. I also consider the volatility of each area's business cycle and its predictive content for future statewide cycles.

JEL codes: E30, E32, E37

Keywords: Coincident Economic Activity Indexes; Mixed-Frequency Dynamic Factor Model; Business Cycles

* Department of Economics; Western Kentucky University; Bowling Green, KY 42101, USA; Christopher.biolsi@wku.edu

I. Introduction

Metrics that parsimoniously summarize the state of an economy's business cycle are extremely valuable indicators, especially for policymakers. They allow officials to filter out potentially noisy signals to cut to the core of an area's economic health. At the national level, an example would be the deviation of Gross Domestic Product (GDP) from its potential (or "output gap") as calculated by the Congressional Budget Office, which provides a sense of whether economic activity is above or below its long-run trend. Other approaches to estimating this object include the popular filtering techniques of Hodrick and Prescott [1997]; Baxter and King [1999]; Morley and Piger [2012]; Hamilton [2018]; and Kamber, Morley, and Wong [2018].

Given the usefulness of such parsimonious indicators for describing economic activity in a certain area, it is not surprising that a number of researchers have since adapted such techniques to subnational jurisdictions, such as U.S. states [Crone and Clayton-Matthews 2005] and a large number of American cities [Arias, Gascon, and Rapach 2016]. These latter studies, rather than focusing on a single aggregate like GDP, instead turn to dynamic factor models [Stock and Watson 1989; 1991] which extract a common latent variable from a wider set of economic statistics. The advantage of this approach, especially at lower levels of aggregation, is that, while there are GDP statistics for states, cities, and counties in the United States, they tend not to be available in as timely a manner as other, narrower measures, like the unemployment rate or average hourly wages. Also, researchers are able to estimate such dynamic factor measures at a higher frequency than that at which many headline statistics are published, which provides a richer sense of the time series dynamics.

In recent years, estimation techniques have been developed that extract common factors from data series of varying measurement frequencies (so-called "mixed-frequency" dynamic factor models). Such methods draw on work in Mariano and Murasawa [2003], with a prominent example being the daily measure of U.S. economic activity introduced in Aruoba, Diebold, and Scotti [2009]. Arias, Gascon, and Rapach [2016] estimate coincident economic activity indexes from mixed-frequency dynamic factor models in their study of 50 large American metropolitan statistical areas, including Cincinnati, OH-KY-IN and Louisville/Jefferson County, KY (also subjects of this analysis).[1] More recently, motivated by the need for timely economic information during the fast-changing pandemic environment, Baumeister, Leiva-León, and Sims [2024] produce weekly state-level indexes from a wide set of quarterly, monthly, and weekly data series.

In this paper, I extend Arias, Gascon, and Rapach [2016] by estimating similar coincident economic activity indexes with a mixed-frequency dynamic factor model for each of the government-designated metropolitan and micropolitan statistical areas with a presence in the state of Kentucky.[2] With the exception of Cincinnati and Louisville/Jefferson County, these cities are not large enough to merit attention from Arias, Gascon, and Rapach [2016], but they are important drivers of the Kentucky state economy, and therefore, their activity levels ought to be of interest to state policymakers.

Each monthly index represents a summary of a number of monthly and quarterly series, and the indexes (in growth rates) span February 1990 to April 2023. I estimate each index in a fashion similar to Arias, Gascon, and Rapach [2016], using an expectations maximization algorithm developed by Bańbura and Modugno [2014]. The attractive aspect of this approach is that it allows estimation of a common factor in spite of the fact that the frequencies of the various series are not uniform and they do not all begin or end in the same period. This allows construction of a business cycle index using a broader set of variables than in the initial exercises of Stock and Watson [1989; 1991], or Crone and Clayton-Matthews [2005], if not as large or as varied as the weekly state-level indexes in Baumeister, Leiva-León, and Sims [2024].

These indexes in hand, I turn to a set of simple empirical models to cultivate a better understanding of local-area business cycles in Kentucky. I start by using a novel Markov Switching algorithm, introduced in Eo and Kim [2016], to identify local business cycle turning points. Then, I estimate how closely each city's index comoves with both the national business cycle and that in the state of Kentucky overall, in an exercise that may be analogous to estimating stock market betas, to see which of the local business cycles are most sensitive to wider economic dynamics.

[1] These indexes had been updated regularly but are now labeled as "Discontinued" in the Federal Reserve Economic Database (FRED).

[2] A full list of the metropolitan and micropolitan statistical areas can be found in Table A1. Metropolitan and micropolitan statistical areas are delineated by the Office of Management and Budget, which is a part of the Executive Office of the President of the United States. A metropolitan statistical area must have an urbanized area of at least 50,000 residents, while a micropolitan statistical area must have an urbanized cluster of at least 10,000 but no more than 50,000 people. For more information, see https://www.census.gov/programs-surveys/metro-micro/about.html. For the rest of this paper, I will use the general term "city" to refer to all of the geographic areas I study in a parsimonious fashion.

Then, I decompose each series into trend and transitory components using the Beveridge-Nelson filter developed by Kamber, Morley, and Wong [2018], so as to get a sense of which cities have the most or least volatile business cycles. I also assess the degree to which each city has fully recovered from the most consequential national recessions in the sample period, namely the Great Recession of 2007 to 2009 and the COVID-19-induced recession of 2020. My final exercise is a Bayesian Model Averaging analysis that seeks to determine which of the indexes are most helpful for predicting future growth in the state of Kentucky, in both the short and medium terms. I also undertake an effort to identify what city-level characteristics might inform on the degree of their co-movement with the national business cycle or the volatility of their output gap.

The rest of this paper proceeds as follows. Section II discusses the maximum likelihood algorithm that I use to construct the coincident economic activity indexes and presents the series themselves. Section III reports the results of simple empirical exercises that analyze the novel indexes. Section IV attempts to assess what city-level traits might explain patterns observed in the empirical exercises. Section V concludes.

II. Estimating Metropolitan and Micropolitan Statistical Area Coincident Indexes

The use of dynamic factor time series models to estimate a series capturing the "state" of the economy in a given geographical area dates back at least to Stock and Watson [1989; 1991]. Motivated by the work of Burns and Mitchell [1946], they posit that there is a latent variable, which I denote as $C_{i,t}$, which summarizes the overall state of the economy for city i at time t. In principle, there could be a number of latent variables, but I only consider one. This common factor drives an $(n \times 1)$ vector of economic statistics, denoted $X_{i,t}$, in the following way:

$$\Delta X_{i,t} = H_i \Delta C_{i,t} + \varepsilon_{i,t} , \tag{1}$$

where H_i is an $(n \times 1)$ vector of factor loadings capturing the dependence of each variable in $X_{i,t}$ on the latent common factor in city i. $\varepsilon_{i,t}$ is a vector of (potentially serially correlated) idiosyncratic components for each variable in $X_{i,t}$. The standard approach in the literature is to estimate this model via the Kalman filter, either using frequentist or Bayesian methods. This is the approach of Stock and Watson [1989; 1991] and Crone and Clayton-Matthews [2005], who estimate monthly coincident economic indexes at the national and state levels, respectively, from four macroeconomic labor market series. In their application of the model to the level of metropolitan statistical areas, Arias, Gascon, and Rapach [2016] make use of a broader set of variables (beyond just labor market series), some of which are not published at the monthly frequency. To construct an index that derives information from both monthly and quarterly series, they employ the expectations maximization algorithm of Bańbura and Modugno [2014], which itself draws on the insights of Mariano and Murasawa [2003], who use parameter restrictions on factor loadings to meld series of different frequencies. The Bańbura and Modugno [2014] algorithm is also capable of accommodating series that start and end at different dates. To avoid being redundant, I point the interested reader to the detailed expositions in Bańbura and Modugno [2014] and Arias, Gascon, and Rapach [2016].

Owing to data limitations, the number of indicators used in the indexes I construct depends first on whether the city in question is a metropolitan or a micropolitan statistical area, as metropolitan statistical areas tend to enjoy better data coverage. Many are labor market variables. The monthly indicators for metropolitan statistical areas are:

- Average Weekly Hours of All Employees: Total Private (from Current Employment Statistics at Bureau of Labor Statistics; Start Date: January 2007)
- Unemployment Rate (from Current Employment Statistics at Bureau of Labor Statistics; Start Date: January 1990)
- All Employees: Goods Producing (from Current Employment Statistics at Bureau of Labor Statistics; Start Date: January 1990)
- All Employees: Private Service Providing (from Current Employment Statistics at Bureau of Labor Statistics; Start Date: January 1990)
- All Employees: Government (from Current Employment Statistics at Bureau of Labor Statistics; Start Date: January 1990)
- Average Hourly Earnings of All Employees: Total Private (from Current Employment Statistics at Bureau of Labor Statistics; Start Date: January 2007)
- Average Weekly Earnings of All Employees: Total Private (from Current Employment Statistics at Bureau of Labor Statistics; Start Date: January 2007)
- Percent Change in Consumer Spending with Debit and Credit Cards (from Chetty, et al. 2023 and derived from data collected by Affinity Solutions; Start Date: February 2020)
- Zillow Home Value Index for All Homes (from zillow.com; Start Date: Various between January 2000 and March 2009)

with Average Hourly Earnings, Average Weekly Earnings, and the Zillow Home Value Index deflated by the national Consumer Price Index. The consumer spending variable is published at a daily frequency until September of 2021 and weekly thereafter, but I aggregate it to a monthly measure for the purpose of this analysis. It is expressed as a percent change relative to January of 2020. The quarterly variables used in the analysis are:

- Total Quarterly Wages (from Quarterly Census of Employment and Wages at Bureau of Labor Statistics; Start Date: 1990:Q1)
- Average Weekly Wages for Employees in Total Covered Establishments (from Quarterly Census of Employment and Wages at Bureau of Labor Statistics; Start Date: 1990:Q1)
- All-Transactions House Price Index (from the U.S. Federal Housing Finance Agency; Start Date: Various between 1990:Q1 and 1993:Q3)
- Private Establishments in All Industries (from Quarterly Census of Employment and Wages at Bureau of Labor Statistics; Start Date: 1990:Q1)

and all of these indicators except Private Establishments are deflated by the national GDP deflator. All variables, with the exception of the unemployment rate and consumer spending, are specified as first differences in the log. The unemployment rate is specified in first differences, while the consumer spending variable is already collected as a percent difference.

For micropolitan statistical areas, the monthly indicators are:

- Unemployment Rate (from Current Employment Statistics at Bureau of Labor Statistics; Start Date: January 1990)
- Employed Persons (from Current Employment Statistics at Bureau of Labor Statistics; Start Date: January 1990)
- Percent Change in Consumer Spending with Debit and Credit Cards (from Chetty, et al. 2023 and derived from data collected by Affinity Solutions; Start Date: February 2020), where available[3]
- Zillow Home Value Index for All Homes (from zillow.com; Start Date: Various between January 2000 and January 2014)

Again, the Zillow Home Value Index is deflated by the national Consumer Price Index. The quarterly series are limited to the number of private establishments in all industries, from the

---

[3] Among micropolitan statistical areas, the consumer spending series is available for Bardstown, KY; Frankfort, KY; London, KY; Madisonville, KY; Mount Sterling, KY; Richmond-Berea, KY; and Somerset, KY.

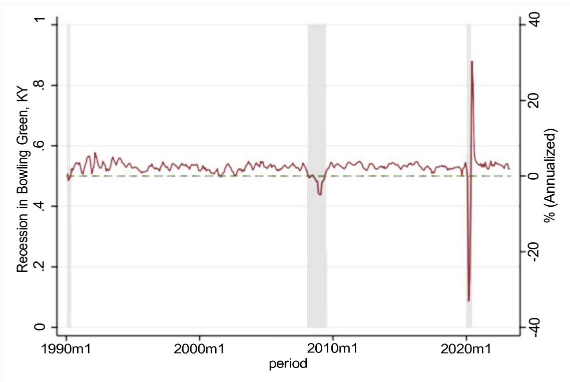
Quarterly Census of Employment and Wages, starting in 1990:Q1. I take log differences of all variables, except the unemployment rate (which is just in differences) and the consumer spending measure.

I use Kalman filter estimation via the Bańbura and Modugno [2014] algorithm to estimate the raw series $\Delta\, C_{i,t}$ for each city i, and then I smooth noisy monthly realizations by computing a three-month moving average. In the case of micropolitan statistical areas, I also apply an AR(12) process in order to remove residual seasonality present in the raw series. Then, the smoothed series is standardized to have a mean of 0 and a standard deviation of 1. The smoothed, standardized series is subsequently calibrated to have the same mean and standard deviation as the annual growth rate of Gross Domestic Product for each city over the years 1990 to 2022 (or 2001 to 2022, for the micropolitan statistical areas), data for which is collected from the Bureau of Economic Analysis. Since the $\Delta C_{i,t}$ is estimated in differences, each observation in the series reports the (smoothed) annualized growth rate of economic activity in city i at time t. The estimated indexes span February 1990 to April 2023.

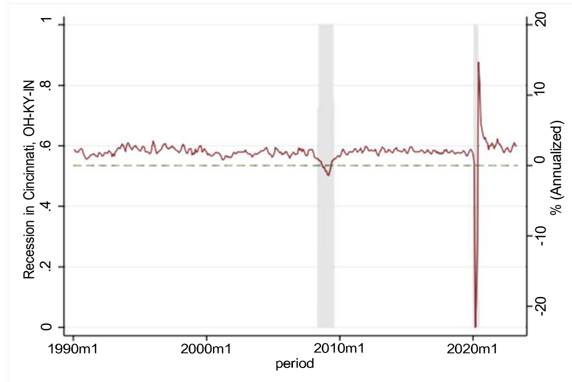
Figures 1 through 5 report the estimated coincident economic activity indexes for each of the cities in the sample. Each panel of the figures also includes shaded bars indicating the timing of city-specific recessions (to be discussed in Section III.i). Because Cincinnati and Louisville/Jefferson County are also included in the analysis of Arias, Gascon, and Rapach [2016], who use a wider set of variables than I employ in this study, it provides an opportunity to assess the validity of my approach. The correlation coefficient between my estimated series for Louisville/Jefferson County and that of the previous study is 0.72 for the years 1990 to 2019, indicating a fairly faithful replication of the already-existing business cycle measures. For Cincinnati, the correlation coefficient is yet higher at 0.89. This offers me a considerable amount of confidence that the estimated series for the other cities are similar to what would be produced by the benchmark Arias, Gascon, and Rapach [2016] approach, were they considering cities as small as those in the current analysis.[4]

[4] The coincident economic activity indexes for Kentucky cities are currently being updated monthly, and they can be found on my website.

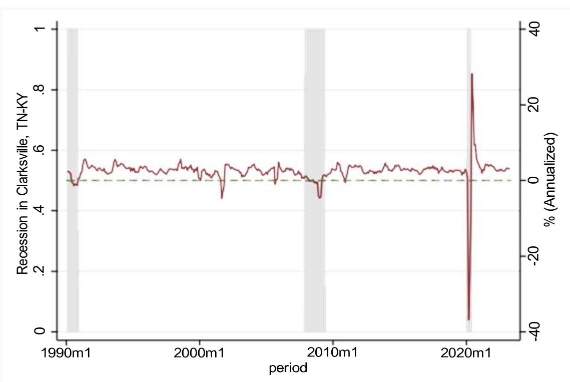
Figure 1: Estimated Coincident Economic Activity Indexes for Kentucky



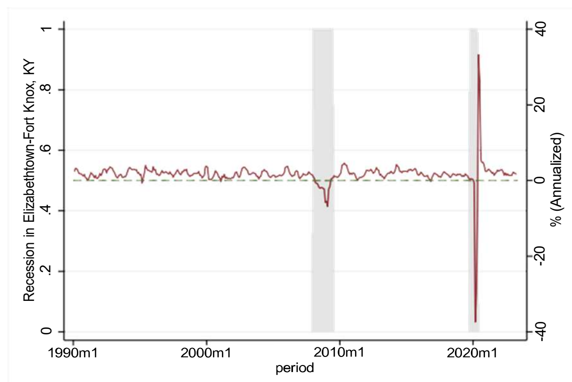
(a) Bowling Green, KY



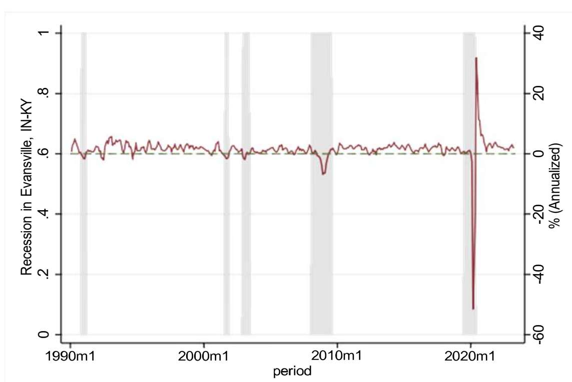
(b) Cincinnati, OH-KY-IN



(c) Clarksville, TN-KY



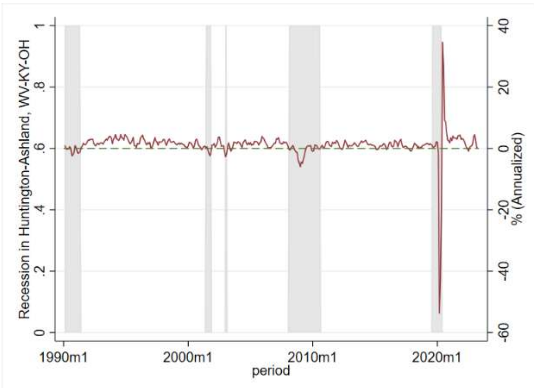
(d) Elizabethtown-Fort Knox, KY



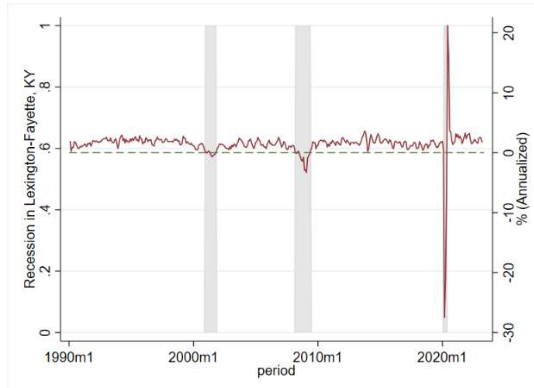
(e) Evansville, IN-KY

Notes: Each panel reports the estimated annualized growth rate of the coincident economic activity index for the named city with a presence in Kentucky. Shaded bars indicate city-specific recession periods.

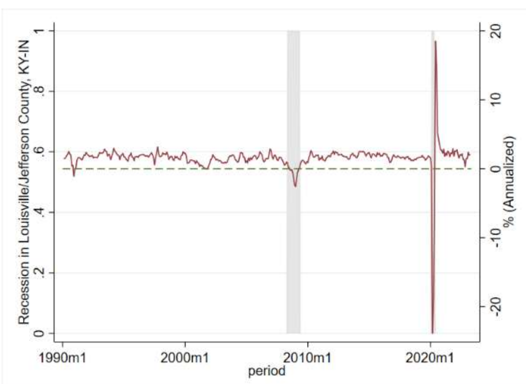
Figure 2: Estimated Coincident Economic Activity Indexes for Kentucky



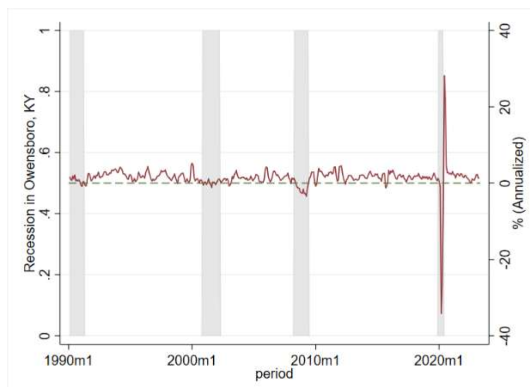
(a) Huntington-Ashland, WV-KY-OH



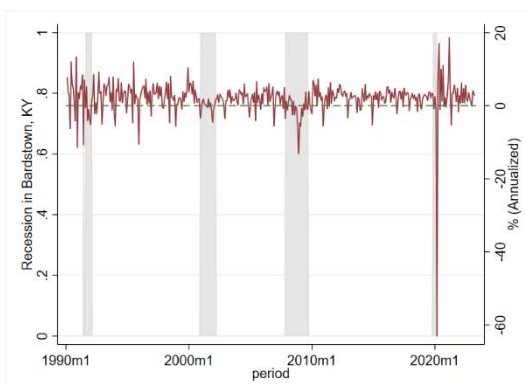
(b) Lexington-Fayette, KY



(c) Louisville/Jefferson County, KY-IN



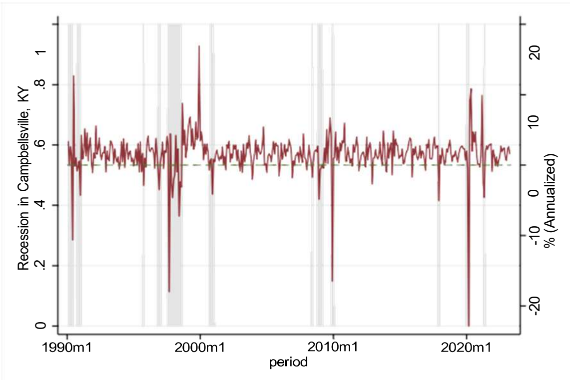
(d) Owensboro, KY



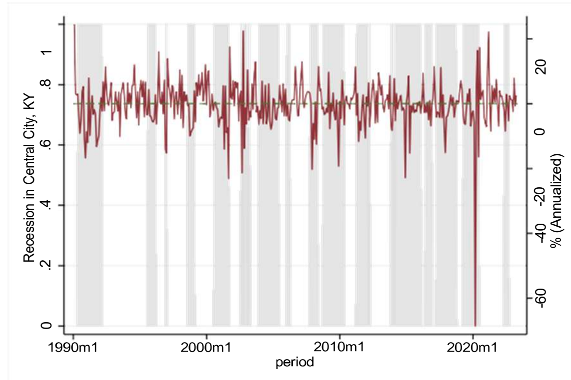
(e) Bardstown, KY

Notes: Each panel reports the estimated annualized growth rate of the coincident economic activity index for the named city with a presence in Kentucky. Shaded bars indicate city-specific recession periods.

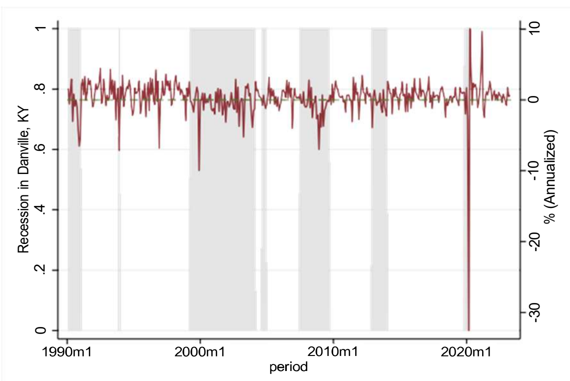
Figure 3: Estimated Coincident Economic Activity Indexes for Kentucky



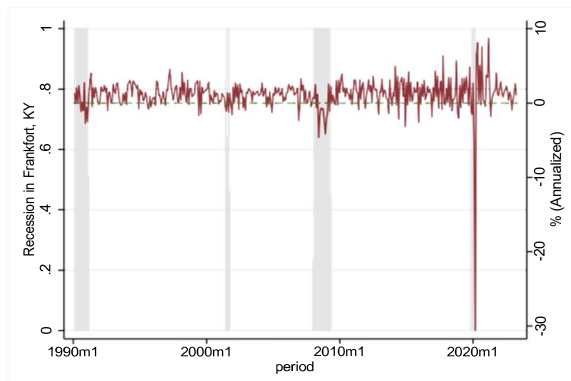
(a) Campbellsville, KY



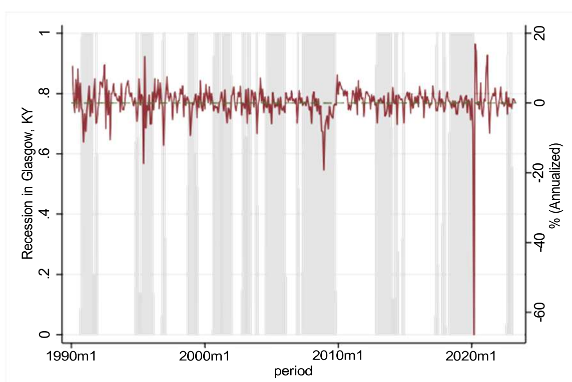
(b) Central City, KY



(c) Danville, KY



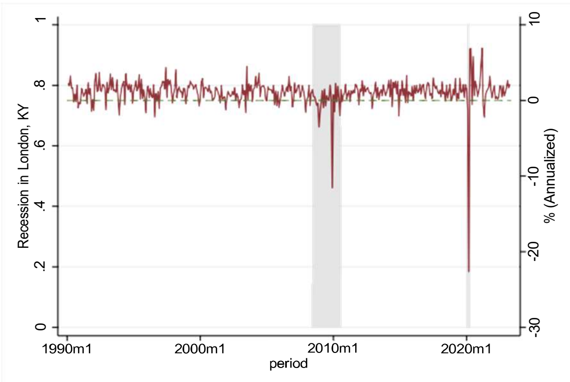
(d) Frankfort, KY



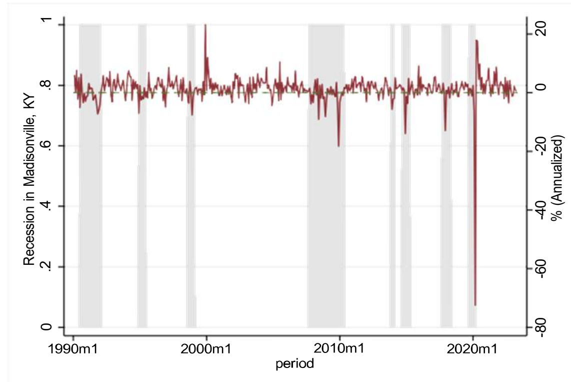
(e) Glasgow, KY

Notes: Each panel reports the estimated annualized growth rate of the coincident economic activity index for the named city with a presence in Kentucky. Shaded bars indicate city-specific recession periods.

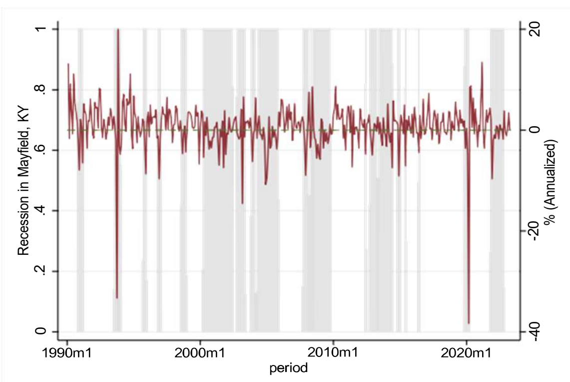
Figure 4: Estimated Coincident Economic Activity Indexes for Kentucky



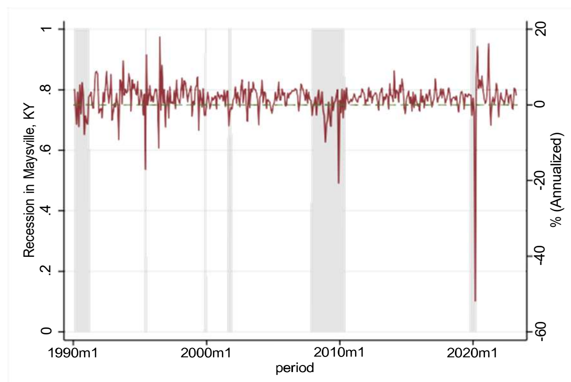
(a) London, KY



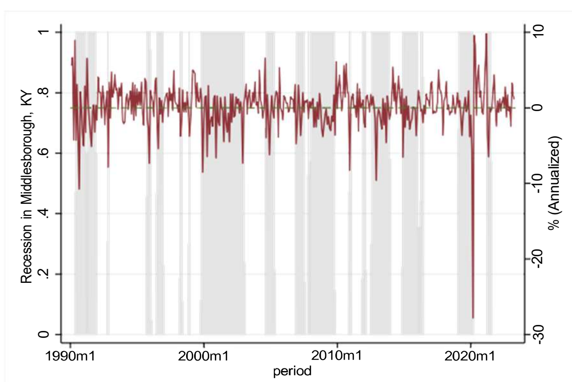
(b) Madisonville, KY



(c) Mayfield, KY



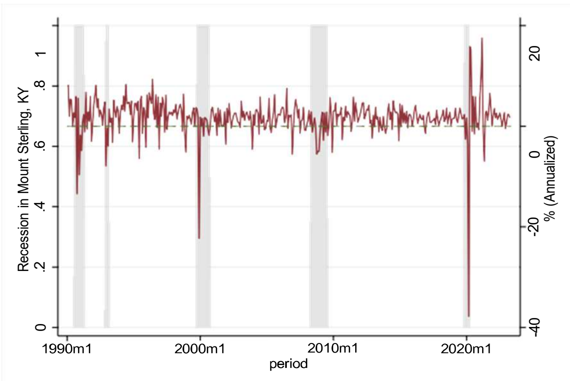
(d) Maysville, KY



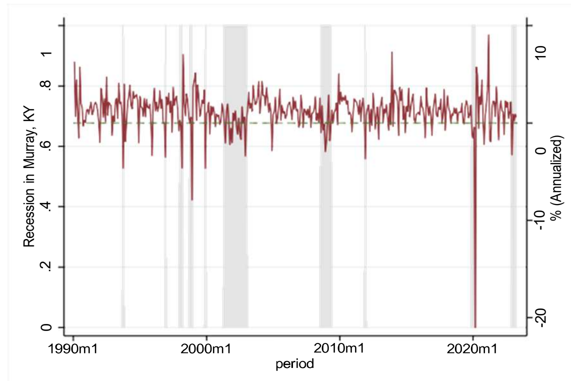
(e) Middlesborough, KY

Notes: Each panel reports the estimated annualized growth rate of the coincident economic activity index for the named city with a presence in Kentucky. Shaded bars indicate city-specific recession periods.

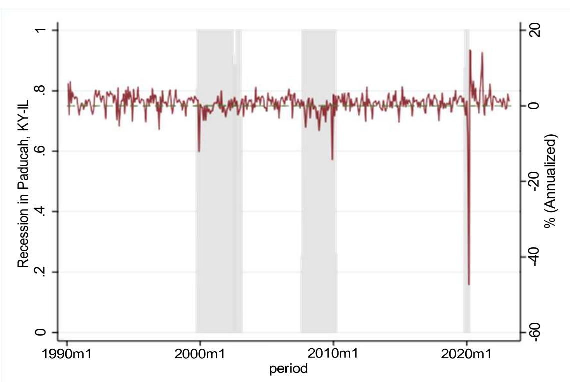
Figure 5: Estimated Coincident Economic Activity Indexes for Kentucky



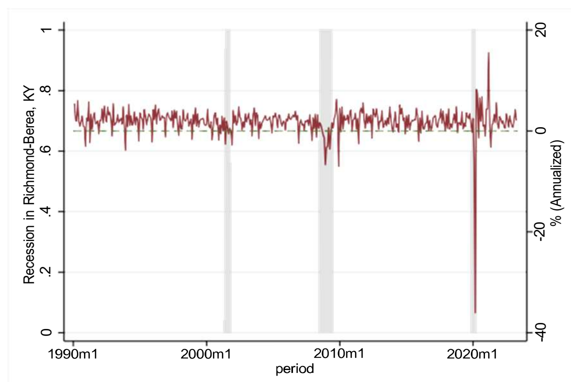
(a) Mount Sterling, KY



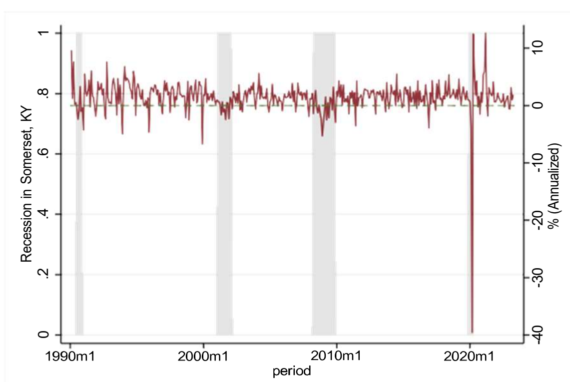
(b) Murray, KY



(c) Paducah, KY-IL



(d) Richmond-Berea, KY



(e) Somerset, KY

Notes: Each panel reports the estimated annualized growth rate of the coincident economic activity index for the named city with a presence in Kentucky. Shaded bars indicate city-specific recession periods.

III. Empirical Exercises

This section proceeds to analyze the estimated coincident economic activity indexes for Kentucky cities with a series of simple empirical exercises. First, I identify city-specific economic recessions, making use of the recently developed time-varying Markov Switching model described in Eo and Kim [2016]. Then, I estimate city-specific correlations with the national business cycle and the business cycle in the state of Kentucky. Third, I use the Beveridge-Nelson filter developed by Kamber, Morley, and Wong [2018] to derive "output gap"-type indicators of the cyclical component of each city's index. Finally, I use a Bayesian Model Averaging algorithm to assess which city's fluctuations are most predictive of future activity in the state as a whole.

i. City-Specific Recessions

Identifying city-specific recessions is complicated by the highly volatile changes occurring at the start of the COVID-19 pandemic. For example, Arias, Gascon, and Rapach [2016] adopt the following algorithm. A city's economy hits a peak in time t if the following three conditions hold:

$$\Delta C_{i,t} > 0 \text{ and } \Delta C_{i,t+1} < 0$$

$$\Delta C_{i,t} + \Delta C_{i,t-1} + \Delta C_{i,t-2} > 0$$

$$\Delta C_{i,t+1} + \Delta C_{i,t+2} + \Delta C_{i,t+3} < 0 \text{ and } \Delta C_{i,t+4} + \Delta C_{i,t+5} + \Delta C_{i,t+6} < 0$$

The first condition seeks to identify a turning point, and the second is meant to filter out noise associated with one-off declines. The third condition is inspired by the conventional rule of thumb that a recession is defined by two consecutive quarters of negative growth. Similarly, for a trough in period t, the following conditions must hold:

$$\Delta C_{i,t} < 0 \text{ and } \Delta C_{i,t+1} > 0$$

$$\Delta C_{i,t} + \Delta C_{i,t-1} + \Delta C_{i,t-2} < 0$$

$$\Delta C_{i,t+1} + \Delta C_{i,t+2} + \Delta C_{i,t+3} > 0 \text{ and } \Delta C_{i,t+4} + \Delta C_{i,t+5} + \Delta C_{i,t+6} > 0$$

Applying this technique to the indexes that I have constructed identifies a number of recessions for each city, but does not identify the sharp contractions taking place in the spring of 2020 as a recession for very many of them (the main reason being that there are not generally two consecutive quarters of decline; the COVID-19 recession nationally is characterized by its sharp and steep, but relatively short-lived, output drop). A second popular approach is to apply the seminal Markov Switching model of Hamilton [1989]. In its simplest form, this model specifies a time series as having the following data-generating process:

$$\Delta C_{i,t} = \mu_{i,0} \times S_{i,t} + \mu_{i,1} \times (1 - S_{i,t}) + e_{i,t} \quad (2)$$

Here, $S_{i,t}$ is a binary variable, taking on a value of 1 when city i is in recession at time t and 0 otherwise. On average, in recessions, city i grows at a rate of $\mu_{i,0}$, while it grows at a rate of $\mu_{i,1}$ in non-recessionary periods. The state indicator $S_{i,t}$ evolves according to a Markov process, with the probability that it has a value of 0 at time t, conditional on having had a value of 0 at time $t-1$ being p, and, analogously, the probability that it has a value of 1 at time t conditional on having had a value of 1 at time $t-1$ is q. Typically, the model is estimated via maximum likelihood.

The COVID recession is a challenge for this algorithm as well, though in a different way. Applying a standard Markov Switching model to my estimated city-level indexes identifies only one recession in many cases, specifically the months at the start of the pandemic. This is because the sharp drops experienced at that time dwarf any other activity declines, dividing the entire sample for each city into "COVID" and "non-COVID" regimes. Thus, whereas the Arias, Gascon, and Rapach [2016] approach does not identify the spring of 2020 as a recession at all, the Markov Switching approach identifies this period as the only recession. Neither outcome is intuitively appealing or intellectually satisfying.

Therefore, I make use of the modified Markov Switching algorithm in Eo and Kim [2016]. They modify Equation 2 in the following way:

$$\Delta C_{i,t} = \mu_{i,0,t} \times S_{i,t} + \mu_{i,1,t} \times \left(1 - S_{i,t}\right) + e_{i,t} \quad (3)$$

Note now that the average growth parameters μ_0 and μ_1 have time indexes. In this formulation, the average growth parameters, μ_0 and μ_1, are allowed to evolve over time, such that each recession and expansion period identified have different expected growth rates. The Eo and Kim [2016] method thus is better able to identify the early pandemic period as a recession without identifying all other periods (such as the time surrounding the Great Recession) as expansions. The algorithm also reports, for each period and for each city, the probability that the area is in recession at that time. I call a given month a recession month if this probability exceeds 0.50.[5] Figure 6 reports the dates of recessions for each city, alongside the conventional National Bureau of Economic Research recession dates for the United States as a whole. Appendix Figures A1 through A5

[5] These are the periods shaded gray in Figures 1 through 5.

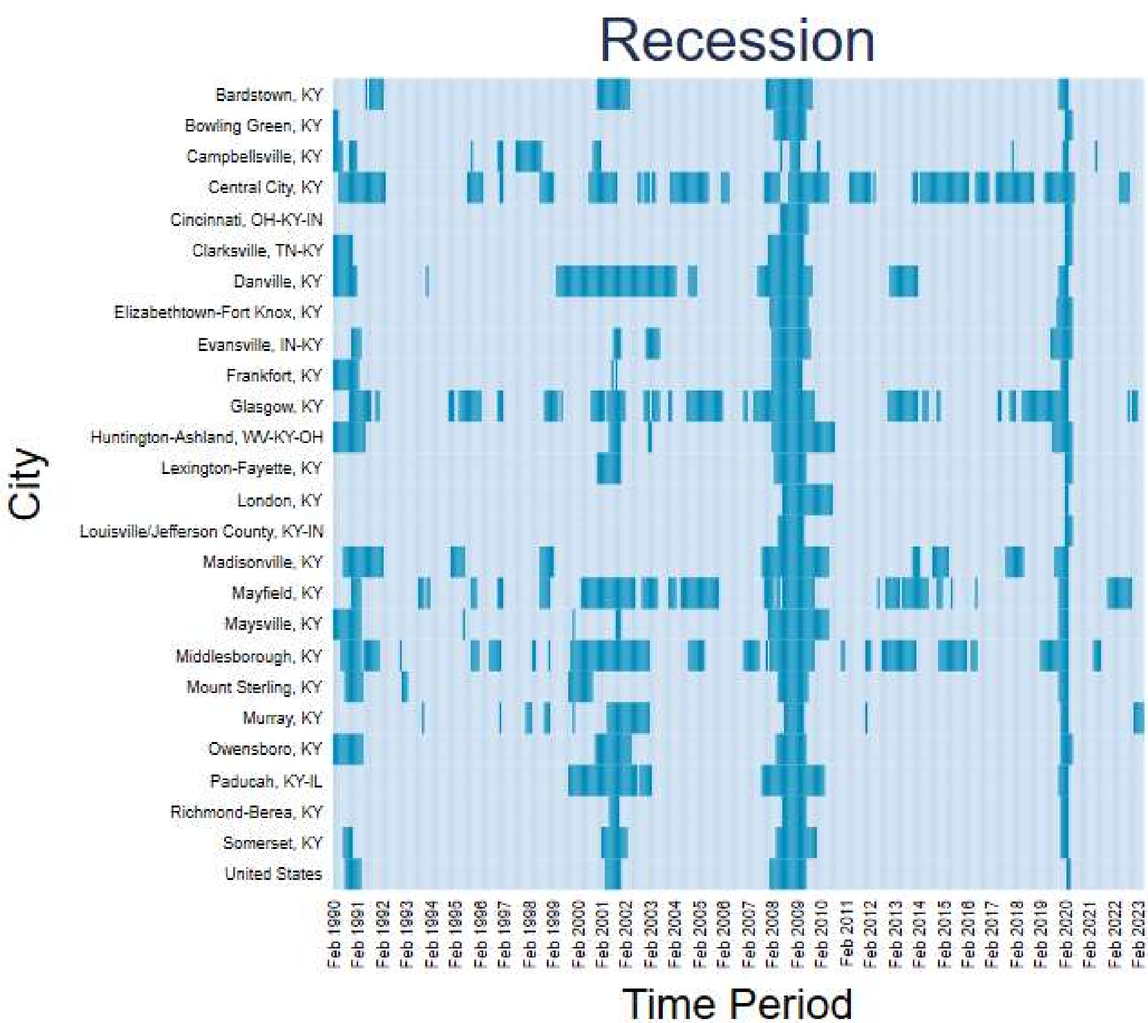
illustrate the estimated recession probabilities over time in each city, based on the estimation technique from Eo and Kim [2016].

The country as a whole experienced four recessions in this sample period, but there is wide heterogeneity among each of the cities in Kentucky that I analyze in terms of the number, timing, and durations of their recessions. That said, all the cities experienced recessions during the 2007 to 2009 financial crisis and during the onset of COVID-19, though their exact timings of peaks and troughs vary. For example, Bardstown, Danville, Glasgow, and Paducah all entered recessions before the country as a whole at the time of the financial crisis. Several, including Central City, Huntington-Ashland, London, Madisonville, Maysville, and Paducah, remained in recession well after the nation began to recover. There was greater synchronicity during the pandemic recession. By February of 2020 (along with the whole country) or the following month, every city was in recession. About three quarters, in fact, had already been in recession by January of 2020. Nearly all had exited recession by June 2020 (the exception being Central City), two months after the estimated end date published by the Business Cycle Dating Committee of the National Bureau of Economic Research.

Generally, the steepest pandemic-era declines took place in March of 2020, which is not surprising, since this is when social distancing and quarantines started to be widespread. The declines ranged between 21.0 percent annualized (in Murray) and 72.5 percent annualized (in Madisonville). There are also sizable declines in several cities in April 2020, and more modest drops in May 2020. Starting in the spring of 2020, I observe some fairly strong recoveries, owing to a widespread bounce back in activity after the end of lockdowns.

An especially notable feature, particularly as it concerns some of the micropolitan areas, is that several enter entirely idiosyncratic recessions at times when the rest of the country is experiencing strong growth. For example, in the mid-to-late 1990s, a time of historically strong productivity growth nationwide, Central City, Glasgow, Madisonville, and Middlesborough endure persistent downturns in activity. Danville contends with an especially long recession around the time of the dot-com bust. The mid-2000s (before the onset of the financial crisis) see recessions visited upon Central City, Glasgow, Mayfield, and Middlesborough. Many of those same cities see continued declines in the mid-2010s, and even since the end of the pandemic. As I will discuss later, several of these cities are on long-run downward trends in economic activity.

Figure 6: Identified Recession Dates



Notes: For each city (and the United States as a whole), the figure indicates which dates are identified as recession periods by the Eo and Kim [2016] methodology using dark shading. For comparison, National Bureau of Economic Research-identified recession dates for the U.S. as a whole are also shown.

ii. Correlation with National and State Business Cycles

In this section, I formally evaluate the correlation of each city's business cycle with that of the country as a whole and with that of the state of Kentucky. One should not read these regressions as speaking to any sort of causal relationship, but rather read them in a manner that is analogous to stock market betas. I estimate the following series of regressions:

$$\Delta C_{i,t} = \alpha_i^{US} + \beta_i^{US} \Delta C_{US,t} + e_{i,t}^{US} \tag{4}$$

$$\Delta C_{i,t} = \alpha_i^{KY} + \beta_i^{KY} \Delta C_{KY,t} + e_{i,t}^{KY} \tag{5}$$

In these regressions, $C_{US,t}$ denotes the coincident economic activity index for the entire United States, and $C_{KY,t}$ represents that for Kentucky. Both indexes are constructed using the methods of Crone and Clayton-Matthews [2005] and obtained from the Federal Reserve Bank of Philadelphia. Equation 4 provides a sense of how closely each city's business cycle tracks that of the United States, and Equation 5 does the same for the state economy.[6] The results of these regressions are reported in Table 1. Because of the mechanical serial correlation induced by taking moving averages of the estimated common factors for each city, I correct the standard errors of each regression using the Newey and West [1987] covariance matrix with a lag of 3. Starting with the first column in Table 1, it is evident that each of the larger metropolitan statistical areas correlate unconditionally with national business cycles. The coefficient on the common factor for the United States ranges from 0.66 for Cincinnati to 1.45 for Huntington-Ashland. In the cases of Bowling Green and Clarksville, the coefficients are just about exactly unity. The estimates are statistically significant at the 1 percent level for all of the metropolitan statistical areas. The second column of Table 1 reports the unconditional co-movement of each city with the state of the economy in Kentucky. In all cases, the coefficient is statistically significant. The greatest degree of co-movement (without making a statement as to the statistical differences between the coefficients) is in Huntington-Ashland, where the magnitude of the coefficient is 1.20, while Cincinnati has the most modest co-movement at 0.52.

The story is very different, however, for the micropolitan statistical areas. In no case is the coefficient for co-movement with the national factor statistically significant at any conventional level, and the point estimates are often negative. When regressed on the statewide factor, the coefficients are again mostly negative, and they are marginally significantly so in the cases of Danville, London, Mount Sterling, Murray, and Paducah. It is important to recall the caveat that the indexes for the micropolitan statistical areas are constructed from a slightly different set of

[6] I also estimate regressions that include both the US factor and the Kentucky factor on the right-hand side. The two factors are very highly correlated, leading to imprecise estimates. These results are available from the author upon request.

Table 1: Correlation with National and State Business Cycles

	$C_{US,t}$	$\Delta C_{KY,t}$
Bowling Green, KY	1.00***	0.91***
	(0.10)	(0.01)
Cincinnati, OH-KY-IN	0.66***	0.52***
	(0.06)	(0.07)
Clarksville, TN-KY	0.98***	0.85***
	(0.12)	(0.11)
Elizabethtown-Fort Knox, KY	1.08***	0.99***
	(0.11)	(0.11)
Evansville, IN-KY	1.26***	1.04***
	(0.14)	(0.13)
Huntington-Ashland, WV-KY-OH	1.45***	1.20***
	(0.13)	(0.12)
Lexington-Fayette, KY	0.77***	0.66***
	(0.07)	(0.07)
Louisville/Jefferson County, KY-IN	0.68***	0.58***
	(0.07)	(0.06)
Owensboro, KY	0.95***	0.86***
	(0.09)	(0.09)
Bardstown, KY	0.19	0.05
	(0.10)	(0.10)
Campbellsville, KY	-0.09	-0.07
	(0.07)	(0.08)
Central City, KY	0.09	-0.13
	(0.16)	(0.11)
Danville, KY	-0.10	-0.14*
	(0.11)	(0.08)
Frankfort, KY	0.00	-0.03
	(0.09)	(0.06)
Glasgow, KY	-0.13	-0.16
	(0.21)	(0.17)
London, KY	-0.03	-0.07*
	(0.08)	(0.05)
Madisonville, KY	-0.10	-0.16
	(0.21)	(0.16)
Mayfield, KY	-0.02	-0.06
	(0.13)	(0.09)
Maysville, KY	0.13	0.08
	(0.18)	(0.13)
Middlesborough, KY	-0.09	-0.10
	(0.11)	(0.09)
Mount Sterling, KY	-0.18	-0.19*
	(0.14)	(0.11)
Murray, KY	-0.02	-0.06*
	(0.07)	(0.04)
Paducah, KY-IL	-0.16	-0.20*
	(0.15)	(0.11)
Richmond-Berea, KY	-0.00	-0.08
	(0.12)	(0.06)
Somerset, KY	-0.11	-0.15
	(0.13)	(0.09)

Notes: This table reports the estimated slope coefficients for

$$\Delta C_{i,t} = \alpha_i^{US} + \beta_i^{US}\Delta C_{US,t} + e_{i,t}^{US} \text{ (Column 1) and}$$

$$\Delta C_{i,t} = \alpha_i^{KY} + \beta_i^{KY}\Delta C_{KY,t} + e_{i,t}^{KY} \text{ (Column 2).}$$

Newey and West [1987] standard errors with three lags are reported in parentheses. *,**, and *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively.

indicator variables compared with the metropolitan statistical areas, so one should employ caution in interpreting these results. Still, it is likely to be the case that the larger economic areas have more robust relationships with wider economic dynamics.

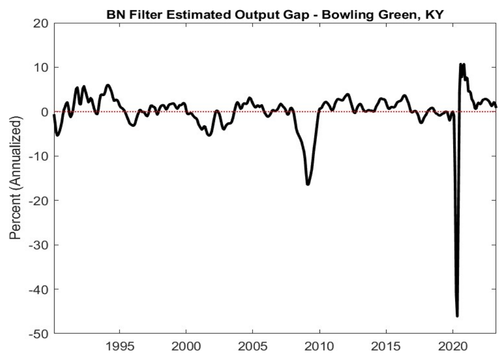
iii. Trend-Cycle Decompositions and the City-Specific Output Gap

Trend-cycle decomposition is a venerable practice in time series analysis, not least because knowing how far a certain series deviates from its long-term trend can provide insight into its short-run behavior. In this section, I decompose each city's coincident economic index into trend and cycle components using the Beveridge-Nelson filter, developed by Kamber, Morley, and Wong [2018], which extends the seminal work of Beveridge and Nelson [1981]. Kamber, Morley, and Wong [2018] show that their model helps the traditional Beveridge-Nelson decomposition deliver more intuitive realizations of the output gap by imposing a low signal-to-noise ratio on the series. In other words, the traditional Beveridge-Nelson decomposition tends to assign a great deal of time series variation in a nonstationary series to its trend component, causing cyclical component estimates to have very low amplitude and low persistence. By restricting the amount of variation assigned to the trend component, Kamber, Morley, and Wong [2018] show that they can produce a series that delivers intuitive estimates of the deviation from trend and also performs reliably in the sense that estimates of the cyclical component are not very sensitive to later data revisions.

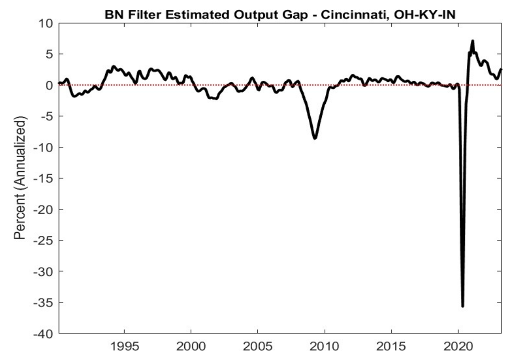
Figures 7 through 11 contain the estimated cyclical components for each city in the sample. Before discussing the results, it is important to note a distinction between these figures and those reported in Figures 1 through 5. Whereas the previously reported estimates detailed the month-to-month annualized changes in economic activity, the series in Figures 7 through 11 report the percent deviations of activity from trend. Thus, the cyclical component can be negative either because of an explicit negative change in economic activity or because of positive growth that is slower than trend growth. A reading of 0 means that the city's economic activity is right on its long-run trend.

It is perhaps most interesting to consider the cyclical deviation from trend for each city during the most important downturns of the last 30 years. For instance, at the depths of the Great Recession, activity in a substantial number of cities was over 10 percent below its potential value, including in most of the larger metropolitan statistical areas. Next, I consider the deviation from trend during the early months of the COVID-19-induced recession. Indeed, economies in all cities

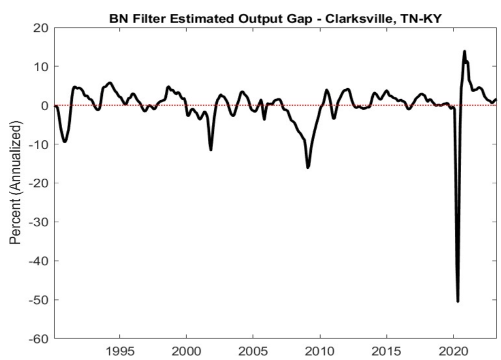
Figure 7: Estimated Cyclical Components of Metropolitan and Micropolitan Statistical Area Coincident Economic Activity Indexes



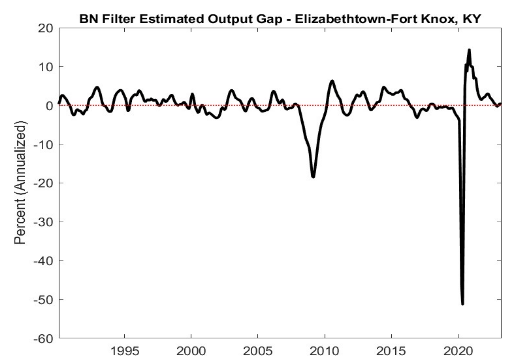
(a) Bowling Green, KY



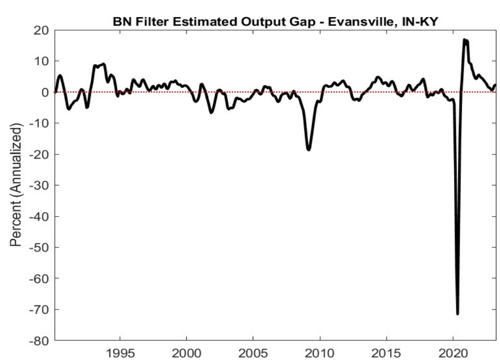
(b) Cincinnati, OH-KY-IN



(c) Clarksville, TN-KY



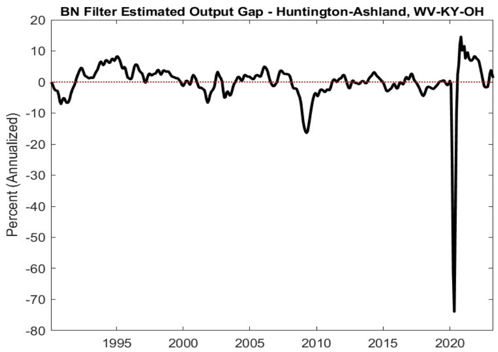
(d) Elizabethtown-Fort Knox, KY



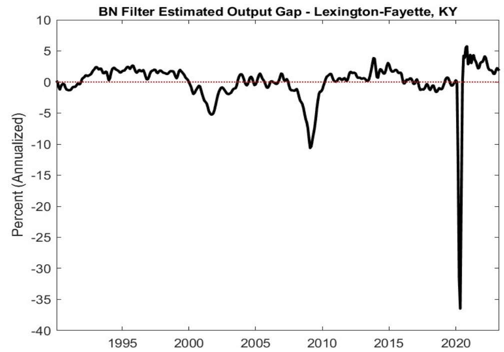
(e) Evansville, IN-KY

Notes: Each panel reports the estimated cyclical component (calculated using the Beveridge-Nelson filter of Kamber, Morley, and Wong, 2018) for the named city with a presence in Kentucky.

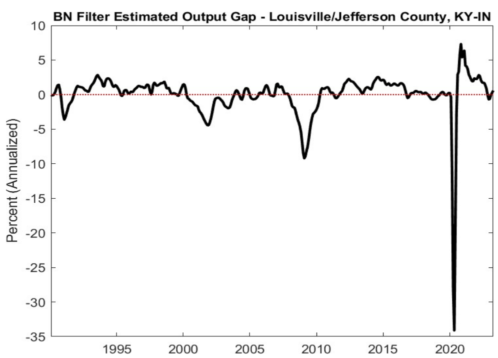
Figure 8: Estimated Cyclical Components of Metropolitan and Micropolitan Statistical Area Coincident Economic Activity Indexes



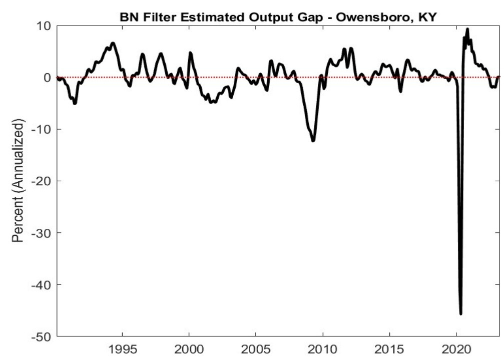
(a) Huntington-Ashland, WV-KY-OH



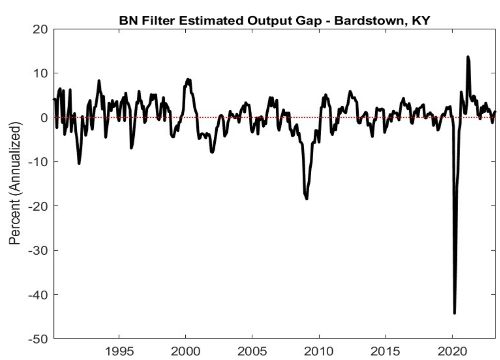
(b) Lexington-Fayette, KY



(c) Louisville/Jefferson County, KY-IN



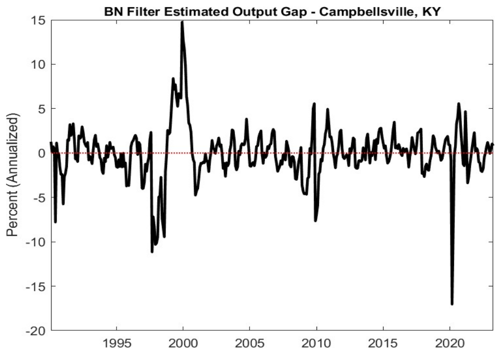
(d) Owensboro, KY



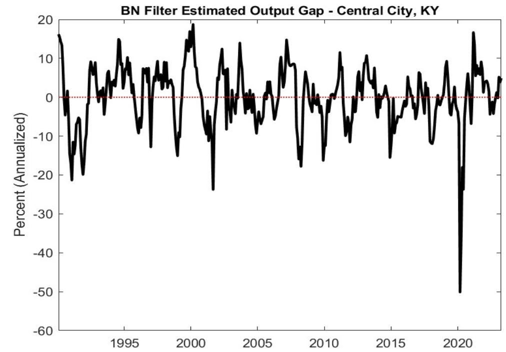
(e) Bardstown, KY

Notes: Each panel reports the estimated cyclical component (calculated using the Beveridge-Nelson filter of Kamber, Morley, and Wong, 2018) for the named city with a presence in Kentucky.

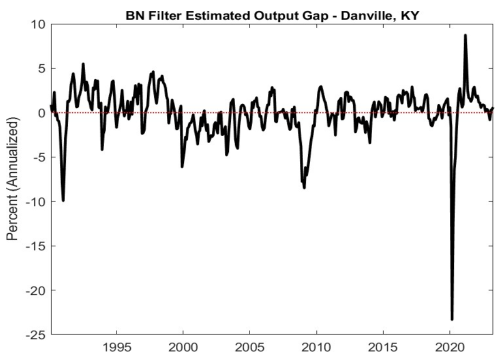
Figure 9: Estimated Cyclical Components of Metropolitan and Micropolitan Statistical Area Coincident Economic Activity Indexes



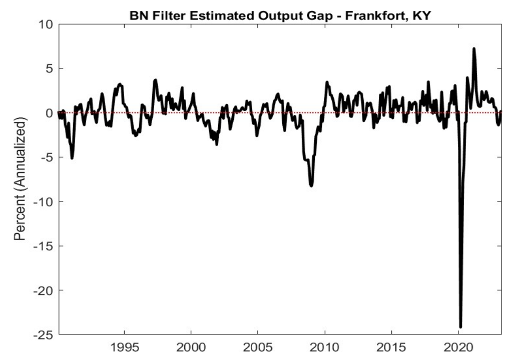
(a) Campbellsville, KY



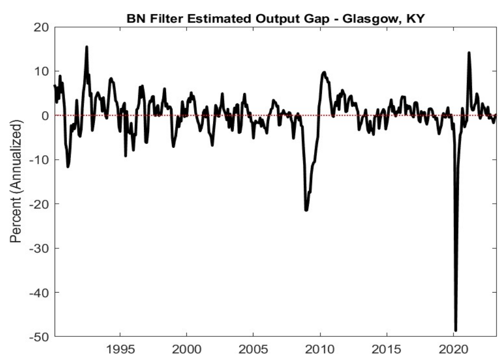
(b) Central City, KY



(c) Danville, KY



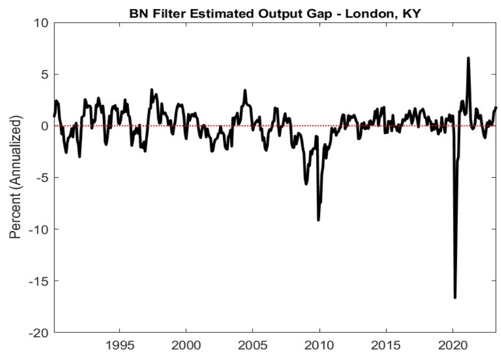
(d) Frankfort, KY



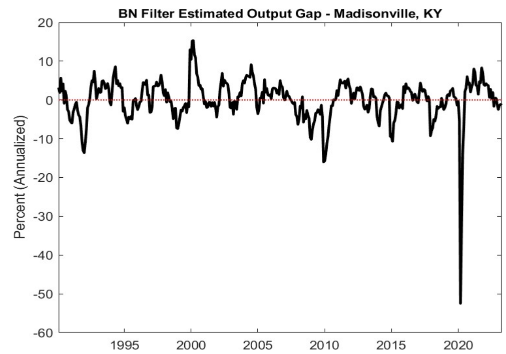
(e) Glasgow, KY

Notes: Each panel reports the estimated cyclical component (calculated using the Beveridge-Nelson filter of Kamber, Morley, and Wong, 2018) for the named city with a presence in Kentucky.

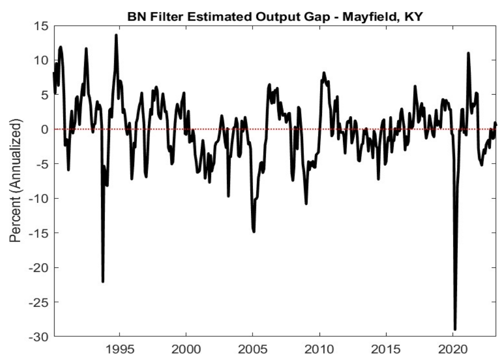
Figure 10: Estimated Cyclical Components of Metropolitan and Micropolitan Statistical Area Coincident Economic Activity Indexes



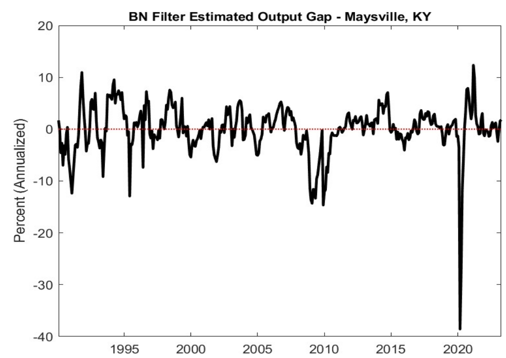
(a) London, KY



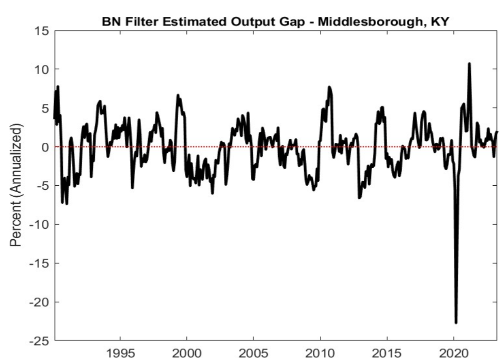
(b) Madisonville, KY



(c) Mayfield, KY



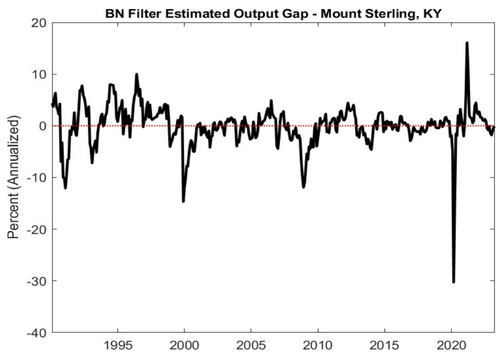
(d) Maysville, KY



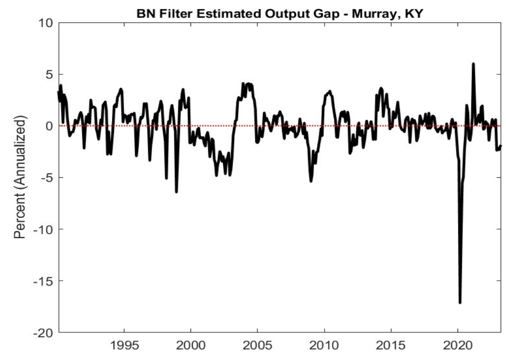
(e) Middlesborough, KY

Notes: Each panel reports the estimated cyclical component (calculated using the Beveridge-Nelson filter of Kamber, Morley, and Wong, 2018) for the named city with a presence in Kentucky.

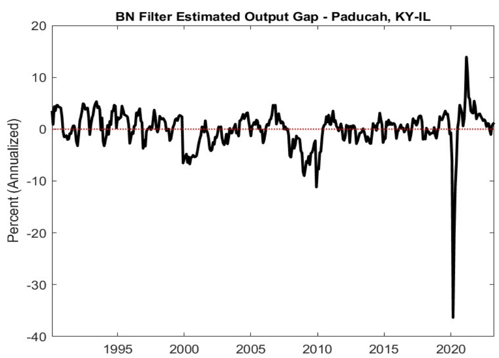
Figure 11: Estimated Cyclical Components of Metropolitan and Micropolitan Statistical Area Coincident Economic Activity Indexes



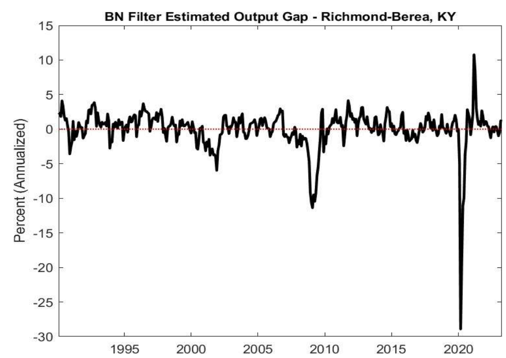
(a) Mount Sterling, KY



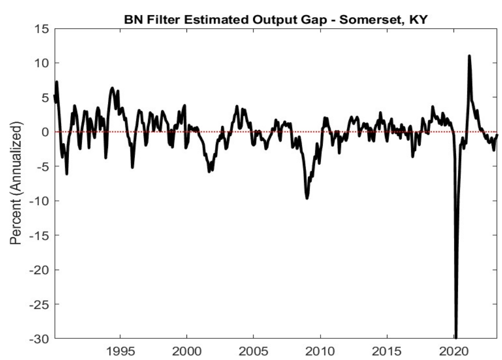
(b) Murray, KY



(c) Paducah, KY-IL



(d) Richmond-Berea, KY



(e) Somerset, KY

Notes: Each panel reports the estimated cyclical component (calculated using the Beveridge-Nelson filter of Kamber, Morley, and Wong, 2018) for the named city with a presence in Kentucky.

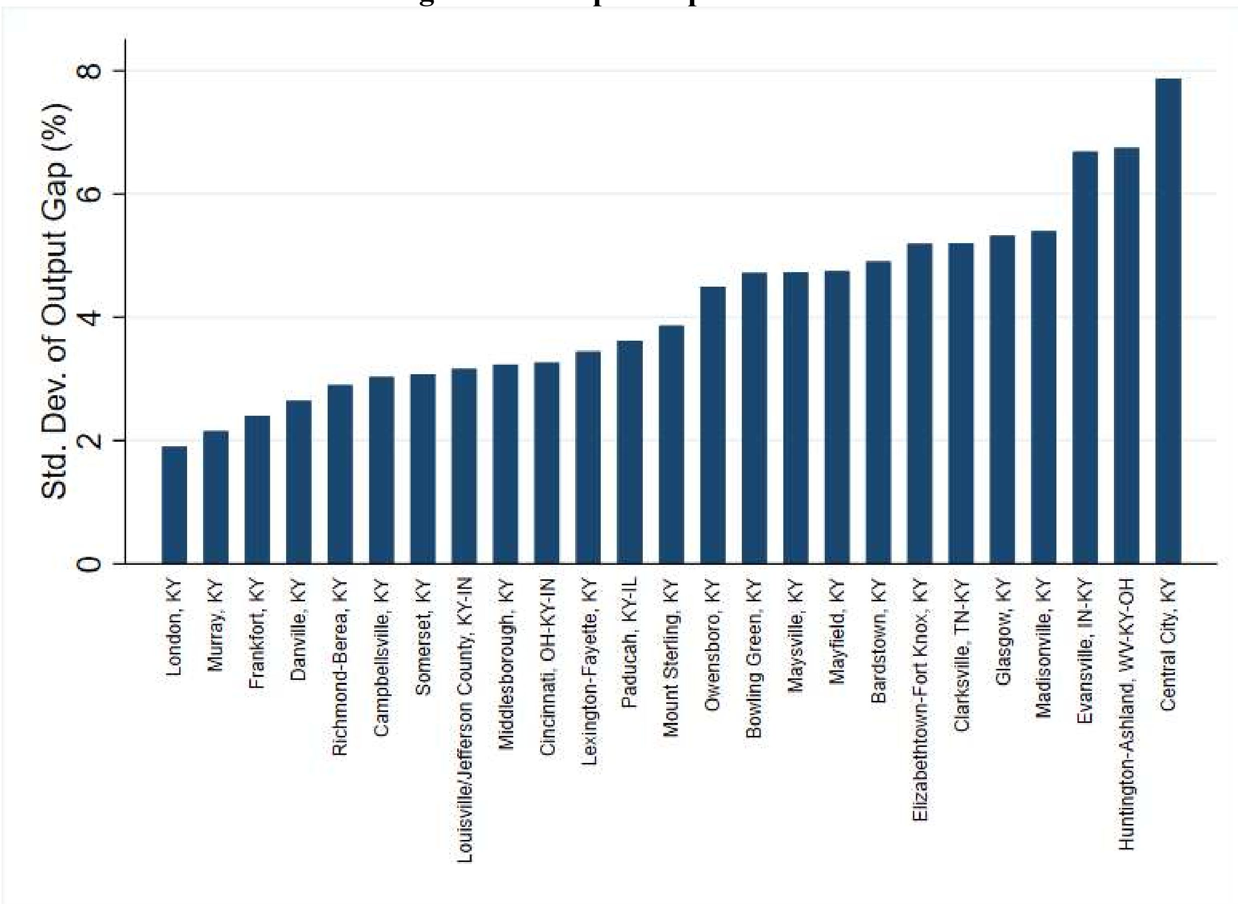
were operating well below their potential levels in the spring of 2020, as Figures 7 through 11 demonstrate. Worst affected were Evansville and Huntington-Ashland, where activity was more than 70 percent below its potential in the spring of 2020, while activity was more than 20 percent down from trend in many other cities. As a purely cyclical phenomenon, several of the micropolitan statistical areas appear to have weathered the pandemic downturn best, with activity only about 15 percent below potential in places such as Campbellsville, London, and Murray. There is some weak evidence in Motie and Biolsi [2021] that, at least early in the pandemic, counties outside of metropolitan statistical areas engaged in less social distancing than those within metropolitan statistical areas, so some of the smaller declines could be associated with that phenomenon. Interestingly, the bounceback from the depths of the recession in most of the cities was strong enough that the local output gaps are actually positive through much of 2021.

To gain insight into which city's business cycle is most volatile, I measure the standard deviation of the estimated output gap in each city, with the results reported in graphical form in Figure 12. There is substantial variation in the volatilities of the cities' business cycles. On the low end are micropolitan areas like London and Murray, with standard deviations of only about 2 percentage points. But, Central City has an 8 percentage point standard deviation, implying quite volatile cycles. Even fairly large areas, like Huntington-Ashland and Evansville experience business cycles with standard deviations above 6 percentage points.

The application of the Beveridge-Nelson filter to these series raises the specter that there may have been permanent declines in potential output in some of the cities. It may be interesting then to assess the extent to which each city has recovered from the most severe recessions, as far as making up the ground lost. To this end, I adopt the following approach. I assign to each city an index value of 100 for January 1990 (one month before the first measurement of $\Delta C_{i,t}$ for each city). Then, I allow the index value to appreciate by the value of $\Delta C_{i,t}$ for each time period t. This produces an inferred level of each series, of which I take logs in order to linearize it. The solid lines in Figures 13 through 17 depict these constructed log level series. For each city then, I calculate the average growth rate of the series up to the date at which the Great Recession is considered to have begun, according to the National Bureau of Economic Research. I produce a counterfactual level of the series that assumes that activity continued to grow at this average level for all of the periods following that recession date (this is depicted in Figures 13 through 17 as the dotted line).

I do the same for the COVID recession, with this counterfactual activity level reported by the dashed lines in Figures 13 through 17.

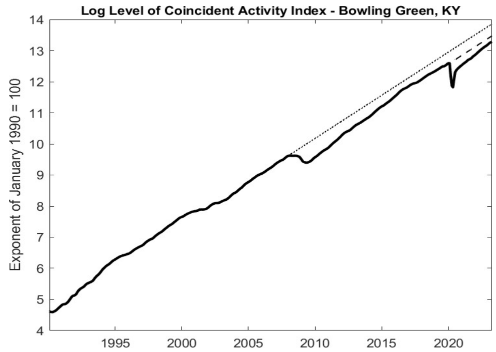
Figure 12: Output Gap Volatilities



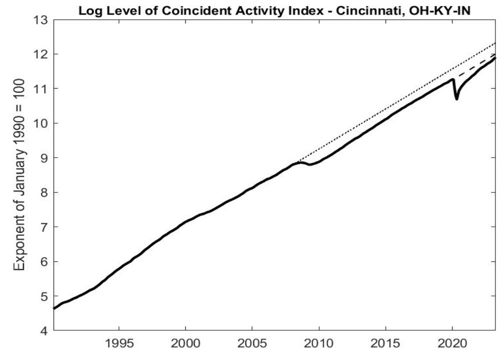
Notes: This figure reports the standard deviations of the estimated Beveridge-Nelson filter cyclical components of the coincident economic activity series for each of the cities in the sample.

These plots reveal interesting heterogeneity across cities in the extent to which they have made up recession-induced losses. First, note that, in the case of most of the cities, the local economy has not regained the level that they were on pace for before the financial crisis (that is, the solid line never fully catches up to the dotted line in most figures). The exceptions include Campbellsville and Frankfort. This is a strong indication that, in many cases, the negative shock associated with the financial crisis has produced a permanent output loss. There are a number of cases, as well, in which the COVID-induced recession has pushed the level of activity even further off the pace, and they have not even reclaimed the trajectory that they were on before the onset of

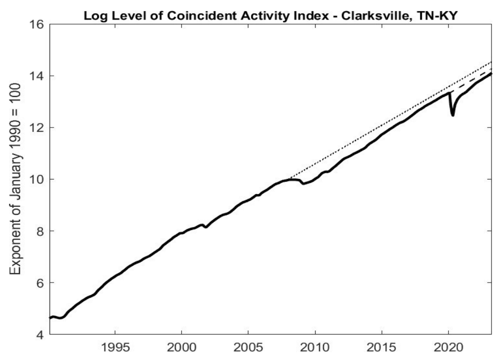
Figure 13: Estimated Levels of Metropolitan and Micropolitan Statistical Area Coincident Economic Activity Indexes



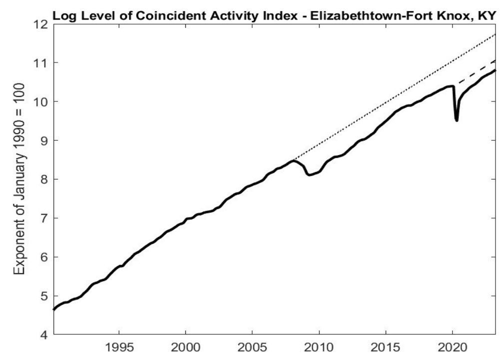
(a) Bowling Green, KY



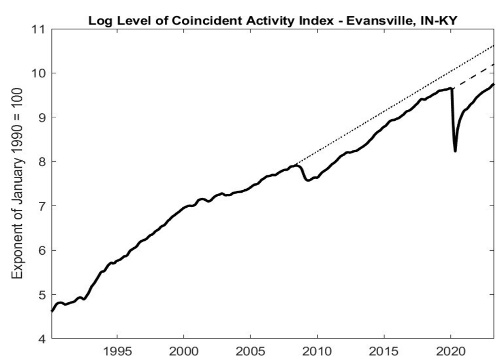
(b) Cincinnati, OH-KY-IN



(c) Clarksville, TN-KY



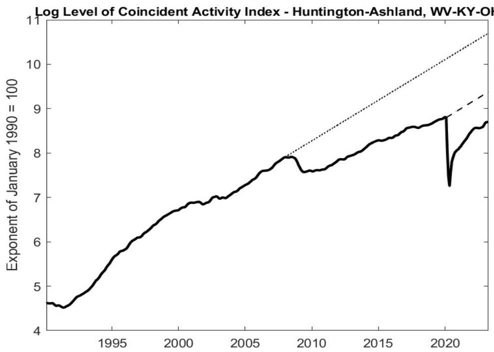
(d) Elizabethtown-Fort Knox, KY



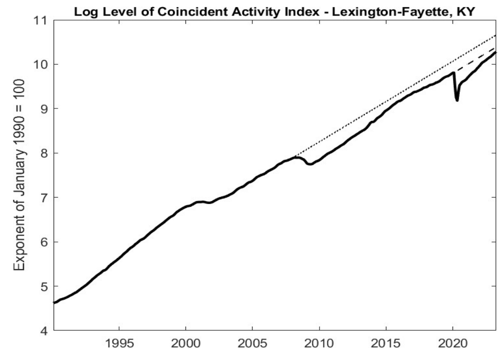
(e) Evansville, IN-KY

Notes: The solid line in each panel reports the estimated log level of the coincident activity index for each city (assuming a value of 100 for January 1990). The dotted line reports what the log level of activity would have been had each city, instead of entering the Great Recession, continued to grow at the average pace to that point. The dashed line reports what the log level of activity would have been had each city, instead of entering the COVID-induced recession, continued to grow at the average pace to that point.

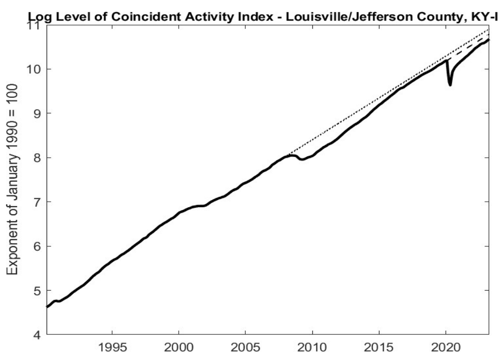
Figure 14: Estimated Levels of Metropolitan and Micropolitan Statistical Area Coincident Economic Activity Indexes



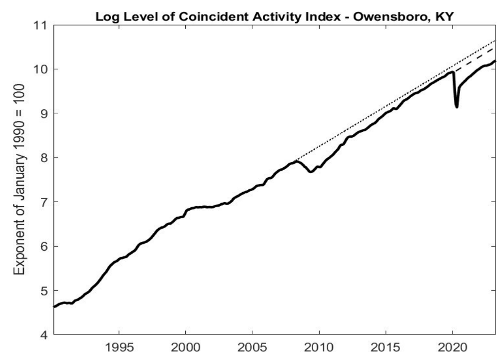
(a) Huntington-Ashland, WV-KY-OH



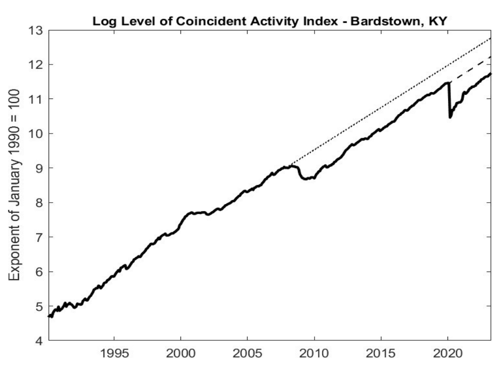
(b) Lexington-Fayette, KY



(c) Louisville/Jefferson County, KY-IN



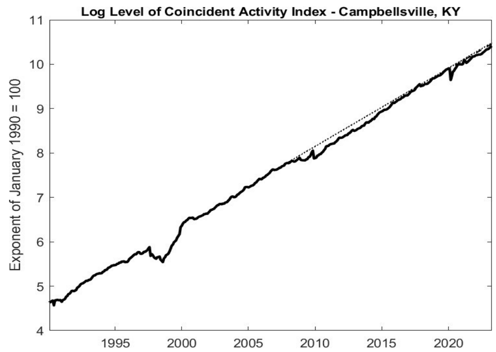
(d) Owensboro, KY



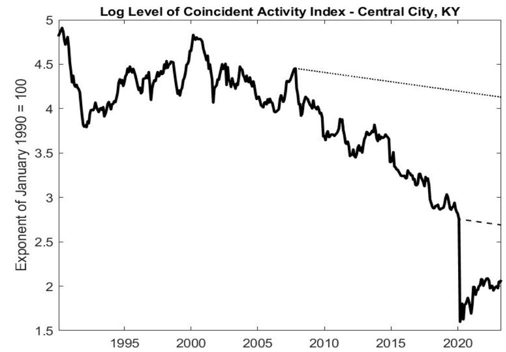
(e) Bardstown, KY

Notes: The solid line in each panel reports the estimated log level of the coincident activity index for each city (assuming a value of 100 for January 1990). The dotted line reports what the log level of activity would have been had each city, instead of entering the Great Recession, continued to grow at the average pace to that point. The dashed line reports what the log level of activity would have been had each city, instead of entering the COVID-induced recession, continued to grow at the average pace to that point.

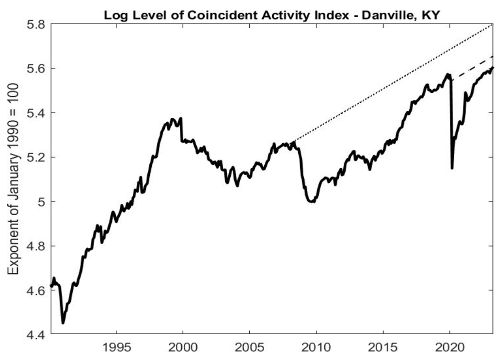
Figure 15: Estimated Levels of Metropolitan and Micropolitan Statistical Area Coincident Economic Activity Indexes



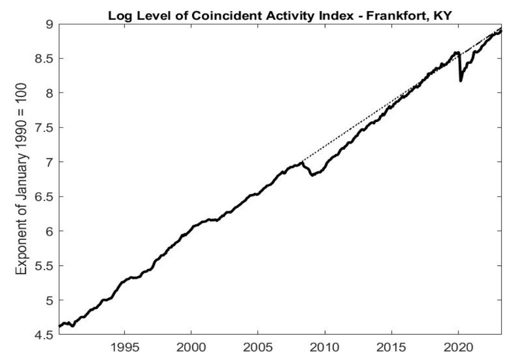
(a) Campbellsville, KY



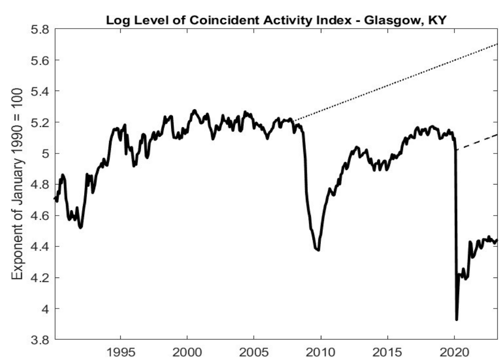
(b) Central City, KY



(c) Danville, KY



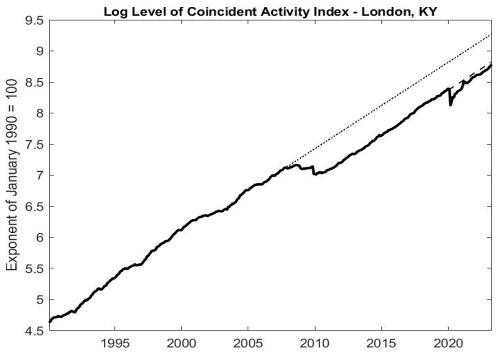
(d) Frankfort, KY



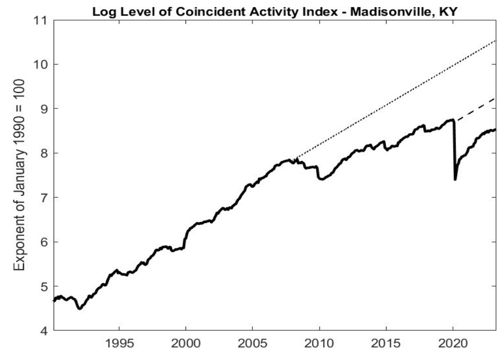
(e) Glasgow, KY

Notes: The solid line in each panel reports the estimated log level of the coincident activity index for each city (assuming a value of 100 for January 1990). The dotted line reports what the log level of activity would have been had each city, instead of entering the Great Recession, continued to grow at the average pace to that point. The dashed line reports what the log level of activity would have been had each city, instead of entering the COVID-induced recession, continued to grow at the average pace to that point.

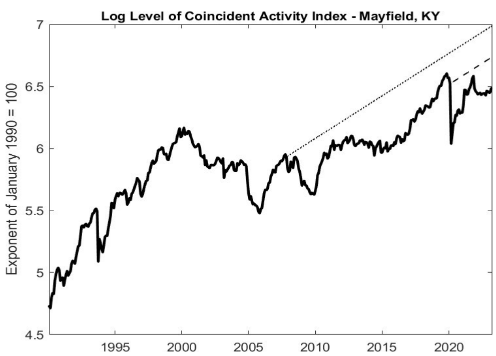
Figure 16: Estimated Levels of Metropolitan and Micropolitan Statistical Area Coincident Economic Activity Indexes



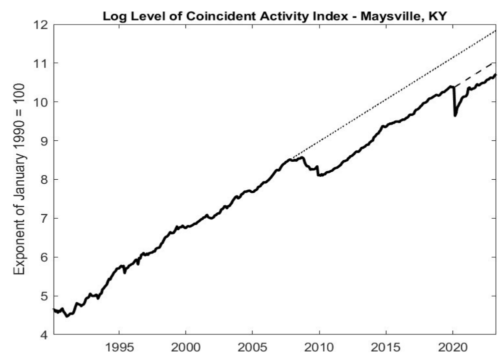
(a) London, KY



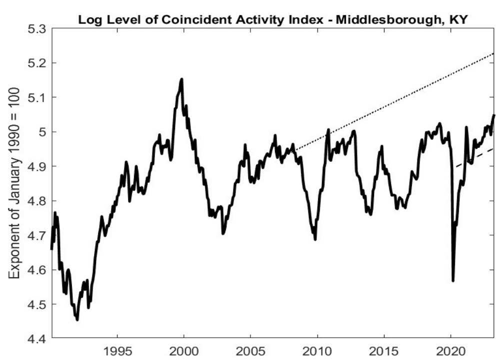
(b) Madisonville, KY



(c) Mayfield, KY



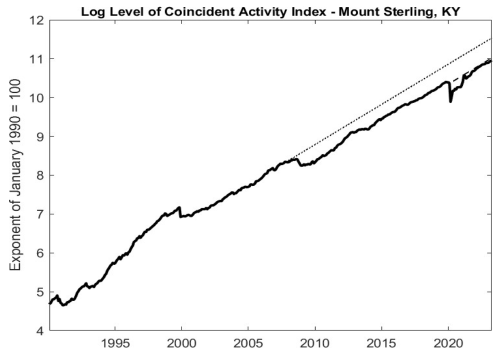
(d) Maysville, KY



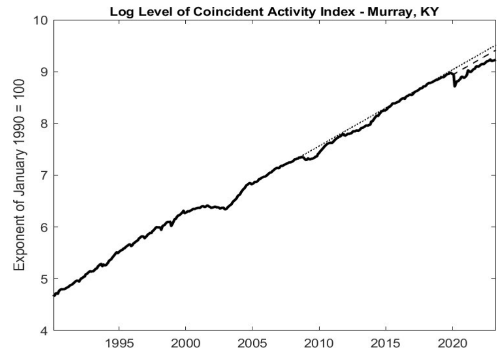
(e) Middlesborough, KY

Notes: The solid line in each panel reports the estimated log level of the coincident activity index for each city (assuming a value of 100 for January 1990). The dotted line reports what the log level of activity would have been had each city, instead of entering the Great Recession, continued to grow at the average pace to that point. The dashed line reports what the log level of activity would have been had each city, instead of entering the COVID-induced recession, continued to grow at the average pace to that point.

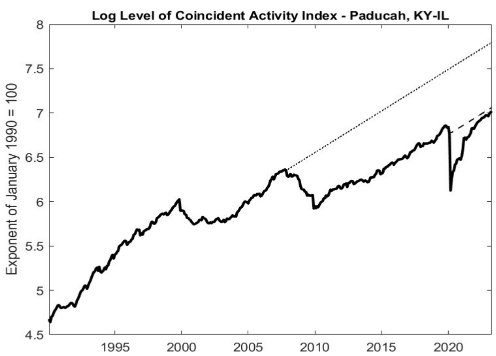
Figure 17: Estimated Levels of Metropolitan and Micropolitan Statistical Area Coincident Economic Activity Indexes



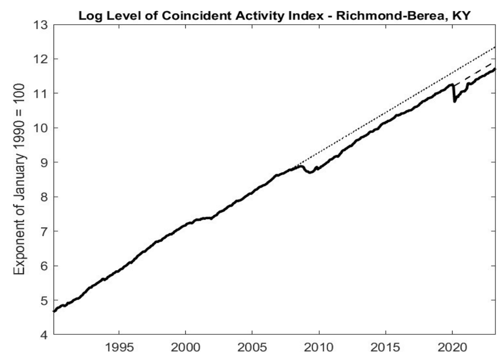
(a) Mount Sterling, KY



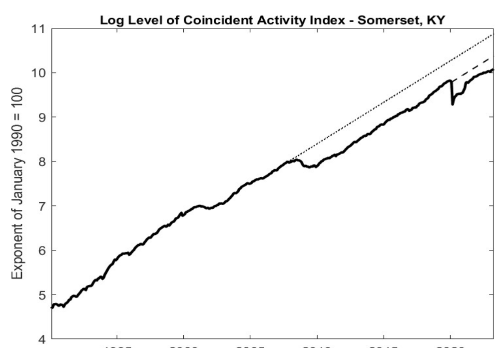
(b) Murray, KY



(c) Paducah, KY-IL



(d) Richmond-Berea, KY



(e) Somerset, KY

Notes: The solid line in each panel reports the estimated log level of the coincident activity index for each city (assuming a value of 100 for January 1990). The dotted line reports what the log level of activity would have been had each city, instead of entering the Great Recession, continued to grow at the average pace to that point. The dashed line reports what the log level of activity would have been had each city, instead of entering the COVID-induced recession, continued to grow at the average pace to that point.

the novel coronavirus. Cities in this situation include Evansville, Huntington-Ashland, Owensboro, Bardstown, Madisonville, Maysville, and Somerset. In other cases, while failing to reach the pre-financial crisis trend, city economies have at least recovered their pre-COVID trends, as happens in Bowling Green, Cincinnati, Clarksville, Lexington-Fayette, Louisville/Jefferson County, London, Mount Sterling, Paducah, and Richmond-Berea.

Of particular interest, however, are those areas where there is no upward trend to speak of. Central City has been declining steadily since the turn of the millennium, with a remarkably sharp (and apparently permanent) drop induced by the pandemic. Glasgow has also barely grown in the 21st century, and it is nowhere close to its pre-pandemic path. Middlesborough is an idiosyncratic case in that its activity has actually exceeded where its pre-COVID trend would have placed it, but this owes largely to the fact that pre-pandemic trend was an especially weak one.

iv. Predicting Future Statewide Activity

The last empirical exercise I consider in this paper is to assess which city's economic activity is most helpful for predicting future statewide activity growth, both in the short run and in the medium term. I note at this point that this is not a formal out-of-sample forecasting exercise, because that would require iteratively re-estimating the mixed-frequency dynamic factor model for each period that I construct a forecast for. Instead, this exercise is only meant to be suggestive of which city's coincident economic activity index contains information most predictive for future statewide growth in sample. Starting with the short run (one step ahead), I consider linear models of the following form:

$$\Delta C_{KY,t+1} = \alpha + \sum_{j=1}^{p} \beta_j \, \Delta C_{j,t} + \varepsilon_t \tag{6}$$

Essentially, I would like to evaluate models that parsimoniously express growth in economic activity in Kentucky as a function of the lag of p local economic activity indexes. The problem is that it is not clear which of the city indexes should be in the predictive model. To determine which city indexes belong, I adopt a Markov Chain Monte Carlo Bayesian Model Averaging algorithm, as employed in Fernández, Ley, and Steel [2001], with program code supplied by Koop [2003]. Of the over 33.5 million possible models, all are assigned equal prior probabilities of being the correct model.[7] Then a model is randomly drawn from a set that includes

[7] Each of the 25 cities can be included or not included in the model, so there are 2^25=33,554,432 possible models.

whatever model is currently in place, plus all those that add one city's index or remove one city's index. Its likelihood function is then compared with that of the current model, and it is kept if its likelihood function is greater. Then, a new candidate model is drawn. Estimation of each model is undertaken via Bayesian techniques. The algorithm samples 110,000 draws, the first 10000 of which are burned to purge any dependence on the initial model chosen.

In addition to the mean and standard deviation of the posterior distribution of each city's loading factor, I also report, in Table 2, the probability that each city's index is included in the model. Of the cities in the analysis, a small number are selected for the model quite often. Madisonville has a 100 percent selection rate, and Frankfort's rate is over 99 percent. They each also have significantly positive loadings for one-step-ahead growth across the state. Maysville and Somerset are each chosen about 80 percent of the time, with loadings that are positive, if a bit noisier in terms of their precision. For metropolitan statistical areas, Cincinnati enters the forecasting model most often, at about 79 percent of the time, which is not very surprising, given that it is the largest area in the study. That said, Cincinnati has a negative loading factor, which suggests that faster growth in Cincinnati in a given month would predict slower growth in the state of Kentucky one month later. It may be the case that faster growth in Cincinnati attracts labor and investment from across the state border, leading to weaker growth on the other side of the Ohio River. The other cities are chosen only sparingly, and their estimated coefficients are very close to zero.

Next, I consider predictions for statewide activity for the ensuing twelve months, as the medium term may be of more interest to state policymakers than the very short run. The estimated regression equation takes the following form:

$$\Delta C_{KY,t+1:t+12} = \alpha + \sum_{j=1}^{p} \beta_j \, \Delta C_{j,t-11:t} + \varepsilon_{t+1:t+12} \tag{7}$$

The dependent variable in this regression is the average monthly growth rate for the statewide economic activity index over periods $t+1$ to $t+12$. The independent variables that the model will choose among are the average monthly growth rates in the coincident economic activity indexes for each of the cities in the analysis, with the average taken over periods $t-11$ to t, such that there is no time overlap between the independent and dependent variables. Table 3 contains the results of this Bayesian Model Averaging exercise. The medium-run prediction exercise points to a somewhat different set of cities as being helpful in forecasting state-level growth over the next year. Notably, Lexington-Fayette and Huntington- Ashland each appear in the model 100 percent of the time, though with different signs.

Table 2: Bayesian Model Averaging Results – 1 Step Ahead

	Probability of Being Included	Coefficient	Std. Dev
Bowling Green, KY	36.51%	0.0437	0.0649
Cincinnati, OH-KY-IN	79.44%	-0.2217	0.1495
Clarksville, TN-KY	14.59%	0.0135	0.0393
Elizabethtown-Fort Knox, KY	10.54%	0.0077	0.0290
Evansville, IN-KY	23.02%	0.0216	0.0470
Huntington-Ashland, WV-KY-OH	7.69%	0.0027	0.0196
Lexington-Fayette, KY	15.93%	0.0266	0.0733
Louisville/Jefferson County, KY-IN	8.46%	-0.0079	0.0528
Owensboro, KY	7.35%	0.0039	0.0215
Bardstown, KY	28.51%	0.0141	0.0255
Campbellsville, KY	4.59%	-0.0003	0.0058
Central City, KY	5.21%	-0.0003	0.0026
Danville, KY	46.19%	0.0554	0.0685
Frankfort, KY	99.41%	0.1973	0.0499
Glasgow, KY	20.50%	0.0090	0.0205
London, KY	7.43%	0.0055	0.0262
Madisonville, KY	100.00%	0.1279	0.0196
Mayfield, KY	13.18%	-0.0038	0.0119
Maysville, KY	80.96%	0.0471	0.0284
Middlesborough, KY	4.00%	0.0000	0.0052
Mount Sterling, KY	6.20%	-0.0012	0.0078
Murray, KY	4.68%	-0.0005	0.0096
Paducah, KY-IL	10.01%	0.0051	0.0195
Richmond-Berea, KY	6.49%	0.0029	0.0153
Somerset, KY	80.02%	0.0986	0.0605

Notes: This table reports the means and standard deviations of the posterior distributions of the coefficients on each city in the linear model $\Delta C_{t+1}^{KY} = \alpha + \sum_{j=1}^{p} \beta_j \Delta C_{j,t} + \epsilon_{t+1}$, as well as the probability that each city appears in a given accepted model draw.

One-year-ahead growth in Kentucky is negatively related to current growth in Huntington-Ashland, but positively related to current growth in Lexington-Fayette, with a factor loading that is both significantly and economically significant. Indeed, it seems as though the surest way to get a sense for future growth in the state of Kentucky is to examine Lexington-Fayette now. Somerset is chosen in 95 percent of models, although its loading is also negative, while Frankfort is selected a little over 80 percent of the time, and it has a positive coefficient. It may be interesting that the two cities that have the strongest positive relationship with future statewide growth are the ones that are home to the state capital and the state's flagship university.

IV. Explaining Cross-City Differences

In the preceding section, I established that there is considerable heterogeneity in terms of the volatility of cities' output gaps, their correlations with national and statewide business cycles, and their predictive content for future state-level dynamics. The purpose of this section is to try to examine what city-specific traits might be useful in explaining this heterogeneity. Specifically, I examine the degree to which a city's education level or industry mix might be behind its correlations with more aggregate business cycles or its volatility.

Table 3: Bayesian Model Averaging Results – Average 1-Year-Ahead Growth

	Probability of Being Included	Coefficient	Std. Dev
Bowling Green, KY	5.68%	-0.0004	0.0120
Cincinnati, OH-KY-IN	60.33%	-0.1286	0.1229
Clarksville, TN-KY	38.78%	0.0396	0.0578
Elizabethtown-Fort Knox, KY	44.79%	-0.0377	0.0483
Evansville, IN-KY	7.72%	0.0030	0.0185
Huntington-Ashland, WV-KY-OH	100.00%	-0.1869	0.0400
Lexington-Fayette, KY	100.00%	0.4837	0.1059
Louisville/Jefferson County, KY-IN	60.85%	-0.1935	0.1803
Owensboro, KY	15.69%	-0.0143	0.0406
Bardstown, KY	12.52%	0.0063	0.0211
Campbellsville, KY	9.35%	-0.0025	0.0107
Central City, KY	18.39%	0.0043	0.0106
Danville, KY	5.63%	-0.0008	0.0155
Frankfort, KY	82.96%	0.1723	0.0979
Glasgow, KY	6.83%	-0.0012	0.0077
London, KY	6.88%	0.0022	0.0209
Madisonville, KY	13.91%	0.0047	0.0150
Mayfield, KY	45.17%	-0.0218	0.0276
Maysville, KY	51.63%	0.0349	0.0388
Middlesborough, KY	5.54%	0.0006	0.0081
Mount Sterling, KY	65.43%	0.0507	0.0446
Murray, KY	5.81%	-0.0019	0.0146
Paducah, KY-IL	71.57%	0.0643	0.0488
Richmond-Berea, KY	5.42%	-0.0006	0.0145
Somerset, KY	95.18%	-0.1601	0.0595

Notes: This table reports the means and standard deviations of the posterior distributions of the coefficients on each city in the linear model $\Delta C^{KY}_{t+1:t+12} = \alpha + \sum_{j=1}^{p} \beta_j \, \Delta C_{j,t-11:t} + \epsilon_{t+1:t+12}$, as well as the probability that each city appears in a given accepted model draw.

I start by simply assessing the differences between metropolitan statistical areas and micropolitan statistical areas. Figure 18 displays bar graphs that take the averages of a number of the metrics that I have examined separately depending on whether the city is a metropolitan or micropolitan statistical area.

From the bar graphs, one can see that metropolitan statistical areas, on average, have more volatile business cycles than do micropolitan statistical areas, and their coefficients for both one-month-ahead state growth and one-year-ahead state growth are less positive.[8] That said, none of these differences are statistically significant (p-values for a test of equality of means range between 0.14 and 0.66).

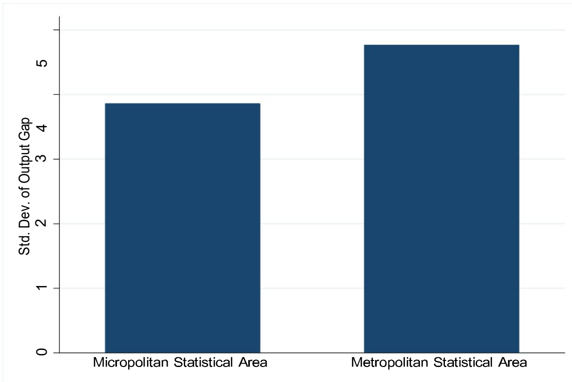
In the case of coefficients on statewide or national business cycles, however, metropolitan statistical areas have higher-magnitude coefficients, and the difference relative to those of micropolitan statistical areas is statistically significant, with the implication that more populated areas appear to track aggregate cycles more closely than do smaller areas. This conjecture is confirmed when examining the correlation of the same coincident economic activity index metrics with an area's log average population over the sample, reported in Appendix Figure A6.[9]

Next, I assess whether a city's education level, proxied by the share of the 18-and-over population with a college degree, might correlate with the statistics calculated in this paper. Figure 19 reports scatter plots of the average bachelor's degree share (collected from the Census Bureau's American Community Survey) between 2009 and 2021 against each of the statistics named above, along with a line of best fit. There is essentially no relationship between average college attainment and predictive content for future growth in Kentucky. Volatility has a negative, but insignificant, relationship with the share holding a bachelor's degree. Correlations with national and statewide business cycles, however, do positively and significantly relate with college education. The more educated cities (which also happen to be the larger urban areas) track more aggregated business cycles much more closely on average than do the micropolitan areas.

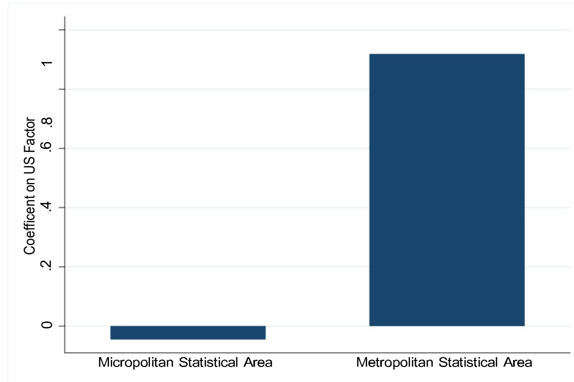
The same relationship appears when considering average poverty rates over time (taken from the Census Bureau for 1993 and from 1997 to 2021). These scatters appear in Figure 20. There is a clear and statistically significant negative relationship between the poverty rate and co-movement with wider cycles, though poverty does not offer any information as to predictive content for future growth in Kentucky, and its relationship with volatility is not statistically

[8] In the case of coefficients on state and national growth and the forecasting coefficients, I weigh each city's observation by the inverse of its standard error, thus giving more precise coefficient estimates greater weight.
[9] Population statistics are obtained from the US Census Bureau.

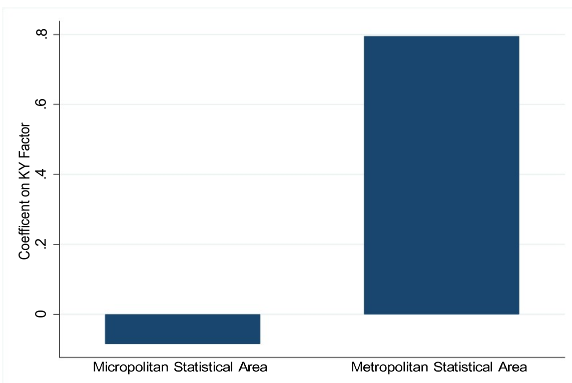
Figure 18: Relationship of MSA status with Index Metrics



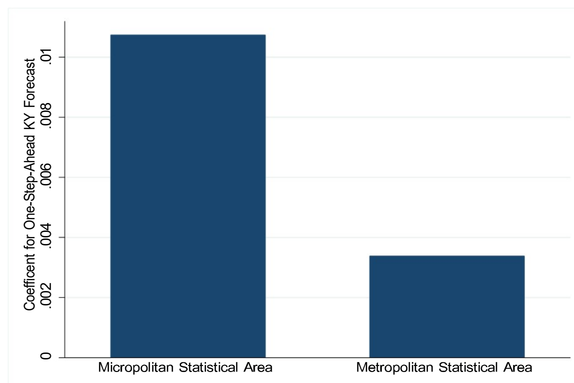
(a) Volatility



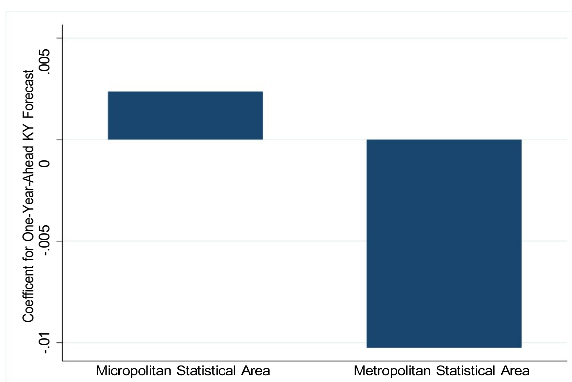
(b) Coefficient on US Growth



(c) Coefficient on State Growth



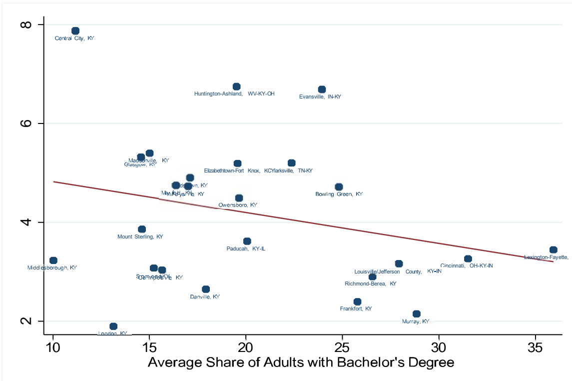
(d) Coefficient for One-Month-Ahead State Growth



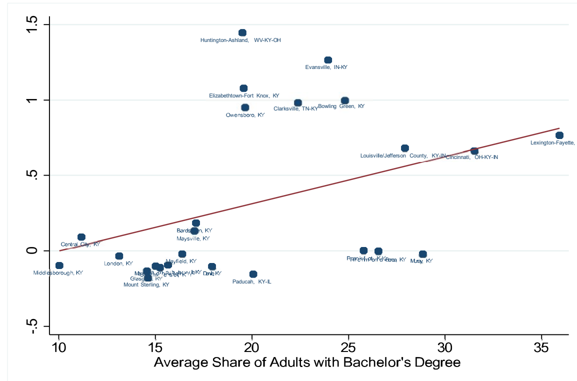
(e) Coefficient for One-Year-Ahead State Growth

Notes: Each panel in the figure reports the average of each statistic depending upon whether each city is a metropolitan statistical area or a micropolitan statistical area. With the exception of the output gap volatility, each city's observation is weighted by the inverse of the standard error of its coefficient.

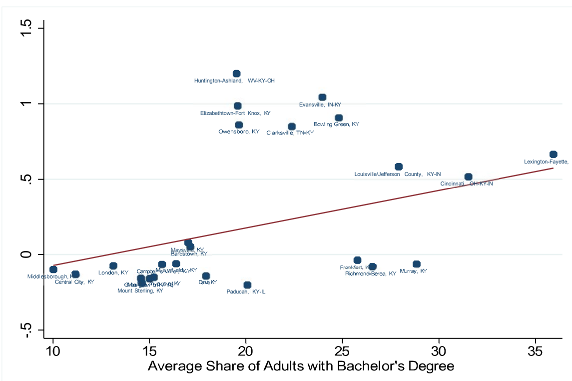
Figure 19: Relationship of Average Share with College Degree with Index Metrics



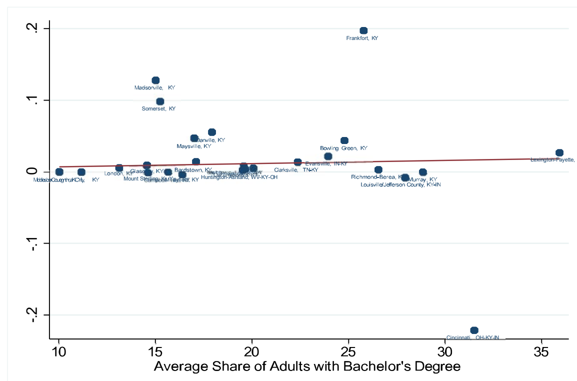
(a) Volatility



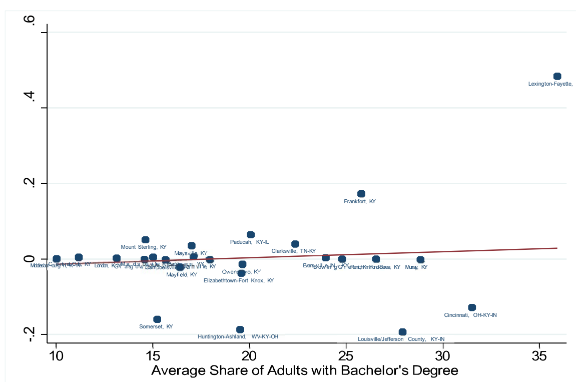
(b) Coefficient on U.S. Growth



(c) Coefficient on State Growth



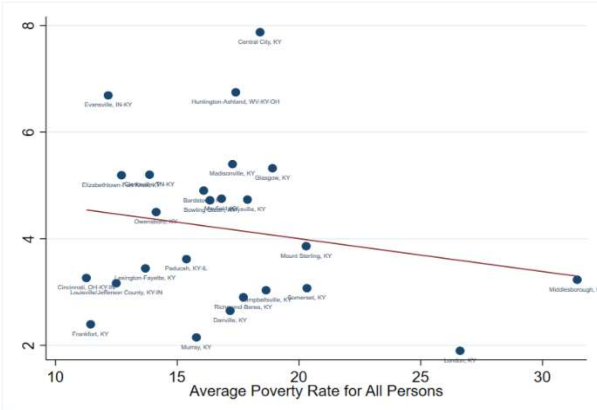
(d) Coefficient for One-Month-Ahead State Growth



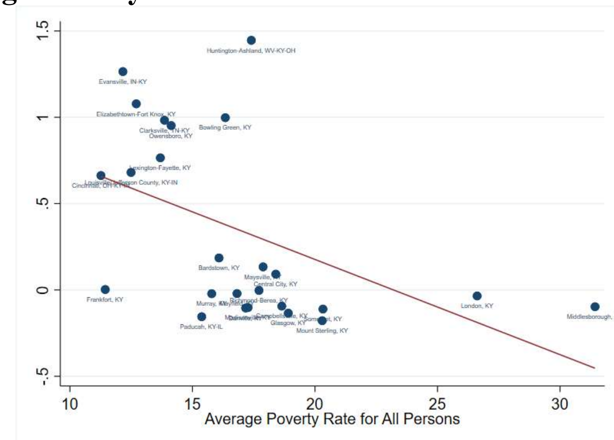
(e) Coefficient for One-Year-Ahead State Growth

Notes: Each panel in the figure scatters the statistic named in the caption against the average share of the 18-and-over population with a college degree over the available sample period in each city. With the exception of the output gap volatility, each city's observation is weighted by the inverse of the standard error of its coefficient.

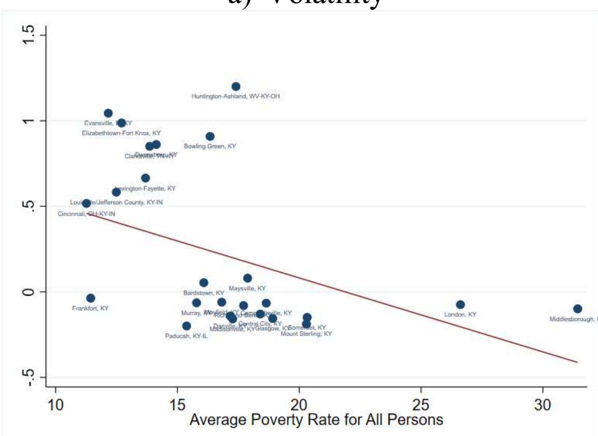
Figure 20: Relationship of Average Poverty Rate with Index Metrics



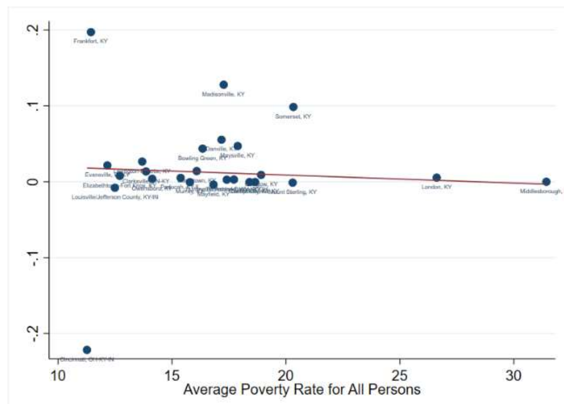
a) Volatility



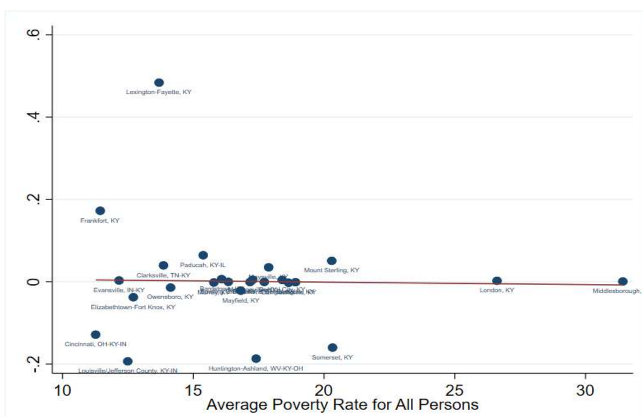
(b) Coefficient on U.S. Growth



(c) Coefficient on State Growth



(d) Coefficient for One-Month-Ahead State Growth



(e) Coefficient for One-Year-Ahead State Growth

Notes: Each panel in the figure scatters the statistic named in the caption against the average poverty rate for all persons over the available sample period in each city. With the exception of the output gap volatility, each city's observation is weighted by the inverse of the standard error of its coefficient.

significant. Of course, the larger metropolitan statistical areas also tend to have lower poverty rates and higher levels of college achievement), so it is difficult to assert that one metric or the other is what is driving the correlation with U.S. and Kentucky-level business cycles.[10]

V. Conclusion

In this paper, I estimate coincident economic activity indexes for 25 metropolitan and micropolitan statistical areas in the state of Kentucky. To do so, I follow the lead of Aruoba, Diebold, and Scotti [2009], Bańbura and Modugno [2014], Arias, Gascon, and Rapach [2016], and Baumeister, Leiva-León, and Sims [2024] in applying a mixed-frequency dynamic factor model to series of both quarterly and monthly frequencies and which start in different periods. Then, I embark on a series of simple empirical exercises analyzing the newly estimated series.

I find that all of the cities analyzed experienced downturns at the time of the Great Recession and at the beginning of the COVID-19-induced slowdown. There is, however, heterogeneity in the precise timings of the beginnings and ends of each recession. Further, not all cities endure downturns at the times of the 1990-1991 or 2001 national recessions, but a number of cities (generally smaller ones) have idiosyncratic recessions at times when the national economy was growing. The larger metropolitan statistical areas correlate significantly on an unconditional basis with both the nationwide business cycle and the state-specific business cycle, but the same cannot be said of the micropolitan statistical areas. A Beveridge-Nelson filtering of the estimated series shows that, of the cities analyzed, Central City's cycles are the most volatile, while London and Murray have the least volatile cycles. The indexes suggest that very few cities have fully recovered from the Great Recession and regained their pre-financial crisis trajectory, though a larger number have at least made back their losses during the pandemic. Some cities, however, have experienced fairly serious economic stagnation since the turn of the millennium, such that they are currently quite far from their previous trends. Finally, the results of a Bayesian Model Averaging exercise suggest that dynamics in Madisonville and Frankfort are most helpful for predicting future changes at the one-period horizon in Kentucky overall. At the one-year-ahead

[10] Appendix Figure A7 reports the correlation with the average share of each city's workforce employed in the manufacturing industry, defined at the 2-digit NAICS classification level. There is no apparent relationship between the importance of manufacturing in the local economy and the statistics that I have estimated in this paper.

horizon, the most useful predictive information is contained in the indexes for Lexington-Fayette, Huntington-Ashland, and Somerset.

I also attempt to assess to what degree certain city-level characteristics might speak to their volatility or co-movement with national or state-level business cycles. The evidence is limited, but it does appear to be the case that larger, more educated, less poverty-stricken metropolitan statistical areas correlate more closely with wider business cycles, but there is no obvious trait that informs on predictive content for future growth in Kentucky.

These indexes should provide analysts and policymakers with comprehensive, almost real-time measures of activity in some of the most important economies in the state. This should help in assessments of current economic conditions and be useful for forming forecasting models of future revenue changes and spending needs. At the very least, they offer a parsimonious summary measure of local economies to allow officials and residents pertinent information that can inform their economic decision-making.

Acknowledgements

I am thankful to the editor, Maria Apostolova-Mihaylova, and two excellent anonymous referees. I am further thankful to Michele Modugno for sharing the MATLAB code for the expectations maximization algorithm. All errors are my own. Declarations of interest: none. Updated estimates of the coincident economic activity indexes can be found on my website (https://sites.google.com/site/cjbiolsi/research).

References

Arias, Maria A., Charles S. Gascon, and David E. Rapach. 2016. "Metro Business Cycles." *Journal of Urban Economics* 94:90-108.

Aruoba, S. Borağan, Francis X. Diebold, and Chiara Scotti. 2009. "Real-Time Measurement of Business Conditions." *Journal of Business & Economic Statistics* 27 (4):417-427.

Bańbura, Marta and Michele Modugno. 2014. "Maximum Likelihood Estimation of Factor Models on Datasets with Arbitrary Pattern of Missing Data." *Journal of Applied Econometrics* 29 (1): 133-160.

Baumeister, C., Leiva-León, D. and Sims, E., 2024. "Tracking weekly state-level economic conditions." *The Review of Economics and Statistics*, 106 (2): 483-504.

Baxter, Marianne and Robert G. King. 1999. "Measuring Business Cycles: Approximate Band-Pass Filters for Economic Time Series." *The Review of Economics and Statistics* 81 (4): 575-593.

Beveridge, Stephen and Charles R. Nelson. 1981. "A New Approach to Decomposition of Economic Time Series into Permanent and Transitory Components with Particular Attention to Measurement of the 'Business Cycle'." *Journal of Monetary Economics* 7 (2): 151-174.

Burns, Arthur F. and Wesley C. Mitchell. 1946. *Measuring Business Cycles*. New York, NY: National Bureau of Economic Research.

Chetty, Raj, John N. Friedman, Michael Stepner, and The Opportunity Insights Team. 2023. "The Economic Impacts of COVID-19: Evidence from a New Public Database Built Using Private Sector Data." NBER Working Paper 27431.

Crone, Theodore M. and Alan Clayton-Matthews. 2005. "Consistent Economic Indexes for the 50 States." *The Review of Economics and Statistics* 87 (4):593-603.

Eo, Yunjong and Chang-Jin Kim. 2016. "Markov-Switching Models with Evolving Regime-Specific Parameters: Are Postwar Booms or Recessions All Alike?" *The Review of Economics and Statistics* 98 (5): 940-949.

Fernández, Carmen, Eduardo Ley, and Mark F.J. Steel. 2001. "Model Uncertainty in Cross-Country Growth Regressions." *Journal of Applied Econometrics* 16 (5): 563-576.

Hamilton, James D. 1989. "A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle." *Econometrica* 57 (2): 357-384.

------------------------ 2018. "Why You Should Never Use the Hodrick-Prescott Filter." *The*

Review of Economics and Statistics 100 (5): 831-843.

Hodrick, Robert J. and Edward C. Prescott. 1997. "Postwar U.S. Business Cycles: An Empirical Investigation." *Journal of Money, Credit, and Banking* 29 (1): 1-16.

Kamber, Güneş, James Morley, and Benjamin Wong. 2018. "Intuitive and Reliable Estimates of the Output Gap from a Beveridge-Nelson Filter." *The Review of Economics and Statistics* 100 (3): 550-566.

Koop, Gary. 2003. *Bayesian Econometrics*. West Sussex, England: John Wiley & Sons, Ltd.

Mariano, Roberto S. and Yasutomo Murasawa. 2003. "A New Coincident Index of Business Cycles Based on Monthly and Quarterly Series." *Journal of Applied Econometrics* 18 (4): 427–443.

Morley, James and Jeremy Piger. 2012. "The Asymmetric Business Cycle." *The Review of Economics and Statistics* 94 (1):208-221.

Motie, Golnaz Baradaran and Christopher Biolsi. 2021. "County-Level Determinants of Social Distancing (or Lack Thereof) during the COVID-19 Pandemic." *Contemporary Economic Policy* 39 (2): 264-279.

Newey, Whitney K. and Kenneth D. West. 1987. "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix." *Econometrica* 55 (3): 703-708.

Stock, James H. and Mark W. Watson. 1989. "New Indexes of Coincident and Leading Economic Indicators." *NBER Macroeconomics Annual* 4: 351-394.

---. 1991. "A Probability Model of the Coincident Economic Indicators." In *Leading Economic Indicators: New Approaches and Forecasting Records*, edited by Kajal Lahiri and Geoffrey H. Moore. Cambridge University Press, 63-89.

A. Appendix Tables and Figures

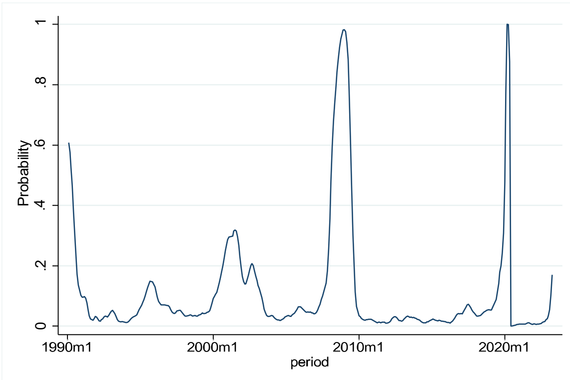
Table A1: List of Metropolitan and Micropolitan Statistical Areas With Presence in Kentucky

Metropolitan Statistical Areas	
Bowling Green, KY	Huntington-Ashland, WV-KY-OH
Cincinnati, OH-KY-IN	Lexington-Fayette, KY
Clarksville, TN-KY	Louisville/Jefferson County, KY-IN
Elizabethtown-Fort Knox, KY	Owensboro, KY
Evansville, IN-KY	

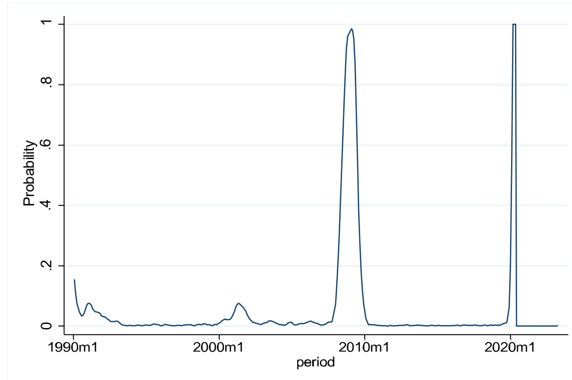
Micropolitan Statistical Areas	
Bardstown, KY	Mayfield, KY
Campbellsville, KY	Maysville, KY
Central City, KY	Middlesborough, KY
Danville, KY	Mount Sterling, KY
Frankfort, KY	Murray, KY
Glasgow, KY	Paducah, KY-IL
London, KY	Richmond-Berea, KY
Madisonville, KY	Somerset, KY

Notes: This table lists the nine metropolitan statistical areas and sixteen micropolitan statistical areas analyzed in the study.

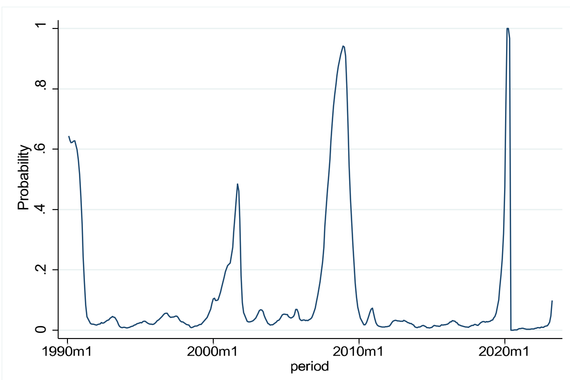
Figure A1: Estimated Probability of Recession in Kentucky Metropolitan and Micropolitan Statistical Areas



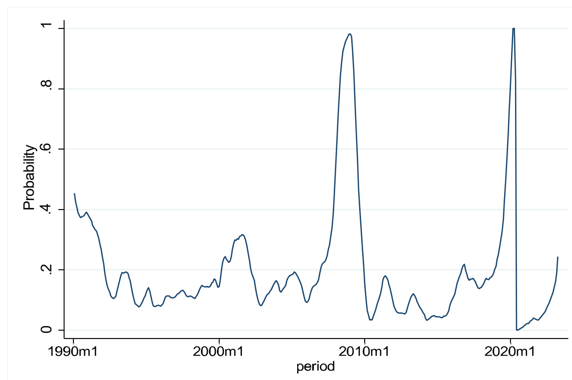
(a) Bowling Green, KY



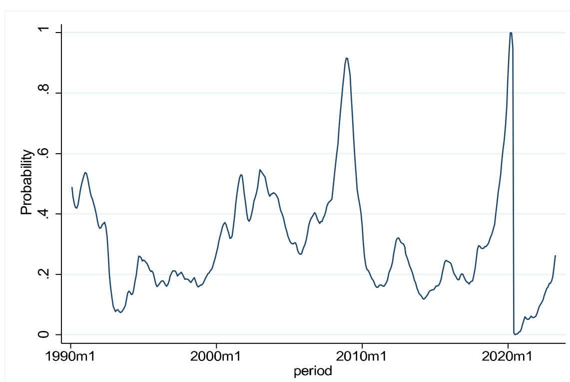
(b) Cincinnati, OH-KY-TN



(c) Clarksville, TN-KY



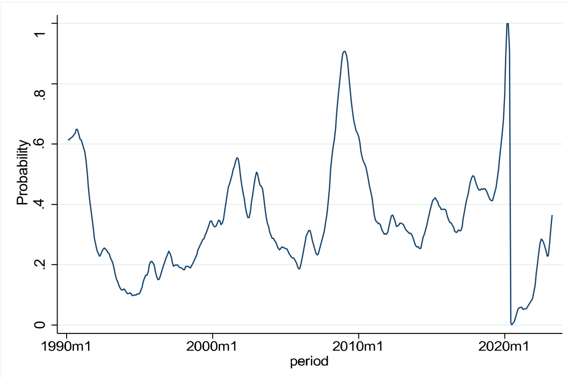
(d) Elizabethtown-Fort Knox, KY



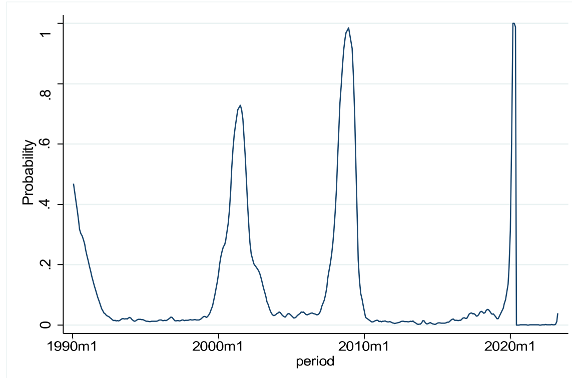
(e) Evansville, IN-KY

Notes: Each panel reports the estimated probability of being in recession in each period for the named metropolitan or micropolitan statistical area with a presence in Kentucky, based on the Markov Switching algorithm of Eo and Kim [2016].

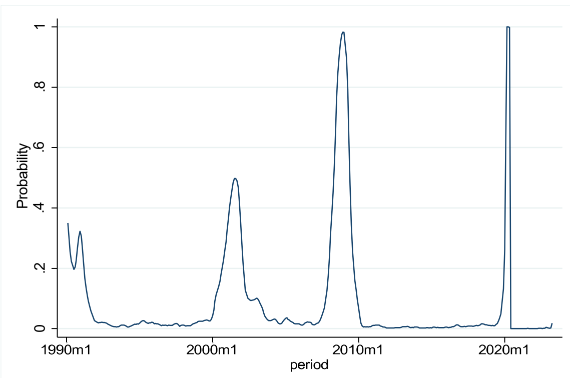
Figure A2: Estimated Probability of Recession in Kentucky Metropolitan and Micropolitan Statistical Areas



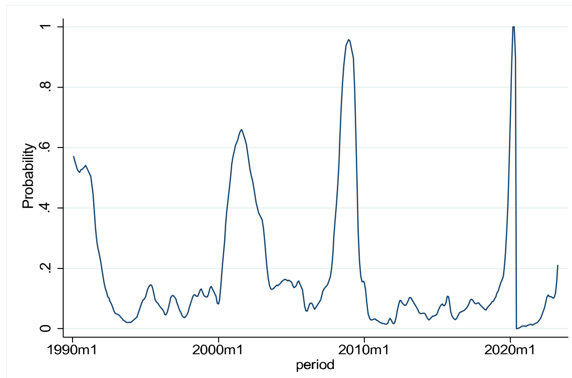
(a) Huntington-Ashland, WV-KY-OH



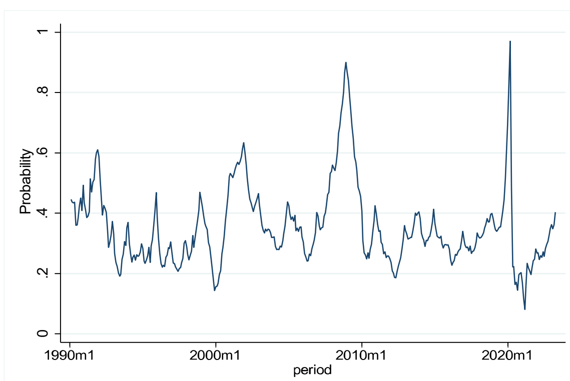
(b) Lexington-Fayette, KY



(c) Louisville/Jefferson County, KY-IN



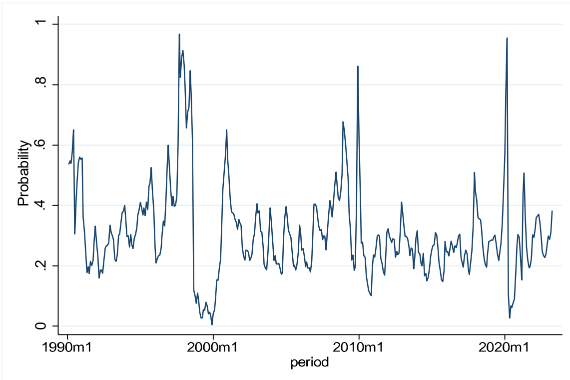
(d) Owensboro, KY



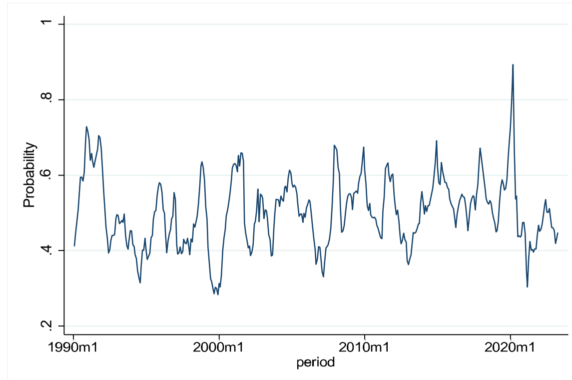
(e) Bardstown, KY

Notes: Each panel reports the estimated probability of being in recession in each period for the named metropolitan or micropolitan statistical area with a presence in Kentucky, based on the Markov Switching algorithm of Eo and Kim [2016].

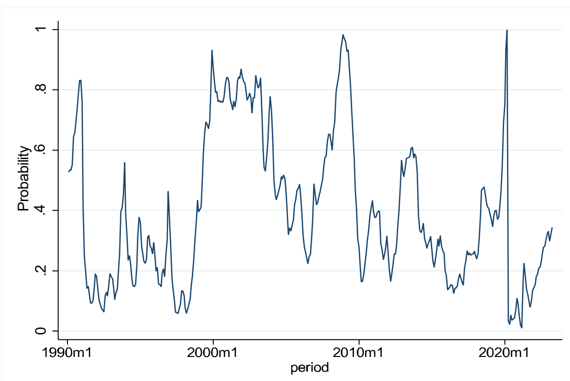
Figure A3: Estimated Probability of Recession in Kentucky Metropolitan and Micropolitan Statistical Areas



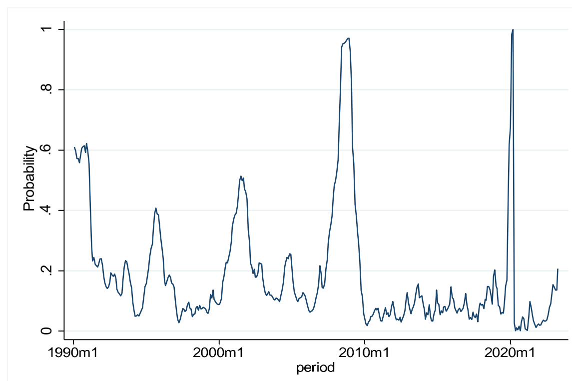
(a) Campbellsville, KY



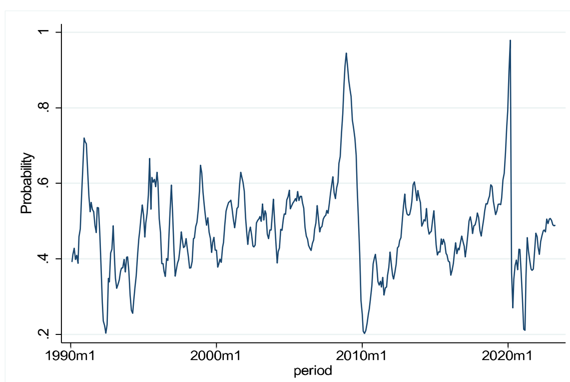
(b) Central City, KY



(c) Danville, KY



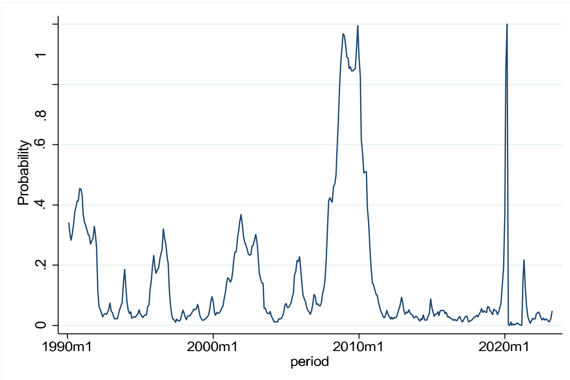
(d) Frankfort, KY



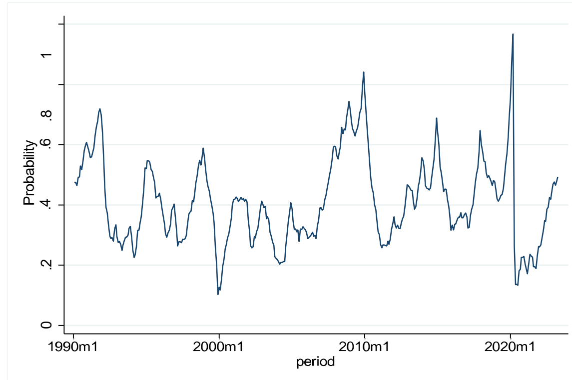
(e) Glasgow, KY

Notes: Each panel reports the estimated probability of being in recession in each period for the named metropolitan or micropolitan statistical area with a presence in Kentucky, based on the Markov Switching algorithm of Eo and Kim [2016].

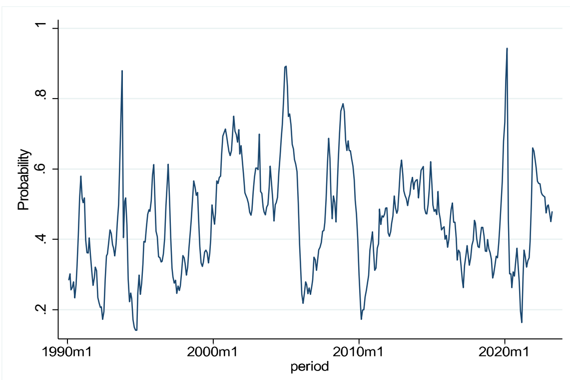
Figure A4: Estimated Probability of Recession in Kentucky Metropolitan and Micropolitan Statistical Areas



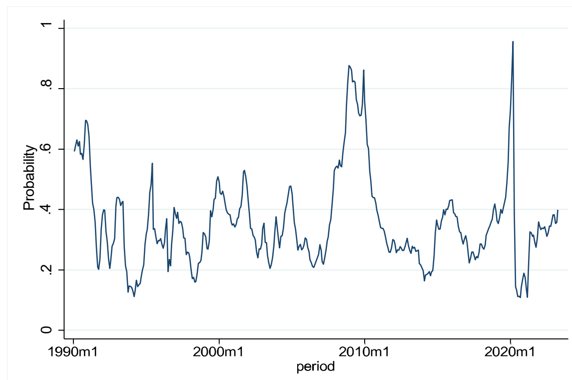
(a) London, KY



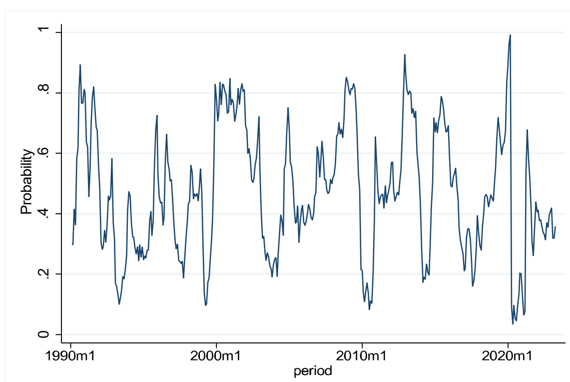
(b) Madisonville, KY



(c) Mayfield, KY



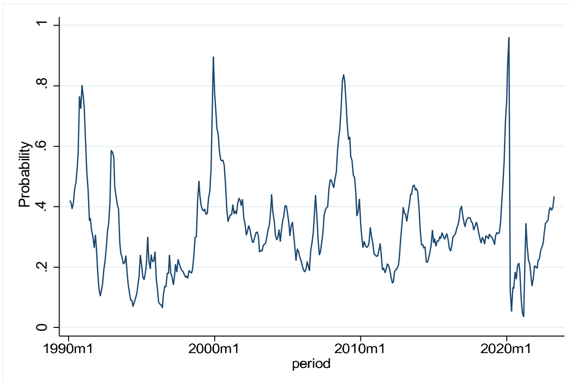
(d) Maysville, KY



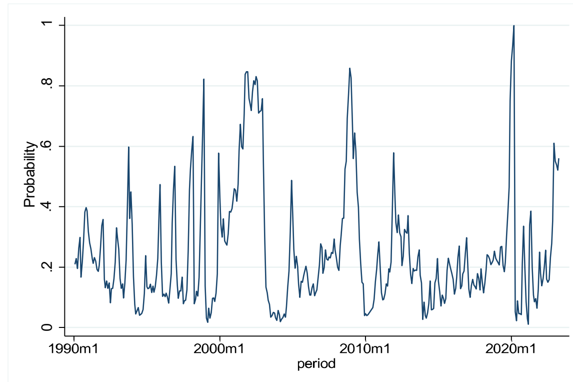
(e) Middlesborough, KY

Notes: Each panel reports the estimated probability of being in recession in each period for the named metropolitan or micropolitan statistical area with a presence in Kentucky, based on the Markov Switching algorithm of Eo and Kim [2016].

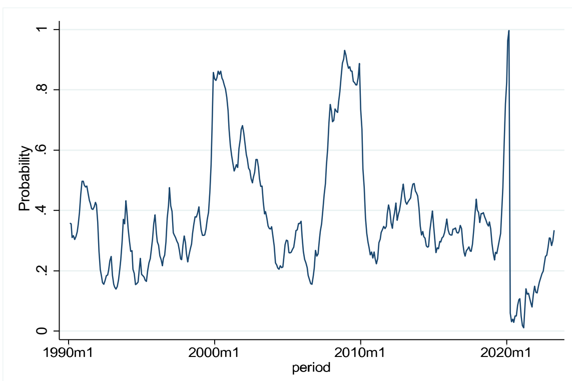
Figure A5: Estimated Probability of Recession in Kentucky Metropolitan and Micropolitan Statistical Areas



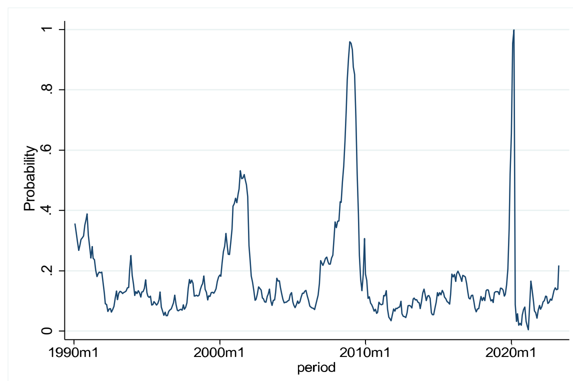
(a) Mount Sterling, KY



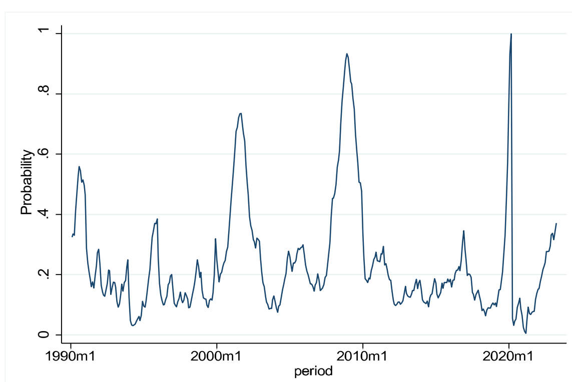
(b) Murray, KY



(c) Paducah, KY-IL



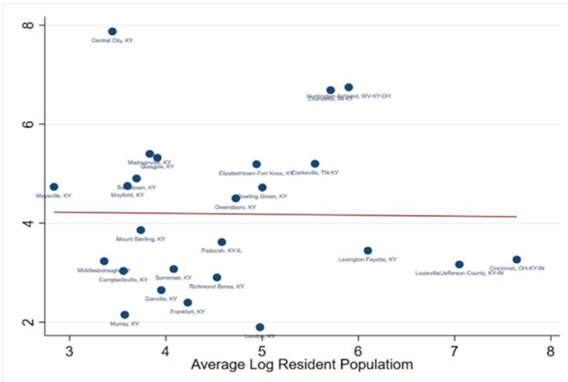
(d) Richmond-Berea, KY



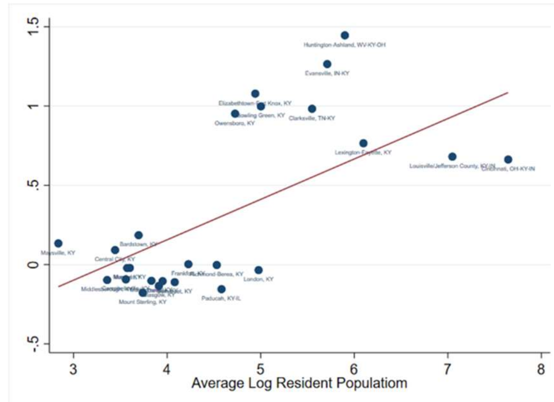
(e) Somerset, KY

Notes: Each panel reports the estimated probability of being in recession in each period for the named metropolitan or micropolitan statistical area with a presence in Kentucky, based on the Markov Switching algorithm of Eo and Kim [2016].

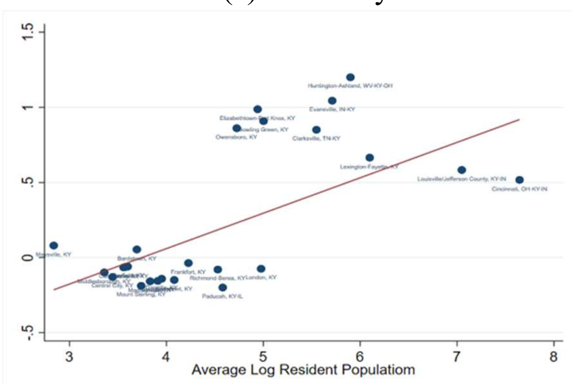
Figure A6: Relationship of Average Population with Index Metrics



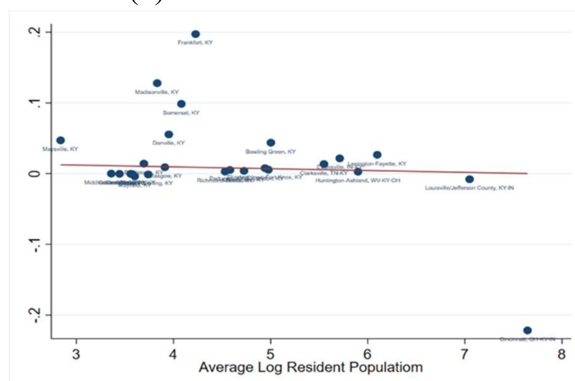
(a) Volatility



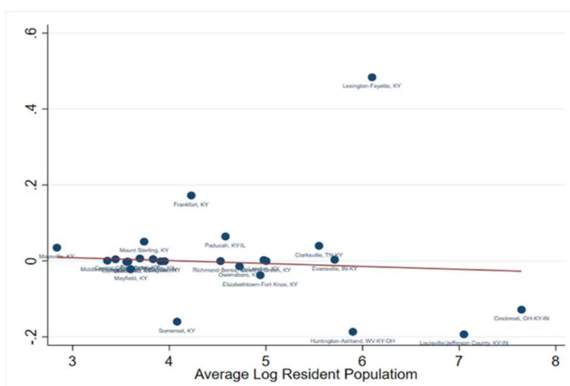
(b) Coefficient on U.S. Growth



(c) Coefficient on State Growth



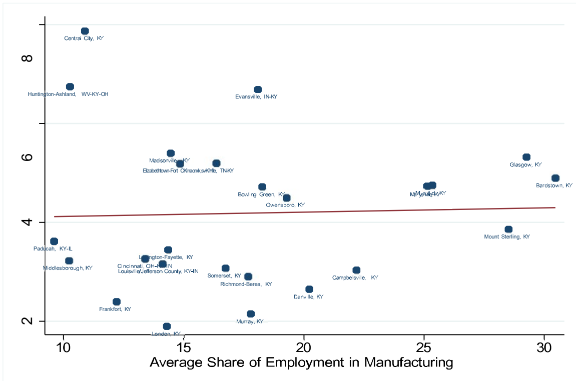
(d) Coefficient for One-Month-Ahead State Growth



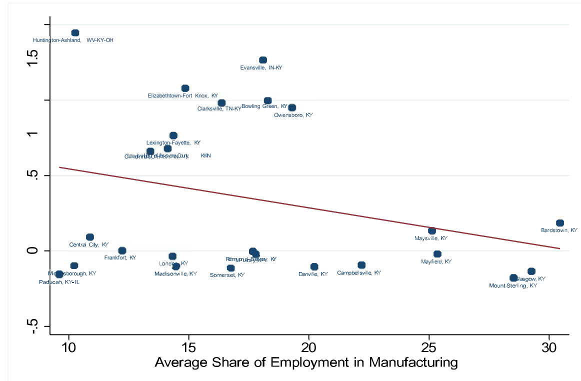
(e) Coefficient for One-Year-Ahead State Growth

Notes: Each panel in the figure scatters the statistic named in the caption against the log average population over the sample period in each city. With the exception of the output gap volatility, each city's observation is weighted by the inverse of the standard error of its coefficient.

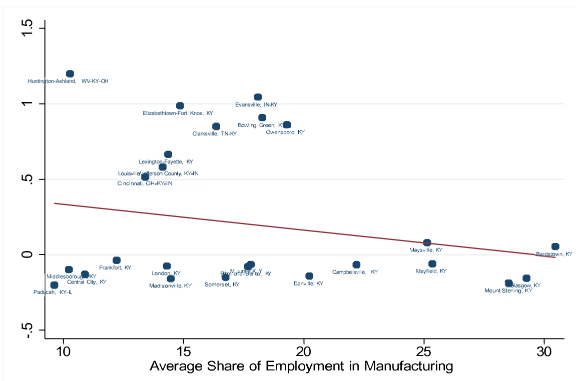
Figure A7: Relationship of Average Manufacturing Share with Index Metrics



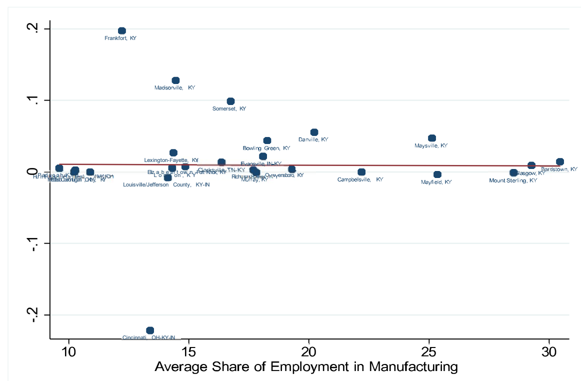
(a) Volatility



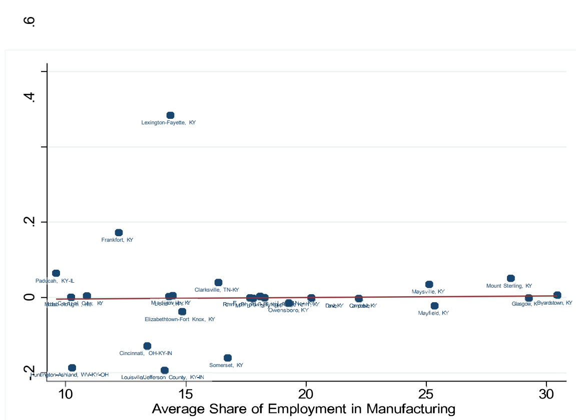
(b) Coefficient on U.S. Growth



(c) Coefficient on State Growth



(d) Coefficient for One-Month-Ahead State Growth



(e) Coefficient for One-Year-Ahead State Growth

Notes: Each panel in the figure scatters the statistic named in the caption against the average share of workers employed in manufacturing over the sample period in each city. With the exception of the output gap volatility, each city's observation is weighted by the inverse of the standard error of its coefficient.

Estimating the Great Recession Effects on Wages and Returns to Schooling Among Occupations: Evidence from Kentucky

Yanan Chen*

Kyle A. Kelly♦

Abstract

This paper examines the effects of the Great Recession on the average annual wage income and the rate of return to schooling in nineteen occupations in Kentucky. Using data from American Community Survey 2002-2019, we find that the changes in the average annual wage income and the rate of return to schooling differ among occupations during and after the Great Recession. The difference in the effects on the rate of return to schooling among occupations can be explained by the changes in the wage gap between high-educated and low-educated workers during and after the recession.

JEL codes: J24, J30

Keywords: Great Recession; Wage Gap; Micer's Earnings Equation

* Corresponding author. Department of Economics and Finance, West Chester University, 700 South High Street, West Chester, PA 19383. ychen@wcupa.edu

♦ Department of Economics and Finance, West Chester University, 700 South High Street, West Chester, PA 19383. kkelly2@wcupa.edu

I. Introduction

The Great Recession was the most severe downturn in the U.S. economy since the 1930s. In December 2007, at the start of the recession, the U.S. unemployment rate was 5.0 percent. While the National Bureau of Economic Research dates the end of the recession in June 2009, the unemployment rate did not reach its peak of 10.0 percent until October 2009. The overall trend of Kentucky's unemployment rate was similar to the entire economy. Its unemployment stood at 5.4 percent in December 2007 and hit a peak of 11.2 percent in June 2009.

We explore how wages and the rate of return to schooling in different occupations were affected by the Great Recession in Kentucky. The rate of return to schooling measures the returns that individuals receive from investing in human capital. It can be empirically estimated as the percentage increase in wage by one more year of schooling given in Mincer's earnings equation [Mincer, 1974]. It is expressed as:

$$lnY_{it} = \alpha_0 + r_s S + \alpha_1 t + \alpha_2 t^2 + \varepsilon_{it} \qquad (1)$$

where lnY_{it} is the logarithm term of an individual i's earnings at year t, S is the individual's total years of schooling, t is the individual's potential work experience, and ε_{it} is the error term. The estimated coefficient associated with the total years of schooling, r_s, represents the average return of an additional year of schooling.

According to the analysis in Reder [1955] and Welch [1979], the wage of unskilled workers is more sensitive to cyclical unemployment than that of the skilled ones. During a recession, wages of unskilled workers are expected to decline by more than wages of skilled workers, which may change the wage differential between skilled and unskilled workers and thus change the rate of return to schooling. A rising unemployment is one indicator that is associated with a recession.

Numerous empirical studies have found a relationship between the unemployment rate and the rate of return to schooling. For example, Kniesner, Padilla and Polachek [1978; 1980] use cross- sectional data from NLS 1967 and 1970 and find that macroeconomic conditions such as unemployment are important determinants of the rate of return to schooling. They find that the relative rate of return to schooling between young Whites and young Blacks is affected by unemployment. During recessions, Blacks fare relatively worse than Whites. King [1980] find similar results. Using NLS data in 1968 and 1971, he finds that the cross-sectional rate of return is positively related to the unemployment rate. Using data from American Community Survey 2000-2017, Chen and Kelly [2020] show that unemployment has positive effects on the rate of return to schooling. The returns to schooling are expected to increase in recessions and decrease in expansions for both men and women.

The macroeconomic effects on returns to schooling have been found in other countries. For example, Psacharopoulos, et al. [1996] show the returns to education are positively related to economic conditions in Mexico. Returns decline during an economic recession and rise again as economic growth resumes and remain high even after a significant expansion of the educational system. Oreopoulos, et al. [2012] find the long-term impact of graduating during a recession is greater for lower skill graduates in Canada.

Previous studies analyze the effects of the Great Recession on the rate of return to schooling. Belfield [2015] finds the returns to schooling for young workers increased in the quarters following the Great Recession in Arkansas. Chen and Kelly [2019] focus on the gender difference in the rate of return to schooling during the Great Recession. They find that the rate of return to schooling for men and women increased during Great Recession, and the gender difference in the returns to schooling decreased in the post-recession period. Chen and Kelly [2017a] find that the female-male difference in the returns to schooling decreased in the post-recession period in Pennsylvania. They also find a positive gap in the White-Black rate of return to schooling in New York, and the gap increased during and after the period of the Great Recession [Chen and Kelly, 2017b].

This paper investigates the effects of the Great Recession on the average annual wage income and the rate of return to schooling in nineteen occupations in Kentucky. We explore the effects by estimating a basic Mincer earnings equation. We use data from 2002 to 2019 from the American Community Survey. This allows us to compare the rate of return to schooling for all occupations both before and after the Great Recession. It also avoids the recession in 2000-2001 so we can focus on the effects of the Great Recession only. Our results show the Great Recession had different effects on the average annual wage income and the rate of return among occupations. In addition, the changes in the average annual wage income and the rate of return were different among occupations in the post-recession years. We explore the difference by examining the wage gap between college and non-college workers in each occupation.

The remainder of the paper is organized as follows. Section II presents our regression model. Section III discusses the data. Section IV provides empirical results from examining the effects of the Great Recession on the annual wage income and the rate of return to schooling in different occupations in Kentucky. Section V explains the different effects of the Great Recession on wages and returns to schooling across occupations by exploring the wage gap between high- and low-educated workers. Section VI concludes.

II. Regression Model

The main purpose of our study is to examine the effects of the Great Recession on the annual wage income and the rate of return to schooling in different occupations in Kentucky. To analyze the problem, we create dummy variables to account for the Great Recession years (2008-2009) and the post-recession years (after 2009). We add dummy variables as well as their interaction terms with schooling in the basic Mincer earnings equation [Mincer, 1974]. The equation takes the following form

$$lnwage_{it} = \beta_0 + \beta_1 S_{it} + \beta_2 S_{it} R + \beta_3 S_{it} PR + \beta_4 R + \beta_5 PR + \gamma X_{it} + \alpha T + \varepsilon_{it} \quad (2)$$

where i is the individual index and t is the year index. $lnwage$ is the logarithm term of annual wage income. S is the schooling variable, which is defined as the individual's total years of education. R is the recession dummy variable, taking on the value of 1 for the Great Recession years, 2008 and 2009, and 0 for the other years. PR is the post-recession dummy variable, taking on the value of 1 for years after 2009, and 0 for the other years. The estimated coefficient of R indicates the difference in the annual wage income between the recession and pre-recession years, and the estimated coefficient of PR indicates the difference in the annual wage income between the post-recession and pre-recession years. $S \cdot R$ and $S \cdot PR$ are the interaction terms of the schooling variable with the recession and post-recession dummies. X_{it} denotes other explanatory variables that may affect the individual's annual wage income. T is a time trend. ε_{it} is the error term with its normal properties.

The rate of return to schooling, $RORS$, is given by the partial derivative of Equation (2):

$$RORS = \partial lnwage_{it}/\partial S = \beta_1 + \beta_2 R + \beta_3 PR \quad (3)$$

where β_1 is a measure of the rate of return to schooling in the pre-recession years. β_2 shows the difference in the rate of return to schooling between the recession and pre-recession periods. β_3 measures the difference in the rate of return to schooling between the post-recession and pre- recession periods. The regression model is applied to all occupations.

III. Data

We select our sample from the American Community Survey (ACS). The ACS is the U.S.

census microdata that are collected, preserved, and harmonized by Integrated Public Use Microdata Series [Ruggles, et al., 2015]. The ACS is an ongoing annual statistical survey that is conducted by the U.S. Census Bureau. It is also the largest survey after the decennial census survey and provides us with enough observations before and after the Great Recession. More importantly, our primary interest is to examine the Great Recession effects on the rate of return to schooling in different occupations. The ACS provides such information on U.S. individuals' occupation. It also gathers information on U.S. households and individuals such as demographics, wage and salary income, education background, employment status, work history, and family interrelationship.

Our sample contains observations from 2002 to 2019. It gives us enough time range to analyze the years before and after the Great Recession. It also avoids the recession in 2000 and 2001 so we can focus on the effects of the Great Recession only. We restrict our sample to individuals between the ages of 18 and 60 who live in Kentucky in each survey year. We drop those individuals who report an unidentified occupation, who have no salary or wage income, who have zero work hours and who are currently attending school in each survey year. Our restricted sample is a pooled cross-section data that contains 297,786 observations.

The annual wage income is the individual's annual wage and salary income. All wage incomes are converted to 2019 dollars using the Consumer Price Index for all urban consumers. The schooling variable is defined as the person's total years of education, which is adjusted by the highest degree completed. The variables we choose as X_{it} in Equation (1) include potential work experience (computed as age – schooling - 6, assuming people go to school at age 6 and work right after school) and a work experience squared term, whether the person is female, the race dummies (whether the person is White and whether the person is Black), whether the person is married, number of children in the household, number of children under age 5 in the household, and the occupation of the respondent. We provide the definitions and the summary statistics of the main explanatory variables in Table 1.

Occupations are identified based on the Census Bureau's 2010 ACS occupation classification scheme. There are originally twenty-seven categories. We first exclude the workers who are unemployed (no occupation for 5+ years) or never worked, and then eliminate the workers in those occupations where Kentucky has a small percentage (less than 1 percent) of workers, such as architecture and engineering, technicians, life, physical, and social science, legal, farming, fishing, and forestry, extraction, and military specific. Our sample contains nineteen occupational categories. The distribution of all the occupational categories is reported in Table 1.

Table 1. Definition and Summary Statistics of the Main Variables

Variables	Definition	Mean (S.D.)
Wage	Annual labor income, adjusted to 2019 dollars	42923.76 (47148.77)
S	Total years of schooling	13.319 (2.270)
Exp	Potential years of work experience; =age-s-6	19.826 (12.296)
Female	=1 if the person is female; 0 otherwise	0.488 (0.500)
White	=1 if the person is White; 0 otherwise	0.904 (0.294)
Black	=1 if the person is Black; 0 otherwise	0.063 (0.243)
Married	=1 if the person is married or permanently cohabiting; 0 otherwise	0.583 (0.493)
Child	Number of own children in the household	0.823 (1.078)
Kid5	number of own children under age 5 in household	0.177 (0.475)
Occupation Variables		
MANG	Management, Business, Science, and Arts	0.081 (0.273)
BUSI	Business Operations Specialists	0.019 (0.137)
FINA	Financial Specialists	0.019 (0.136)
COMP	Computer and Mathematical	0.018 (0.131)
COMM	Community and Social Services	0.018 (0.132)
EDUC	Education, Training, and Library	0.066 (0.248)
ARTS	Arts, Design, Entertainment, Sports, and Media	0.012 (0.110)
HEAL	Healthcare Practitioners and Technicians	0.067 (0.250)
HSUP	Healthcare Support	0.023 (0.151)
PROT	Protective Service	0.020 (0.139)
FOOD	Food Preparation and Serving	0.055 (0.227)
BUIL	Building and Grounds Cleaning and Maintenance	0.032 (0.176)
PERS	Personal Care and Service	0.024 (0.154)
SALE	Sales and Related	0.099 (0.298)
OFFI	Office and Administrative Support	0.144 (0.351)
CONS	Construction	0.048 (0.214)
INST	Installation, Maintenance, and Repair	0.062 (0.187)
PROD	Production	0.097 (0.294)
TRAN	Transportation and Material Moving	0.077 (0.266)

Notes: Data source: American Community Survey 2002-2019

IV. Empirical Results

We start by examining the effects of the Great Recession on the average annual wage income and the rate of return to schooling for Kentucky workers using Equation (2). To tease out the effects of occupations within the same industry category, we use industry fixed effects estimation. We code our industry categories according to the North American Industrial

Classification System (INDNAICS). The results for the entire sample are reported in Table 2-1 Column 1. The estimated recession dummy, R, and the estimated post-recession dummy, PR, are both negative and statistically significant at the 1% level. It suggests that compared to the pre-recession years, the average annual wage income of Kentucky workers during and after the Great Recession was lower. The estimated schooling coefficient is 0.116 and is statistically significant at the 1% level, showing that in the pre-recession years, each additional year of schooling would increase the annual wage income by an average of 11.6% for Kentucky workers. The estimated coefficient of the schooling and recession dummy interactive term, $S * R$, is 0.016 and is statistically significant at the 1% level. This indicates that the rate of return to schooling for Kentucky workers increased by an average of 1.6 percentage points in the recession years. The estimated coefficient of the schooling and the post-recession dummy interactive term, $S * PR$, is 0.007 and is statistically significant at the 1% level. Compared to pre-recession years, the rate of return to schooling for Kentucky workers increased by an average of 0.7 percentage points after the recession.

We then analyze the Great Recession effects on the average annual wage income and the rate of return to schooling for each occupation using Equation (2). The results are reported in Table 2-1 Column 2 to Column 10 and Table 2-2. The sign on the coefficient for the recession dummy, R, is negative and statistically significant for five occupations: COMM (community and social services), EDUC (education, training, and library), HEAL (healthcare practitioners and technicians), PROT (protective service), and PROD (production). Wages for these five occupations declined during the recession. In contrast, the average annual wage income for workers in occupation INST (installation, maintenance, and repair) increased during the recession, given by the positive and significant estimated coefficient on the recession dummy, R. For the rest of the occupations, there is no statistical evidence showing the Great Recession has effects on their average annual wage income. In the post-recession years, the coefficient on PR is negative and significant for MANG (management, business, science, and arts), BUSI (business operations specialists), COMP (computer and mathematical), HEAL (healthcare practitioners and technicians), HSUP (healthcare support), PROT (protective service), but positive and significant for FOOD (food preparation and serving), INST (installation, maintenance, and repair), PROD (production), and TRAN (transportation and material moving).

For all nineteen occupations in Kentucky, the estimated rates of return to schooling are positive and statistically significant at the 1% level in the pre-recession years, given by the estimated coefficient of schooling, S. The top five occupations with the highest rate of return to schooling are EDUC (education, training, and library), SALE (sales and related), ARTS (arts, design, entertainment, sports, and media), COMP (computer and mathematical), and FINA (financial specialists). In the pre-recession years, each additional year of schooling in those five occupations would increase the annual wage income by an average of 21.0%, 17.2%, 16.6%, 14.6% and 14.2%, respectively. The five occupations with the smallest rate of return to schooling are HSUP (healthcare support), BUSI (business operations specialists), OFFI (office and administrative support), PERS (personal care and service), and BUIL (building and grounds cleaning and maintenance). Each additional year of schooling in the pre-recession years increases annual wage income by an average of 8.6%, 8.8%, 9.1%, 9.3%, and 10.1%, respectively.

The effects of the Great Recession on the rate of return to schooling differ among occupations. The estimated coefficient of the schooling and recession dummy interaction term, $S * R$, is positive and statistically significant for the following four occupations: COMM (community and social services), EDUC (education, training, and library), HEAL (healthcare practitioners and technicians), and PROT (protective service). In those occupations, the rate of return to schooling increased by an average of 5.5, 5.6, 7.0 and 5.1 percentage points in the recession years, respectively. The Great Recession reduced the returns to schooling for the following three occupations: FOOD (food preparation and serving), CONS (construction), and INST (installation, maintenance, and repair), given by the negative and statistically significant estimated coefficient of $S * R$. In the recession years, the rate of return to schooling decreased by an average of 5.4, 2.3 and 6.1 percentage points in those occupations, respectively.

The changes in the rate of return to schooling are also different among occupations in the post-recession years. The estimated coefficient of schooling and post-recession dummy, $S * PR$, is positive and statistically significant for the occupations of BUSI (business operations specialists), EDUC (education, training, and library), and HEAL (healthcare practitioners and technicians). For those occupations, the rate of return to schooling increased by an average of 2.9, 3.5 and 7.4 percentage points in the post-recession years. According to the negative and statistically significant estimated coefficient of $S * PR$, the rate of return to schooling decreased in the post-recession years for the following six occupations: FOOD (food preparation and serving),

Table 2-1. Estimated Effects of Great Recession on Annual Wage Income and Rate of Return to Schooling by Occupation

	(1) All	(2) MANG	(3) BUSI	(4) FINA	(5) COMP	(6) COMM	(7) EDUC	(8) ARTS	(9) HEAL	(10) HSUP
S	0.116***	0.136***	0.088***	0.142***	0.146***	0.124***	0.210***	0.166***	0.135***	0.086***
	(0.001)	(0.004)	(0.009)	(0.010)	(0.010)	(0.009)	(0.005)	(0.016)	(0.005)	(0.012)
S*R	0.016***	0.004	-0.002	-0.000	0.001	0.055***	0.056***	0.010	0.070***	-0.013
	(0.002)	(0.007)	(0.018)	(0.019)	(0.020)	(0.018)	(0.009)	(0.035)	(0.008)	(0.023)
S*PR	0.007***	0.003	0.029***	-0.005	-0.016	0.015	0.035***	0.012	0.074***	0.005
	(0.002)	(0.005)	(0.010)	(0.013)	(0.012)	(0.010)	(0.005)	(0.020)	(0.005)	(0.014)
R	-0.272***	-0.106	0.032	-0.046	-0.053	-0.942***	-0.847***	-0.141	-1.067***	0.149
	(0.033)	(0.109)	(0.263)	(0.289)	(0.296)	(0.277)	(0.149)	(0.508)	(0.127)	(0.292)
PR	-0.210***	-0.121*	-0.488***	-0.041	0.136	-0.359**	-0.552***	-0.318	-1.160***	-0.172
	(0.022)	(0.070)	(0.154)	(0.195)	(0.180)	(0.160)	(0.093)	(0.299)	(0.075)	(0.184)
Exp	0.079***	0.073***	0.072***	0.052***	0.082***	0.070***	0.084***	0.117***	0.078***	0.063***
	(0.001)	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.007)	(0.002)	(0.004)
Exp^2	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.002***	-0.002***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	-0.359***	-0.346***	-0.259***	-0.342***	-0.178***	-0.103***	-0.260***	-0.353***	-0.365***	-0.191***
	(0.004)	(0.010)	(0.021)	(0.022)	(0.024)	(0.022)	(0.016)	(0.040)	(0.014)	(0.034)
White	0.034***	0.099***	-0.015	0.279***	-0.101***	0.225***	0.172***	0.178*	-0.103***	0.178***
	(0.009)	(0.028)	(0.058)	(0.064)	(0.038)	(0.065)	(0.037)	(0.094)	(0.031)	(0.063)
Black	-0.065***	-0.065*	-0.065	0.221***	-0.147**	0.253***	0.328***	0.102	-0.053	0.289***
	(0.011)	(0.036)	(0.067)	(0.079)	(0.060)	(0.070)	(0.046)	(0.120)	(0.040)	(0.068)
Married	0.189***	0.166***	0.110***	0.199***	0.176***	0.090***	0.084***	0.191***	0.078***	0.076***
	(0.004)	(0.012)	(0.024)	(0.024)	(0.025)	(0.024)	(0.017)	(0.049)	(0.013)	(0.023)
Child	-0.005***	0.014***	0.004	-0.011	-0.000	-0.001	-0.067***	-0.042*	-0.006	-0.043***
	(0.002)	(0.005)	(0.013)	(0.012)	(0.013)	(0.012)	(0.008)	(0.025)	(0.006)	(0.012)
Kid5	0.076***	0.042***	0.100***	0.075***	0.059**	0.057**	0.127***	0.217***	0.086***	-0.056**
	(0.004)	(0.012)	(0.026)	(0.024)	(0.025)	(0.024)	(0.016)	(0.051)	(0.012)	(0.023)
Year	0.009***	0.006***	0.002	0.016***	0.011**	0.011**	0.000	0.004	0.003	0.017***
	(0.001)	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.008)	(0.002)	(0.004)
Constant	-10.753***	-4.469	5.462	-24.293***	-14.079	-14.355*	6.049	-1.473	2.771	-25.160***

Notes: Data source: American Community Survey: 2002-2019 Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 2-2. Estimated Effects of Great Recession on Annual Wage Income and Rate of Return to Schooling by Occupation

	(11) PROT	(12) FOOD	(13) BUIL	(14) PERS	(15) SALE	(16) OFFI	(17) CONS	(18) INST	(19) PROD	(20) TRAN
S	0.131***	0.127***	0.101***	0.093***	0.172***	0.091***	0.102***	0.141***	0.115***	0.124***
	(0.010)	(0.009)	(0.012)	(0.014)	(0.006)	(0.005)	(0.007)	(0.008)	(0.005)	(0.007)
S*R	0.051**	-0.034**	-0.029	-0.008	-0.012	0.005	-0.023*	-0.061***	0.011	-0.016
	(0.020)	(0.016)	(0.019)	(0.027)	(0.011)	(0.009)	(0.013)	(0.016)	(0.011)	(0.013)
S*PR	0.017	-0.049***	-0.035***	-0.015	-0.002	-0.006	-0.031***	-0.040***	-0.037***	-0.046***
	(0.013)	(0.011)	(0.013)	(0.016)	(0.007)	(0.006)	(0.009)	(0.010)	(0.007)	(0.008)
R	-0.650**	0.321	0.218	-0.019	0.065	-0.103	0.173	0.717***	-0.235*	0.018
	(0.268)	(0.197)	(0.227)	(0.342)	(0.139)	(0.117)	(0.159)	(0.203)	(0.133)	(0.157)
PR	-0.392**	0.511***	0.159	0.044	-0.093	-0.030	0.213*	0.414***	0.260***	0.272***
	(0.176)	(0.134)	(0.166)	(0.217)	(0.094)	(0.076)	(0.111)	(0.125)	(0.083)	(0.099)
Exp	0.118***	0.078***	0.080***	0.112***	0.105***	0.097***	0.065***	0.061***	0.067***	0.078***
	(0.004)	(0.003)	(0.004)	(0.005)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
Exp^2	-0.002***	-0.001***	-0.001***	-0.002***	-0.002***	-0.002***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	-0.458***	-0.218***	-0.557***	-0.345***	-0.659***	-0.200***	-0.625***	-0.283***	-0.418***	-0.467***
	(0.028)	(0.018)	(0.025)	(0.033)	(0.013)	(0.010)	(0.049)	(0.038)	(0.011)	(0.017)
White	0.244***	-0.086**	-0.048	-0.061	0.139***	0.130***	0.270***	0.063	0.086***	0.045
	(0.082)	(0.036)	(0.057)	(0.062)	(0.037)	(0.027)	(0.044)	(0.052)	(0.028)	(0.038)
Black	0.311***	-0.159***	-0.158**	-0.081	0.057	0.084***	-0.054	-0.092	-0.050	-0.178***
	(0.091)	(0.044)	(0.065)	(0.073)	(0.043)	(0.031)	(0.059)	(0.064)	(0.032)	(0.042)
Married	0.230***	0.005	0.298***	0.090***	0.234***	0.145***	0.401***	0.235***	0.249***	0.323***
	(0.027)	(0.022)	(0.027)	(0.033)	(0.015)	(0.010)	(0.019)	(0.018)	(0.012)	(0.015)
Child	-0.006	-0.042***	0.068***	-0.083***	-0.012	-0.030***	0.012	0.003	0.021***	0.011
	(0.013)	(0.011)	(0.014)	(0.018)	(0.008)	(0.005)	(0.009)	(0.009)	(0.006)	(0.008)
Kid5	0.131***	0.098***	0.012	0.116***	0.065***	0.102***	0.072***	0.058***	0.007	0.090***
	(0.025)	(0.022)	(0.031)	(0.034)	(0.015)	(0.012)	(0.019)	(0.019)	(0.013)	(0.016)
Year	0.008	0.012***	0.023***	0.020***	0.007***	0.006***	0.019***	0.004	0.012***	0.016***
	(0.005)	(0.004)	(0.005)	(0.006)	(0.003)	(0.002)	(0.004)	(0.003)	(0.002)	(0.003)
Constant	-8.141	-16.516**	-39.513***	-33.396***	-7.707	-3.530	-29.572***	0.119	-16.485***	-25.057***
	(9.589)	(7.210)	(10.150)	(11.480)	(5.327)	(3.808)	(7.034)	(6.621)	(4.496)	(5.536)
Obvs	5,911	16,299	9,579	7,208	29,374	42,758	14,343	10,824	28,985	22,880
R-squared	0.351	0.133	0.206	0.182	0.381	0.216	0.190	0.182	0.204	0.238

Notes: Data source: American Community Survey: 2002-2019 Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

BUIL (building and grounds cleaning and maintenance), CONS (construction), and INST (installation, maintenance, and repair), PROD (production), and TRAN (transportation and material moving). Compared to the pre-recession years, the rate of return to schooling for those six occupations decreased by an average of 4.9, 3.5, 3.1, 4.0, 3.7 and 4.6 percentage points in the post-recession years, respectively.

V. Explaining the Difference in Great Recession Effects on Returns to Schooling Among Occupations

Our results show that in Kentucky, the average annual wage income and the rate of return to schooling are affected differently among occupations by the Great Recession. In this section, we provide an explanation on the difference in the Great Recession effects on the rate of return to schooling in occupations. We argue that the Great Recession may affect occupations differently through their wage structures. Given the same number of years of schooling, the rate of return to schooling depends on the wage gap between the high-educated and the low-educated workers. The greater the wage gap, the greater returns to schooling. In general, recessions lower the annual wage income or slows down the growth rate of the annual wage income for both high- and low-educated workers. If a recession decreases more the average annual wage income for those with less schooling than for those with more schooling, the wage gap between the two educational groups would increase and thus the rate of return to schooling would increase during the recession.

In contrast, if the average annual wage income for workers with more schooling decreases by a greater amount than for those with less schooling during the recession, the wage gap would decrease and thus the returns to schooling would decrease in the recession years.

To test our hypothesis, we divide our sample into two subgroups by schooling years: non-college workers (schooling years less than 16) and college workers (16 years of schooling or more). For each occupation, we calculate the average annual wage income in pre-recession years (2002-2007), recession years (2008-2009) and post-recession years (2010-2019) for the two educational groups. We then calculate the percent change in the average annual wage income between pre-recession years and recession years, as well as pre-recession and post-recession years for both educational groups. The results are reported in Table 3. Overall, for all time periods and across all occupations, the average annual wage income of college workers was greater than that of non-college workers. In addition, the average annual wage income decreased for non-

Table 3. The Average Annual Wage Income and the Percent Change in Average Wage Income by Occupation and Educational Level

		Wage			% Change in Wage	
		Before Recession 2002-2007 (1)	Recession Years 2008-2009 (2)	After Recession 2010-2019 (2)	Between (1) and (2)	Between (1) and (3)
Total	Non-College	34192.41	33829.21	32556.98	-1.06%	-4.78%
	College	68477.55	70045.40	69223.57	2.29%	1.09%
MANG	Non-College	60152.00	58989.79	58218.80	-1.93%	-3.21%
	College	100619.00	101734.00	100078.1	1.11%	-0.54%
BUSI	Non-College	49181.86	52667.35	47138.95	7.09%	-4.15%
	College	69648.31	67926.26	69965.13	-2.47%	0.45%
FINA	Non-College	44695.21	46956.55	45464.98	5.06%	1.72%
	College	79704.45	77204.19	80942.34	-3.14%	1.55%
COMP	Non-College	53468.61	57656.51	54268.22	7.83%	1.50%
	College	76625.41	77711.70	79178.50	1.42%	3.33%
COMM	Non-College	30542.20	27897.53	28350.61	-8.66%	-7.18%
	College	44199.11	44791.16	43633.19	1.34%	-1.28%
EDUC	Non-College	18453.43	18883.89	17685.21	2.33%	-4.16%
	College	47159.63	48169.85	46308.15	2.14%	-1.81%
ARTS	Non-College	32178.53	29771.77	26984.98	-7.48%	-16.14%
	College	49312.67	56626.78	50563.12	14.83%	2.54%
HEAL	Non-College	42870.84	43705.11	41171.02	1.95%	-3.96%
	College	89735.65	100696.50	95103.88	12.21%	5.98%
HSUP	Non-College	22107.89	22736.65	22975.50	2.84%	3.92%
	College	37396.70	29789.86	37280.93	-20.34%	-0.31%
PROT	Non-College	35996.81	37526.12	32237.34	4.25%	-10.44%
	College	55597.39	59287.97	53611.72	6.64%	-3.57%
FOOD	Non-College	13302.78	12761.96	12963.42	-4.07%	-2.55%
	College	24230.55	17910.17	19086.82	-26.08%	-21.23%
BUIL	Non-College	21698.55	21317.08	21512.57	-1.76%	-0.86%

	College	35468.35	35194.05	31929.51	-0.77%	-9.98%

Table 3. The Average Annual Wage Income and the Percent Change in Average Wage Income by Occupation and Educational Level (continued)

		Wage			% Change in Wage	
		Before Recession 2002-2007 (1)	Recession Years 2008-2009 (2)	After Recession 2010-2019 (2)	Between (1) and (2)	Between (1) and (3)
PERS	Non-College	16395.39	14540.72	16014.38	-11.31%	-2.32%
	College	25561.90	36876.05	24566.23	44.26%	-3.90%
SALE	Non-College	30817.81	29208.75	27837.27	-5.22%	-9.67%
	College	75819.79	70700.55	77768.46	-6.75%	2.57%
OFFI	Non-College	29317.56	30081.64	28341.40	2.61%	-3.33%
	College	39037.63	38816.83	38812.16	-0.57%	-0.58%
CONS	Non-College	39463.04	39725.41	39541.06	0.66%	0.20%
	College	55026.15	63927.94	56249.49	16.18%	2.22%
INST	Non-College	47367.30	46681.44	46836.14	-1.45%	-1.12%
	College	58655.94	58255.30	59178.32	-0.68%	0.89%
PROD	Non-College	39337.59	39228.46	37581.91	-0.28%	-4.46%
	College	59693.66	55407.04	52794.04	-7.18%	-11.56%
TRAN	Non-College	35004.73	33805.14	32714.92	-3.43%	-6.54%
	College	78106.21	82791.95	63798.38	6.00%	-18.32%

Notes: Data source: American Community Survey: 2002-2019 college workers but increased for college workers in the recession and post-recession years.

The last two columns in Table 3 report the percent change in annual wage income between pre-recession years and recession years, and between pre-recession and post-recession years for non-college workers and college workers, respectively. For all workers, the wage gap between college and non-college increased in the recession and post-recession years, which should increase the rate of return to schooling during and after the recession. This is consistent with what we reported in Table 2. For COMM (community and social services) workers, the average annual wage income decreased by 8.66% for non-college workers and increased by 1.34% for college workers in the recession years, which increased the wage gap between the two groups and thus increased the rate of return in this occupation during the Great Recession. For EDUC (education, training, and library) workers, the increase in the average annual wage income of college workers (4.35%) was greater than that of non-college ones (2.33%). The wage gap between the two groups increased and therefore also increased the rate of return for this occupation in the recession years. Similar results are also found for workers in HEAL (healthcare practitioners and technicians), and PROT (protective service). For workers in the occupations of FOOD (food preparation and serving), as well as INST (installation, maintenance, and repair), the decrease in the average annual wage income of college workers was greater than that of non-college ones. The wage gap between the two educational groups decreased, which explains a decrease in their rate of return to schooling during the Great Recession as we observed in Table 2.

The change in the rate of return to schooling in the post-recession years can also be explained by changes in the wage gap between college and non-college workers. For occupations BUSI (business operations specialists), EDUC (education, training, and library), and HEAL (healthcare practitioners and technicians), the average annual wage income decreased for non-college workers and increased for college ones, which increased the wage gap and thus increased the rate of return to schooling. For occupations of FOOD (food preparation and serving), BUIL (building and grounds cleaning and maintenance), PROD (production), and TRAN (transportation and material moving), the average annual wage income decreased for both college and non-college workers. However, the decrease in average annual wage income for college workers was greater than for non-college ones, which decreased the wage gap and therefore decreased workers' rate of return to schooling in those occupations.

VI. Conclusion

We analyze the effects of the Great Recession on the average annual wage income and the rate of return to schooling in nineteen occupations in Kentucky from 2002 to 2019 using the American Community Survey. Our findings are as follows. First, the Great Recession had different effects on the average annual wage income among occupations. The Great Recession significantly decreased the average annual wage income for workers in occupations of COMM (community and social services), EUDC (education, training, and library), HEAL (healthcare practitioners and technicians), PROT (protective service), and PROD (production), while it significantly increased the average annual wage income of workers in INST (installation, maintenance, and repair). Second, the rate of return to schooling in different occupations changed differently during the recession years. The Great Recession significantly increased the rate of return to schooling for the occupations of COMM (community and social services), EDUC (education, training, and library), HEAL (healthcare practitioners and technicians), and PROT (protective service), and decreased workers' returns to schooling in occupations of FOOD (food preparation and serving), CONS (construction), and INST (installation, maintenance, and repair).

Furthermore, the changes in the average annual wage income and the rate of return to schooling were also different among occupations in the post-recession years. The average annual wage income after the recession was lower for MANG (management, business, science, and arts), BUSI (business operations specialists), COMP (computer and mathematical), HEAL (healthcare practitioners and technicians), HSUP (healthcare support), PROT (protective service), but higher for FOOD (food preparation and serving), INST (installation, maintenance, and repair), PROD (production), and TRAN (transportation and material moving). The rate of return to schooling after the recession was higher for occupations of BUSI (business operations specialists), EDUC (education, training, and library), and HEAL (healthcare practitioners and technicians), and lower for the occupations of FOOD (food preparation and serving), BUIL (building and grounds cleaning and maintenance), CONS (construction), and INST (installation, maintenance, and repair), PROD (production), and TRAN (transportation and material moving).

We explain the difference in the returns to schooling by examining the wage gap between high-educated and low-educated workers. We separate all the workers into college and non-college groups. Given the same years of schooling, the rate of return to schooling should increase as the wage gap between the two educational groups increases, and vice versa. The Great Recession increased the wage gap between college and non-college workers for COMM (community and social services), EDUC (education, training, and library), HEAL (healthcare practitioners and technicians), PROT (protective service). Therefore, the rate of return in those occupations increased during the recession years. For workers in FOOD (food preparation and serving), and INST (installation, maintenance, and repair), the wage gap between the two educational groups decreased and thus the rate of return to schooling decreased. The results are consistent with our findings in Table 2. In the post-recession years, the changes in the rate of return to schooling in different occupations can also be explained by the changes in the wage gap between college and non-college workers in occupations.

References

Belfield, Clive. 2015. "Weathering the Great Recession with Human Capital? Evidence on Labor Market Returns to Education from Arkansas." CAPSEE Working Paper: 1-40.

Chen, Yanan, and Kyle A. Kelly. 2017a. "The Impact of the Great Recession on the Gender Difference in the Rate of Return to Schooling in Pennsylvania." *Pennsylvania Economic Review* 24(2): 31-45.

Chen, Yanan, and Kyle A. Kelly. 2017b. "The Great Recession Effects on Hourly Wages and the Rate of Return to Schooling between Whites and Blacks in New York." *New York Economic Review* 48: 3-20.

Chen, Yanan, and Kyle A. Kelly. 2019. "The Gender Difference in Hourly Wage and the Returns to Schooling over the Great Recession in the U.S." *Research in Economics* 73(2): 190-198.

Chen, Yanan, and Kyle A. Kelly. 2020. "Rate of Return to Schooling and Business Cycles." *Applied Economics* 52(34).

Kniesner, Thomas J., Arthur H. Padilla, and Solomon W. Polachek. 1978. "The Rate of Return to Schooling and the Business Cycles." *Journal of Human Resources*, Spring 1978: 264-277.

Kniesner, Thomas J., Arthur H. Padilla, and Solomon W. Polachek. 1980. "The Rate of Return to Schooling and the Business Cycles: Additional Estimates." *Journal of Human Resources*, Spring 1980: 273-277.

King, Randall H. 1980. "Some Further Evidence on the Rate of Return to Schooling and Business Cycles." *Journal of Human Resources*, Spring 1980: 264-272.

Mincer, Jacob. 1974. *Schooling, Experience, and Earnings*. New York: National Bureau of Economic Research and Columbia University Press.

Oreopoulos, Phillip, Till von Wachter, and Andrew Heisz. 2012. "The Short- and Long-Term Career Effects of Graduating in a Recession." *Applied Economics* 4(1): 1-29.

Psacharopoulos, George, Eduardo Velez, Alex Panagides, and Hongyu Yang. 1996. "The Returns to Education during Boom and Recession: Mexico 1984, 1989 and 1992." *Education Economics*

4(3): 219-230.

Reder, M. W. 1955. "The Theory of Occupational Wage Differentials." *American Economic Review* 45(5): 833-852.

Ruggles, Steve, Katie Genadek, Ronald Goeken, Josiah Grover, and Matthew Sobek. 2015. "Integrated Public Use Microdata Series: Version 6.0 [dataset]." Minneapolis, MN: University of Minnesota. http://doi.org/10.18128/D010.V6.0.

Welch, Finis. 1979. "Effects of Cohort Size on Earnings: The Baby Boom Babies' Financial Bust." *Journal of Political Economy* 87(5): 65-97

Evaluation of a Community-Based Food Program Support Project

Christopher R. Bollinger*

Lauren DiRago-Duncan

Hyungsoo Kim

Joann Lianekhammy

Kara Riesing

Ann Vail

Alexander T. Vazsonyi†

Abstract

The RCPNC piloted a project to provide local community organizations with financial support and training resources to improve USDA food program outreach in persistently poor communities. To evaluate the effectiveness of the resource and training program, data were collected using a survey on food security as well as county level participation rates in six USDA food programs (SNAP, NSLP, SBP, SFSP, WIC, CACFP). Survey results showed few differences between the participating counties and national trends. An analysis of participation rates indicated weak evidence of a modest positive impact on SNAP, but also a decrease in the use of WIC.

JEL codes: H43, H53, I32

Keywords: Community based outreach, training program

* Corresponding Author, Christopher R. Bollinger, Department of Economics, University of Kentucky, Lexington, KY, 40506, crboll@uky.edu.; Lauren DiRago-Duncan, Lexmark; Hyungsoo Kim & Alexander T. Vazsonyi, Department of Family Sciences, University of Kentucky; Joann Lianekhammy, Family and Consumer Sciences Extension, University of Kentucky; Kara Riesing, Department of Economics, Miami University; Ann Veil, University of South Carolina, Graduate School.

† This project was funded by the U.S. Department of Agriculture, Food and Nutrition Service, CN-OPS-RCPNC-2015-KY.

I. Introduction

Food insecurity remains a significant problem throughout the U.S. [Coleman-Jenson et al, 2022; Davis, 2010; Wauchope and Shatuck, 2010]. Both poverty and food insecurity are high among persistently poor rural counties in the U.S. [McGranahan, 2015; Farrigan, 2018]. The United States Department of Agriculture (USDA) Food and Nutrition Service (FNS) administers a variety of programs designed to provide access to food for children who are in financial need. The Supplemental Nutrition Assistance Program (SNAP), the National School Lunch Program (NSLP), the School Breakfast Program (SBP), the Summer Food Service Program (SFSP), the Special Supplemental Nutrition Program for Women, Infant and Child (WIC), the Child and Adult Care Food Program (CACFP), and the Food Distribution Program on Indian Reservations (FDPIR) are all designed to provide nutrition to children. Evidence suggests that these programs are often underutilized by eligible families. Coleman-Jenson et al. [2018] report that participation among food insecure individuals was 58% in 2017 (coinciding with the timing of this study). Reasons for low participation rates include a lack of information about the programs, lack of physical access to the program, as well as stigma [Davis, 2010; Wauchope and Shatuck, 2010; Gunderson, 2014]. Outreach to provide access to families, particularly in rural and high-poverty areas, is challenging. Outreach is typically provided by local organizations, including school districts, religious organizations, and community action groups. These groups are often poorly funded and may lack training, experience and other resources which would improve their effectiveness in the outreach and education missions. The present investigation examined the effectiveness of a quasi-experimental project designed to provide support and training to these community groups in order to improve the use of safety net food programs. It was hypothesized that the provision of support and training at the community level to these outreach organizations would positively impact and improve participation rates when compared to business-as-usual counties or populations.

II. Intervention Project

With funding from the U.S. Department of Agriculture, Food and Nutrition Service, the University of Kentucky Rural Child Poverty Nutrition Center (RCPNC) in conjunction with Altarum Institute and the Southern Rural Development Center, planned and carried out an intervention project which was designed to provide local community organizations with both financial support and training resources to improve outreach systems for USDA food assistance programs in persistently poor communities. Community organizations serving the 322 persistently poor counties in the U.S. were eligible to apply to receive the support.

The RCPNC team developed a Request for Applications (RFA) released July 24, 2015. The RFA called for creative project proposals aimed at increasing coordination among child nutrition programs through a community-participatory approach. Eligibility was restricted to state or local government or nonprofit organizations for work conducted in one of the 322 targeted (Persistently Poor) counties. A total of 50 organizations, representing 68 counties, proposed projects. The RCPNC recruited twenty-six individuals with expertise in community development and supplemental food programs who reviewed the applications. Each application was reviewed and scored by three of the twenty-six individuals. Selection was based upon a variety of factors including a county needs assessment, institutional organization, and the number of children potentially served. Seventeen projects representing 33 counties were initially selected and funded. Two awardees exited the project prior to completion, reducing the number of counties which completed the project to 17. Project analyses focused on three nested groups of counties: 322 total eligible counties, 68 applicant counties, and 17 grantee counties. We provide a map highlighting these counties.

This intervention sought to develop and improve coordination efforts among USDA child nutrition programs through collaborative partnerships to increase participation of the programs. Grantees were provided training sessions through both face-to-face workshops and webinars. Grantees were then guided in conducting a community needs assessment of their home community. This provided a basis to prioritize the needs of the community. Grantees then developed implementation strategies as well as communication and coordination plans that utilized available resources. By either developing or joining a community coalition, grantees sought to use multiple resources within their community. There were five major activities undertaken by the grantees within their community coalition: 1) developing relationships and sharing knowledge and resources collectively; 2) advancing and supporting the coalition’s focus such as understanding how each of the programs overlapped and intersected; 3) serving as advisors and collaborators on specific projects such as identifying new meal sites for a SFSP; 4) promoting events and resources, such as disseminating information through diverse channels; and 5) volunteering at events and activities. The project was designed to ultimately benefit food insecure households by reducing barriers to participation in food programs which have been shown [Ratcliffe et al., 2011; Kreider et al., 2012; Kabbani and Kmeid, 2005; Herman et al., 2004; Gunderson et al., 2012; Gregorey et. al. 2015] to reduce the likelihood of food insecurity.

III. Literature review

USDA supplemental nutrition programs have been documented to reduce food insecurity [Ratcliffe et al., 2011; Kreider et al., 2012; Kabbani and Kmeid, 2005; Herman et al., 2004; Gunderson et al., 2012; Gregorey et. al. 2015; Gunderson, et. al 2017; Gregory, 2020]. Literature also shows positive externalities of these programs affecting other areas of well-being. Gunderson et al. [2012] find that receiving free or reduced-price lunches through NSLP leads to improved health outcomes among children. Change in caloric content of lunches provided through NSLP lead to improvements in standardized test scores [Figlio and Winicki, 2005]. Others [Hoynes and Schanzenbach, 2009; Teihan et al., 2017; Millimet et al., 2018] show that participation in food stamp programs leads to a decrease in out-of-pocket food expenditures which potentially allows for reallocating the additional cash flow to other necessities. Blundell and Pistaferri [2003] find that food assistance programs reduce the effects of a permanent income shock to low-income families, allowing for consumption smoothing. Considering the wide range of positive externalities imposed by food assistance programs, it is important to increase participation in these food assistance programs among eligible households.

While many interventions – at both the national and regional level – have been developed to improve participation rates, these are typically designed around the benefits or application process. The present intervention is therefore unique in that it provides development to local community organizations which in turn work with eligible families and children. To the best of our knowledge, no interventions with similar goals and approach have been piloted or evaluated. Building local infrastructure may have longer-lasting effects and may be more effective, since community organizations can tailor their efforts to specific local issues found in their community. While development of community organization does not directly impact food program usage, it was hypothesized that improved coordination and targeting of outreach and education systems as well as resources in the community would lead to higher program participation and usage, and in turn, reduced food insecurity.

To evaluate the success of the intervention project two strategies were employed. First, data were collected using a survey from residents of the counties served by the intervention at three time points during the project: fall of 2016 (shortly after counties were selected), fall of 2017, and fall of 2018, at the end of the project. The survey collected basic demographic information, information regarding access to and prior use of food programs, and the USDA Food Security Assessment (using a twelve-month window and assessing both adult and child food security). The timing of the survey, late fall, was similar to the reference period for the December U.S. Current Population Survey, which also includes the USDA Food Security assessment.

The second strategy was to use county-level counts of participation in the targeted programs. Data were collected on participation rates in six programs: NSLP, SBP, SNAP, WIC, SFSP, and SSO. Using regression analysis to control for county level differences, populations who were eligible versus those who applied were compared.

IV. Data

Two complimentary approaches were taken to evaluate the project. The first included a data collection of food insecurity in the treated counties. The timing and structure were designed to be parallel to the December Current Population Survey Food Supplement. These data were used to compare trends and results between the participating counties and similar regions. The second involved collection of participation in five of the USDA programs (NSLP, SBP, SNAP, WIC, SFSP and SSO). These were collected for all participating and eligible counties. Additional demographic and economic data at the county level were also obtained.

i. Food Security Survey and CPS Food Security Data

Survey data were collected from a convenience sample of families residing in the counties served by the grant. Grantee organizations advertised the survey which was available online and through "pick up" printed surveys. Grantee organization personnel were not allowed to recruit, but simply provided announcements that a survey was being fielded. Survey respondents were anonymous volunteers. The survey had four sections asking questions about attitudes toward and knowledge of food programs, transportation access, the USDA Food Security Assessment, and demographic and economic data. The survey was relatively short (most questions were from the Food Security Assessment). Both paper and online methods of administration were used.

The survey was conducted at three points in time: October and November of 2016, October and November of 2017, and September and October of 2018. The timing was selected for three reasons. First, this represented the beginning of the school year, a period when contacting families with existing relationships to the grantees, new families, and families generally within the community was relatively simple. Many of the organizations were associated with school districts, so advertising at schools was common.

Second, since many of the awardees were involved in the summer food program, this made completing the survey shortly after the summer particularly informative and made the summer food program more salient for respondents. Finally, this timing coincided with the December Current Population Survey which also fields the USDA Food Security Assessment.

Sample sizes were modest, with 790 individuals responding in the first year, 723 responding in the second year, and 736 responding in the third year. It should also be noted that the survey was conducted on a convenience sample which may not be representative of the population as a whole. The survey instrument is included in the appendix.

ii. Descriptive Results

Item non-response impacted the quality of the data. Table 1 presents sample sizes by year using different response criteria for inclusion.

Table 1: Sample Sizes for Survey

Year	Returned Surveys	Any FS	Complete FS	Complete FS and Demographics	Complete FS, Demographics and Income*
2016	816	808	775	708	567
2017	733	729	708	665	554
2018	747	746	703	648	512
Total	2296	2283	2186	2021	1633

Notes: *Analysis sample used in all tables below except as noted.

The first column of Table 1 presents the total number of surveys returned. For electronic surveys, this includes any survey started; for paper returns, this includes any survey returned with at least one answer (all returned surveys were entered). Since the main variable of interest is the Food Security (FS) measure, we consider two different approaches to missing data in the components of the measure. First, any case where at least one of the food security component questions was answered was used; this is the second column of Table 1, labelled "Any FS." As can be seen by comparing column 1 and column 2, nearly all respondents (at least 99% in each year) answered at least one of the food security questions. Second, cases were limited to those where no more than one answer was missing. Analysis of the missing data pattern demonstrated a concentration of responses which were complete or contained only one missing value, and another concentration with many values missing. Comparing columns 2 and 3, the overwhelming majority of respondents who answered any of the food security questions answered at least all but one of them (at least 94% in each year). Missing values in various demographic variables (age, gender, and race) further reduced sample sizes. Column 4 presents the sample size of those who completed most of the food security questions and had complete demographic information. Again, over 90% of the column three respondents reported complete demographics. Those with complete food security and complete demographics exceeded 86% of the original returned surveys in each year. The highest rate of missing data occurred in the income questions. Overall, the sample with complete food security, demographic and income data represents 71% of the initial respondents, and 75% of those who completed the food security battery (no more than one missing). While the sample of complete responses was the focus in the paper, the impact on the sample sizes focusing on non-response in the key food security questions and in the income and demographic variables was also considered and evaluated.

All analyses were carried out on various combinations of the four samples above (columns two through five). Qualitatively, the main results are quite robust across samples and included in the appendix. The main focus was on the sample of complete responses to food security, demographics and income. Those with missing income were more likely to be food insecure than the group with income above 150% of the poverty line and the group between 133% and 150% of the poverty line. Missing income respondents were less likely to be food insecure than those either between the poverty line and 133% of the poverty line or those below the poverty line. However, including or excluding that group in the analysis had little impact on coefficients on other variables.

To address the concern related to the fact that the data were collected from a convenience sample that was not necessarily representative of the region in which it was collected, sampling weights were developed. The weights were developed using STATA's ipfweight command and raked up to income the income and race categories of the county from which they were drawn. The county level income and race data were obtained from Census five-year American Community Survey data.

To provide context and some comparison, data from the survey were compared to data from the December Current Population Survey (CPS) which also includes the Food Security measure. The CPS is a national survey, designed to be representative at both the national and regional level. Data from 2014 through 2018 were included. A decision was made to start with 2014 to have multiple years prior to the beginning of the project (in 2016) but to remain in the post- great recession and recovery era. Following Farnham [2017] and Hoop et al [2022], household supplement weights for the CPS data were used.

Table 2 presents sample means for both our survey and the CPS survey. The results from the CPS are not strictly comparable to the counties in our survey: those counties are designated as persistently poor and differ significantly in demographics from the states from which they are drawn. Because these are rural counties, they are not identified in the CPS data.

Table 2: Means Sample Means for Survey and CPS

	Survey Analysis Sample unweighted	Survey Analysis Sample weighted	CPS Full Sample weighted	CPS Eligible States weighted	CPS Applied States weighted	CPS Treated States weighted
Age	42.35	43.36	51.25	50.49	50.39	50.24
HH Food Insecure	0.429	0.297	0.121	0.140	0.139	0.139
CH Food Insecure	0.405	0.291	0.160	0.180	0.179	0.178
Poverty	0.353	0.263	0.105	0.129	0.128	0.127
100 to 133% of Poverty Line	0.181	0.0785	0.0386	0.0461	0.0459	0.0458
133 to 150% of Poverty Line	0.178	0.0924	0.0395	0.0450	0.0448	0.0446
Above 150% of Poverty Line	0.287	0.566	0.817	0.780	0.782	0.782
White	0.329	0.562	0.786	0.756	0.750	0.748
Black	0.361	0.279	0.133	0.187	0.194	0.194
Asian	0.00245	0.00299	0.0513	0.0265	0.0272	0.0287
Native American	0.0710	0.0367	0.0131	0.0149	0.0128	0.0135
Other Race	0.237	0.119	0.0163	0.0156	0.0154	0.0154
Less than HS	0.0882	0.0623	0.0979	0.119	0.118	0.120
High School	0.336	0.239	0.443	0.469	0.468	0.465
Trade School	0.126	0.0816	0.0448	0.0494	0.0496	0.0487
Associates Degree	0.132	0.138	0.0593	0.0545	0.0546	0.0536
Bachelors and above	0.317	0.479	0.355	0.308	0.310	0.313
Male	0.149	0.173	0.498	0.492	0.492	0.493
Hispanic	0.138	0.110	0.136	0.130	0.126	0.137
Sample Size	1,633	1,633	232,823	71,541	62,223	53,927

Four samples from the CPS are presented: the full national sample, the sample of households from states which contained an eligible county, states which contained a county that applied, and states which contained a county that was funded. Overall, our survey is younger, has more African American and Native American respondents, and has a higher percentage of those with trade school or associate's degrees. Our survey was frequently answered by women. The CPS demographics represent the "head of the household" as reported in the survey. This may explain certain differences like gender or education. The much higher response to "other" in our survey may indicate that the lack of multi-race categories led to more respondents choosing "other".

When comparing the demographics of the CPS samples to our samples, two things become immediately clear: our sample is significantly poorer than the CPS sample and experiences much higher rates of household and child food insecurity. The overall rate of household food security in the CPS samples is between 12.1% and 13.9%. This is much lower than the 42.9% of our unweighted sample or 29.7% of our weighted sample. Across the four CPS samples, in Table 5, poverty rates ranged between 10.5% and 12.7%. In contrast, our survey reveals a 35.3% rate with that falling to a 29.1% rate when weighted. This is not surprising and consistent with the selection of persistently poor counties and the selection of populations who are interacting with food program providers. However, our sample appears to be as well or better educated than the CPS sample. Our weighted results place only 6% of the sample with less than a high school degree, while even the full sample of CPS has 9.8% with less than a high school degree (and fully 12% for the treated states). Similarly, the study sample (weighted) has 47.9% with at least a bachelor's degree, while the full sample of the CPS only reports 35.5%, and the treated states sample reports only 31.3%.

iii. Program Participation Data

Administrative data were collected at the county level on participation in each of six programs: NSLP, SBP, SNAP, WIC, SFSP and SSO. Collecting these data required contacting administrative offices at the state and often county level. Some states and counties did not respond to requests. The details of the data collection are summarized in the appendix, while Table 3 provides sample counts for these variables.

Participation rates for programs such as SNAP and WIC are the ratio of participants to county population. Participation rates for school-based programs are the ratio of participants to enrolled students. Control variables were obtained from Census county estimates derived from American

Community Survey data. The study analysis uses the poverty rate, the median household income, the unemployment rate, the total county population, the percent with a high school degree or higher, and the number of African Americans.

Table 3 presents the means of these variables for four groups of counties. The full sample includes 322 of the persistently poor counties. The number of years where data were obtained on each program varies from seven years for SNAP and only five years for other programs. Sample sizes are given in Table 4. The second group of counties are those who applied to participate in the trial, the third group are the counties which were selected for participation, while the fourth group are those who received the grant and participated through the entire program.

Participation rates in the NSLP range from 74.8% to 82.4%, SBP participation ranges from 50% to 60.7%, SNAP participation ranges from 9% to 16.5%, SSO participation ranges from 2 to 4%, and SFSP participation ranges from 1.9% to 3.3%. The average poverty rate for these counties is over 25%, with the selected counties and grant counties averaging nearly 30%. The unemployment rate is over 11% on average in these counties. As noted in other data above, these counties are poor, have troubled labor markets, and low educational attainment.

V. Empirical Strategies and Main Results

i. Empirical Strategies

Our first set of results focus upon measurements of food insecurity. As noted above our survey was fielded only in the treated counties. We estimate linear probability models focusing on before and after implementation:

$$PR[FI_i = 1] = \alpha_1 Year2_i + \alpha_2 Year3_i + \boldsymbol{X_i \beta} \qquad (1)$$

.

where *FI* is the indicator for food insecurity; *Year2* and *Year3* are the second and third years of the study period, and ***X*** includes and intercept and other sets of control variables known to be correlated with food insecurity. Identification here is based on the first period (year 1, the omitted category) being prior to any activity from the grant. If the grant project had significant impacts on food insecurity we should see negative coefficients on years 2 and 3.

Table 3: Sample Size for County Level Data

	Full		Applied		Selected		Grantees	
	Before	After	Before	After	Before	After	Before	After
NSLP Participation Rate	1384	568	299	110	142	50	82	32
	(319)	(310)	(67)	(61)	(32)	(30)	(18)	(16)
SBP Participation Rate	759	344	143	51	67	17	50	19
	(232)	(178)	(43)	(26)	(18)	(9)	(14)	(10)
SNAP Participation Rate	1610	322	340	68	165	33	90	18
	(322)	(322)	(68)	(68)	(33)	(33)	(18)	(18)
WIC Participation Rate	629	115	171	36	83	16	58	11
	(152)	(115)	(39)	(36)	(19)	(16)	(14)	(11)
WIC Women	531	84	139	26	74	13	49	8
Participation Rate	(121)	(84)	(29)	(26)	(16)	(13)	(11)	(8)
WIC Children	1001	173	207	40	89	15	69	11
Participation Rate	(210)	(173)	(43)	(40)	(18)	(15)	(14)	(11)
SSO Participation Rate	302	77	39	11	19	5	19	5
	(80)	(77)	(11)	(11)	(5)	(5)	(5)	(5)
SFSP Participation Rate	435	108	63	17	29	7	32	8
	(118)	(108)	(16)	(17)	(7)	(7)	(8)	(8)
Poverty Rate	1610	644	340	136	165	66	90	36
	(322)	(322)	(68)	(68)	(33)	(33)	(18)	(18)
Median HH Income	1610	644	340	136	165	66	90	36
	(322)	(322)	(68)	(68)	(33)	(33)	(18)	(18)
Unemployment Rate	1610	644	340	136	165	66	90	36
	(322)	(322)	(68)	(68)	(33)	(33)	(18)	(18)
Population (1000 people)	1610	644	340	136	165	66	90	36
	(322)	(322)	(68)	(68)	(33)	(33)	(18)	(18)
High school or more	1610	644	340	136	165	66	90	36
	(322)	(322)	(68)	(68)	(33)	(33)	(18)	(18)
African American	1610	644	340	136	165	66	90	36
	(322)	(322)	(68)	(68)	(33)	(33)	(18)	(18)

Notes: Overall number of county-year observations with number of counties in parenthesis.

Table 4: Summary Statistics for County Data Measures

	Full		Applied		Selected		Grantees	
	Before	After	Before	After	Before	After	Before	After
NSLP Participation Rate	76.05	80.32	78.42	82.40	74.81	79.61	70.37	74.67
	(24.27)	(18.49)	(17.29)	(18.46)	(20.35)	(20.88)	(25.01)	(23.81)
SBP Participation Rate	50.00	58.79	56.71	59.68	60.70	56.29	55.05	56.21
	(29.46)	(41.00)	(24.36)	(18.20)	(25.42)	(15.37)	(21.32)	(14.57)
SNAP Participation Rate	23.80	24.49	26.01	26.62	26.89	27.48	26.62	27.39
	(6.496)	(6.560)	(6.557)	(6.642)	(6.721)	(6.599)	(7.151)	(7.283)
WIC Participation Rate	16.49	15.49	11.57	9.646	11.08	9.112	13.78	11.41
	(19.36)	(17.79)	(17.46)	(15.01)	(18.83)	(16.10)	(22.04)	(19.24)
WIC Women	3.940	4.282	2.253	2.063	2.480	2.163	3.114	2.788
Participation Rate	(4.630)	(4.583)	(3.863)	(3.549)	(4.141)	(3.578)	(4.985)	(4.558)
WIC Children	7.895	7.418	6.053	5.100	7.365	6.409	8.491	7.725
Participation Rate	(11.87)	(11.27)	(11.37)	(10.12)	(14.07)	(12.99)	(15.83)	(15.13)
SSO Participation Rate	3.318	4.023	2.868	3.050	2.161	2.612	2.161	2.612
	(4.305)	(4.970)	(1.996)	(2.085)	(0.538)	(1.348)	(0.538)	(1.348)
SFSP Participation Rate	2.889	3.263	2.319	2.740	1.651	1.674	1.918	1.988
	(2.853)	(3.324)	(2.517)	(2.277)	(1.732)	(1.750)	(1.899)	(1.847)
Poverty Rate	27.55	27.62	29.42	29.60	30.95	30.77	28.96	29.02
	(5.579)	(6.258)	(5.630)	(5.998)	(6.630)	(6.930)	(5.973)	(6.251)
Median HH Income	31355.2	32552.8	29912.1	30511.7	30010.3	30254.3	31043.9	31576.2
	(4772.4)	(5310.3)	(4449.3)	(4848.9)	(4992.2)	(5691.9)	(5086.4)	(6197.5)
Unemployment Rate	12.20	11.48	13.90	12.89	14.98	13.62	12.58	11.48
	(4.331)	(4.255)	(4.769)	(4.585)	(4.784)	(4.798)	(3.441)	(3.179)
Population (1000 people)	31.86	32.25	45.05	45.79	62.04	63.60	91.82	95.23
	(73.47)	(77.30)	(104.3)	(110.6)	(144.3)	(153.6)	(189.7)	(202.9)
High school or more (%)	73.91	76.35	73.44	75.98	72.65	74.99	72.49	74.92
	(6.455)	(6.099)	(6.553)	(6.503)	(7.542)	(7.477)	(9.301)	(9.097)
African American	7854.0	7849.2	10990.0	10816.0	12112.5	11862.8	7908.5	7835.0
	(16678.0)	(17519.0)	(12231.4)	(12303.5)	(11985.6)	(11734.8)	(8398.3)	(8375.5)

Notes: Sample means with sample standard deviation in parenthesis. Sample sizes are provided in table 3 above.

However, economic conditions vary as well. In order to provide context, we estimate the same models using the Current Population Survey data for the states containing eligible counties. We cannot identify participation (or even the eligible counties) in CPS data because county is suppressed to provide confidentiality (some urban counties are included in the public use data, but only large ones, all eligible counties are small and rural). Differences in the coefficients on time provide some context as to the macro-economic conditions affecting food security in these areas.

To more carefully measure the impact of the project on program participation, county level data were also analyzed. The primary underlying model was is a treatment effect model where we compared county level participation rates for the six programs between the counties which participated in the project were compared to and those that did not. Selection of a comparison group is crucially important, as is controlling for both differences in characteristics between those counties with participating organizations ($Grant_{it}$ =1) and those counties without participating organizations ($Grant_{it}$ =0). Two comparisons groups were used in the analysis. The first group used all 322 counties (where data were available) that were in the list of persistently poor counties and thus eligible to submit grant proposals and participate in the project. The second comparison group included only those 68 counties (again with available data) which applied for a grant.

It should be noted that Concern arises that counties with an organization choosing to apply for the project may systematically differ in important – but difficult to measure – ways from eligible counties with no such organization. Hence each analysis below was conducted using both the full sample as comparison and the applied group.

In estimating treatment effects from a project where assignment to treatment was clearly not random, it was important to control for differences between the treatment and control groups. We operationalized the treatment effect estimation using two different, but complimentary, approaches. In the first approach, we estimated fixed effects linear regression models with controls for education, race, income, population, unemployment, and poverty rates. The linear model was specified with a simple indicator for counties which received and participated in the grant project. We have data prior to the beginning of the grants which allows the estimation of a fixed effects model. This model is best understood as isolating the change in participation before and after the project, while controlling for differences across counties. The estimation equation is given by:

$$Y_{it} = \beta_0 + \boldsymbol{X_{it}\beta_1} + \beta_2 Grant_{it} + \lambda_i + \varepsilon_{it} \qquad (2)$$

where, Y_{it} is the participation rate in NSLP, SBP, SNAP, WIC, SFSP, or SSO in county i at time t. The variables included in the vector $\boldsymbol{X}_{it}$ are the unemployment rate, population, percent of population with greater than high school education, and the count of the Black or African American population in the county. $Grant_{it}$ takes the value 1 when county i receives a grant and continues throughout the period of the grant. We call these treated counties, grantees, or the treatment group. In some of the models, median household income and/or poverty rate are also included in the analysis. λ_i controls for county fixed effects and standard errors are clustered at the county level.

The main restriction with this model is that the impact of the project is assumed to be a simple shift in participation rate. Other models would include interactions with control variables which would allow for differential impacts across county types. However, given the small number in the treatment group, we focus on a simple model. Recent work [Callaway and Sant'Anna, 2021] has noted that when treatment is staggered, care must be taken in assessing the treatment effects. However, the treatment here began at the same point, and thus we work with standard approaches.

The second approach was to use propensity score matching to make average comparisons. The propensity score calculates the probability that a particular county would be included in the treatment group, conditional on the control variables. This probability provides a way to find "similar" counties in the control group (counties eligible for grants) to compare to the treated counties. It is essentially a weighted average of the difference in the outcome between treated ($Grant_{it}$ =1) counties and control counties. It relaxes the assumption of the linear model that the impact does not vary with other factors, but we are unable to use fixed effects to control for unobserved factors.

ii. Survey and CPS Food Security Measures

In Table 5, food security indicators for the analysis sample by year are presented, both weighted and unweighted. The trends don't change in meaningful ways with the weights, indicating that the characteristics of typical respondents were similar across the three years. However, the level is lower with the weighted estimates, suggesting that the typical respondent had characteristics that were associated with food insecurity, and less typical of the county. A significant drop in 2017 occurred. The difference is statistically significant in some models below. Differences were found in comparison to models based on data from 2016 and 2018; thus, caution should be used to draw strong conclusions based on this. The child indicator follows a similar pattern of dropping in 2017 and returning to similar levels in 2018.

Table 5: Survey Food Insecurity by Year

Measure	2016	2017	2018	Total
HH Indicator	44.3%	39.0%	45.7%	42.9%
Child Indicator	42.8%	36.1%	42.5%	40.5%
Weighted				
HH Indicator	34.3%	26.8%	28.1%	29.7%
Child Indicator	34.5%	22.8%	31.7%	29.1%
Sample Size:	567	554	512	1,633

Income is a significant determinant of food insecurity; in Table 6, food security indicators are presented by income group again for both weighted and the overall survey. One row is included for those not reporting income (note that percentages in the first column do not include the missing income group). The sample here is disproportionately poor, as is to be expected from the selection of persistently poor counties. Given the advertising for the survey, it likely reached more families already in contact with the grantees, who are likely disproportionately poor even for those counties. Overall, 35% of the households have income below the federal poverty threshold, 18% are between the poverty line and 133% of the poverty threshold, and slightly less than 18% are between 133% and 150% of the federal poverty threshold. The pattern in Table 3 is unsurprising: 67% of families living below the poverty threshold are food insecure and 58% of the families with children are child food insecure. The percentage of families who are food insecure falls as income rises. Only 9.8% of families with incomes over 150% of the federal poverty threshold are food insecure.

Food insecurity percentages change little when the weights are applied, although the percentages in any income group do change. This indicates that the weights are largely detecting differences in income levels. Overall trends are not particularly sensitive to weighting, and that controlling for income (as is typically done in a regression analysis) will address the main difference in the poverty rates due to observable sample selection. While models were tested using weights, the present discussion focused on unweighted results, the weighted results are reported in the appendix.

Table 6: Food Insecurity by Income Level for Survey

Income Group	Percent of Analysis Sample	HH Indicator	Child Indicator
Below Federal Poverty Line	35.3%	67.4%	58.6%

100% to 133% Poverty	18.2%	55.9%	47.6%
133% to 150% Poverty	17.8%	34.5%	27.4%
Over 150% of Poverty Line	28.7%	9.8%	7.1%
Missing Income*	NA	48.3%	38.0%
Weighted			
Below Federal Poverty Line	26.3%	68.9%	60.2%
100% to 133% of Poverty	7.9%	56.3%	42.6%
133% to 150% of Poverty	9.2%	28.7%	23.2%
Over 150% of Poverty Line	56.6%	8.0%	5.6%
Missing Income*	NA	52.0%	33.8%

Notes: *This row is not part of the analysis sample. Sample Size 1,633 for Analysis sample. There were 470 surveys with complete food security but missing income.

Because survey responses are only available from the treated counties, the estimation approach used first examined the changing food insecurity in these counties during the period of the project. The initial survey was completed at the beginning of the grant (fall 2016) and thus reflects the food insecurity levels prior to the project intervention (since the insecurity question asks about the prior year). Comparison of that year to the next two years provides some measure of the possible impact of the program. Those results are then compared to similar specifications from the CPS which provide measures of the overall trends in similar states. These results should be viewed not as causal but as measuring possible correlations and differences between treated counties and untreated ones. In the next section, a more careful analysis examines the impact on participation rates.

Table 7 presents estimates of the trends in food insecurity controlling for groups of characteristics. Linear probability models were used as they are more simply interpreted and closer to the simple trends presented in Table 3. It is also important to note that this was based on the unweighted sample [Solon et al, 2015]. Both weighted and probit estimates are reported in the appendix. Four specifications are presented: only year dummies, year dummies with income group, year dummies with demographic controls, and a full model with year dummies, income groups, and demographic controls. Table 7 provides evidence that the coefficient on year 2017 is relatively stable across all four specifications, varying between -.053 and -.057. This coefficient implies that the household food insecurity rate was between 5.3 and 5.7 percentage points lower in 2017 than the reference year of 2016. While not statistically significant in the baseline model (with no controls), the coefficient slightly rose in magnitude and became significant when either income group or demographics were included in the model (columns two and four). It is important to note, however, that the coefficient in 2018 is not statistically significant and positive across these specifications. Generally, it can be concluded that there was no clear effect by the program.

In Table 8, similar models for child food insecurity are presented. Again, the coefficient in 2017 is not statistically significant in any specification, however, the magnitude – .039 to -.067 is economically significant. It is also important to note that the inclusion of income does appear to mitigate the time differential (columns 2 and 4 have similar estimates at -.039 and -.046). While not significant, the pattern is similar to Table 7, with a drop in 2017 and a return to baseline in 2018. Again, the data provide little evidence of a programmatic impact.

Column four in both tables demonstrates that income is clearly one of the most important determining factors of food insecurity. In column three race and education are statistically significant in the household models, education only in the child models. When income is added, only less than high school and bachelor's and above remain significant. Even these fall substantially in magnitude.

To provide context and comparison, in Tables 9 and 10, we estimate the same models using the CPS data for eligible states. Eligible states were selected as this group had the highest poverty rate of the four samples, although still significantly below the poverty rates of both the survey and the eligible counties. The models were estimated on all other subsamples with qualitatively similar results and are available in the appendix. In the survey, the bracketed income questions were designed to categorize household income into the four groups used in the analysis (the income categories were conditioned on the household size question and exactly match the categories). However, in the December CPS, the income categories were measured differently, and thus poverty group is an approximation. This should reduce the importance of income and increase the importance of variables associated with actual income. As noted above, the CPS supplement weights were used for this analysis.

Table 7: Linear Probability Regressions on Household Food Insecurity Indicator Survey Analysis Sample

Food Insecure (HH)	Base	Income	Demographics	Full
Year 2017	-0.053	-0.054	-0.057	-0.055
	(0.029)	(0.026)*	(0.028)*	(0.026)*
Year 2018	0.014	0.031	0.015	0.030
	(0.030)	(0.026)	(0.028)	(0.026)
Below Federal Poverty		0.579		0.493
		(0.024)**		(0.033)**
100% to 133% Poverty		0.464		0.406
		(0.032)**		(0.036)**
133% to 150% Poverty		0.248		0.218
		(0.031)**		(0.032)**
Age/100			-0.173	0.008
			(0.089)	(0.085)
African American			0.068	0.008
			(0.029)*	(0.027)
Native American			0.118	0.070
			(0.049)*	(0.044)
Other Race			0.074	0.048
			(0.036)*	(0.034)
Less than High School			0.141	0.088
			(0.043)**	(0.043)*
Trade School			-0.102	-0.055
			(0.040)*	(0.038)
Associate's Degree			-0.188	-0.042
			(0.039)**	(0.039)
Bachelors Degree plus			-0.346	-0.112
			(0.029)**	(0.033)**
Male			-0.035	-0.027
			(0.033)	(0.031)
Hispanic			0.045	0.028
			(0.041)	(0.038)
Intercept	0.443	0.105	0.601	0.169
	(0.021)**	(0.020)**	(0.052)**	(0.056)**
R^2	0.00	0.24	0.14	0.25

Notes: Dependent variable = 1 if food insecure; n=1,633, robust standard errors, significance * p<0.05; ** p<0.01.

Table 8: Linear Probability Regressions on Child Food Insecurity Indicator Survey Analysis Sample

Food Insecure (Child)	Base	Income	Demographics	Full
Year 2017	-0.067	-0.039	-0.066	-0.046
	(0.036)	(0.034)	(0.035)	(0.034)
Year 2018	-0.003	0.029	0.009	0.030
	(0.037)	(0.033)	(0.035)	(0.033)
Below Federal Poverty		0.515		0.408
		(0.029)**		(0.040)**
100% to 133% Poverty		0.402		0.335
		(0.039)**		(0.043)**
133% to 150% Poverty		0.204		0.172
		(0.037)**		(0.038)**
Age/100			0.168	0.202
			(0.150)	(0.143)
African American			0.007	-0.033
			(0.036)	(0.035)
Native American			0.094	0.055
			(0.064)	(0.061)
Other Race			0.034	0.023
			(0.048)	(0.045)
Less than High School			0.190	0.166
			(0.052)**	(0.052)**
Trade School			-0.110	-0.080
			(0.048)*	(0.047)
Associate's Degree			-0.209	-0.100
			(0.048)**	(0.049)*
Bachelor's Degree plus			-0.343	-0.165
			(0.037)**	(0.042)**
Male			0.000	0.011
			(0.042)	(0.040)
Hispanic			0.001	-0.013
			(0.054)	(0.051)
Intercept	0.428	0.075	0.460	0.121
	(0.026)**	(0.027)**	(0.072)**	(0.077)
R^2	0.00	0.17	0.13	0.20

Notes: Dependent variable = 1 if child food insecure; n=1,060, robust standard errors, significance * p<0.05; ** p<0.01.

Table 9: Linear Probability Regressions on Household Food Insecurity Indicator, CPS Weighted Eligible States Sample

	Base	Income	Demographics	Full
Year 2014	0.016	0.009	0.013	0.008
	(0.005)**	(0.005)	(0.005)*	(0.005)
Year 2015	-0.001	-0.001	-0.002	-0.001
	(0.005)	(0.005)	(0.005)	(0.005)
Year 2017	-0.008	-0.004	-0.007	-0.004
	(0.005)	(0.005)	(0.005)	(0.005)
Year 2018	-0.019	-0.013	-0.017	-0.013
	(0.005)**	(0.005)**	(0.005)**	(0.005)**
Year 2019	-0.022	-0.010	-0.017	-0.009
	(0.005)**	(0.005)*	(0.005)**	(0.005)
Below Federal Poverty		0.310		0.257
		(0.006)**		(0.006)**
100% to 133% Poverty		0.216		0.176
		(0.009)**		(0.009)**
133% to 150% Poverty		0.179		0.147
		(0.009)**		(0.009)**
Age/100			-0.164	-0.124
			(0.008)**	(0.008)**
Black			0.095	0.070
			(0.005)**	(0.005)**
Native American			0.103	0.077
			(0.016)**	(0.016)**
Other Race			0.122	0.105
			(0.016)**	(0.016)**
Less than HS			0.110	0.052
			(0.006)**	(0.006)**
Trade School			-0.021	-0.004
			(0.007)**	(0.007)
Associate's Degree			-0.031	-0.010
			(0.007)**	(0.007)
Bachelor's and above			-0.108	-0.070
			(0.003)**	(0.003)**
Male			-0.047	-0.029
			(0.003)**	(0.003)**
Hispanic			0.008	-0.002
			(0.005)	(0.005)
Intercept	0.146	0.086	0.252	0.173
	(0.004)**	(0.003)**	(0.007)**	(0.006)**

Notes: Household supplement weight used. Dependent variable = 1 if household food insecure; n=71,541. Robust standard errors, significance * p<0.05; ** p<0.01.

Table 10: Linear Probability Regressions on Child Food Insecurity Indicator, CPS Weighted Eligible States Sample

	Base	Income	Demographics	Full
Year 2014	0.038	0.030	0.035	0.030
	(0.010)**	(0.010)**	(0.010)**	(0.010)**
Year 2015	0.000	0.000	-0.001	-0.000
	(0.010)	(0.010)	(0.010)	(0.010)
Year 2017	0.001	0.005	0.000	0.003
	(0.011)	(0.010)	(0.010)	(0.010)
Year 2018	-0.021	-0.014	-0.019	-0.014
	(0.011)*	(0.010)	(0.010)	(0.010)
Year 2019	-0.024	-0.012	-0.019	-0.012
	(0.011)*	(0.010)	(0.010)	(0.010)
Below Federal Poverty		0.313		0.256
		(0.010)**		(0.011)**
100% to 133% Poverty		0.219		0.178
		(0.014)**		(0.015)**
133% to 150% Poverty		0.182		0.142
		(0.018)**		(0.018)**
Age/100			0.007	0.066
			(0.028)	(0.027)*
Black			0.089	0.056
			(0.009)**	(0.009)**
Native American			0.112	0.081
			(0.027)**	(0.026)**
Other Race			0.166	0.151
			(0.031)**	(0.030)**
Less than HS			0.090	0.030
			(0.012)**	(0.012)*
Trade School			-0.030	-0.010
			(0.014)*	(0.013)
Associate's Degree			-0.044	-0.021
			(0.013)**	(0.012)
Bachelor's and above			-0.143	-0.090
			(0.006)**	(0.006)**
Male			-0.079	-0.053
			(0.006)**	(0.006)**
Hispanic			0.006	-0.010
			(0.009)	(0.009)
Intercept	0.181	0.104	0.226	0.127
	(0.007)**	(0.007)**	(0.014)**	(0.014)**

Notes: Household supplement weight used. Dependent variable = 1 if child food insecure; n=21,191.
Robust standard errors, significance * p<0.05; **

Unweighted estimates are provided in the appendix. Additionally, additional years were used, beginning the sample in 2014 and continuing through 2019. To be comparable, 2016 was used as the baseline year for the indicators. While the estimates of this sample to those of our sample were compared, this should not be considered as treatment effect estimates.

In Table 9, the coefficients on year 2017 are negative, but small and not statistically significant. The estimates in Table 7 are significantly different than these. Moreover, the coefficient on 2018 for CPS results is between -1% and -2%, while the corresponding coefficient in Table 7 (based on our survey) was between -.3% and 3%. Comparing the two full models, the coefficients differed significantly. The fact that the return to baseline apparent in both Table 5 and the regressions in Table 7 is very different than the CPS data, suggests that very different forces might be at work. However, given the fact that the eligible states also contain many more economically advantaged areas, this may explain the remaining difference. Again, these results do not seem to indicate a strong impact by the program in comparison to national or eligible state trends.

The results in Table 10 are quite similar to Table 9: small negative changes (around -.2%) from 2016 to 2017 and much larger decline to 2018 (-1.3% to -2.2%). Tests between the models also found significant differences. Thus, while the treated counties appear to have different trends than the eligible counties, the differences do not clearly point to a treatment effect from the program, but rather to other factors.

In conclusion, there were significant differences between survey findings and the overall trends in the Current Population Survey data. However, this does not necessarily imply anything about the project. It may suggest that the project was ineffective in reducing food insecurity. However, the trends observed in the Current Population may be dominated – even within the restricted samples – by more wealthy urban areas. Economic conditions, provision of programs such as SNAP, and a variety of other differences may be leading to vastly different trends. Therefore, caution should be used about drawing any strong conclusions pro or contra programmatic effects.

iii. County Level Participation Measures

Models were estimated based on participation in six different programs: National School Lunch Program (NSLP), School Breakfast Program (SBP), Supplemental Nutrition Assistance

Program (SNAP), the Special Supplemental Nutrition Program for Women, Infants and Children (WIC), Seamless Summer Option (SSO), and Summer Food Service Program (SFSP). It was expected that the SFSP would show the largest effect, since all grantees included this project in their target programs, and ten included it as a primary target. Additionally, it was expected both NSLP and SBP to have large effects since these programs were targeted by nine of the original fifteen grantees. Outside of the two major school-based programs, SNAP and WIC are the largest and most salient programs and were also targeted by many of the grantees.

Initially, a fixed effects regression analysis was completed. Table 11 presents regression results examining the effect of treatment on National School Breakfast program. As noted above, we used two different control groups: all persistently poor counties and those counties who applied. Columns one and two present basic regressions which include fixed effects for the counties but no other control variables. The results for these regressions are economically and statistically significant: the grantee counties show a slightly larger than 6 percentage point increase in participation. The remaining columns add additional control variables, and the estimated magnitudes declined between 2 and 4 percent points. It is interesting and important to note that throughout the specifications, the coefficient on treatment is positive; the project appears to have increased participation. As we knew from the outset, the small number of grantees (15 grantees affecting just barely 30 counties) would provide very low statistical power. These results are quite encouraging in their robustness across specification and provide evidence of positive effects. It is also noteworthy that in general, the effect when compared to the counties which applied, is largest across all but the first simple specification. Counties which did not apply to the project may have participated in other projects or may have had plans for other interventions, issues that are unknown and ones that we cannot address in model specifications.

Table 12 presents the same specifications for the NSBP. In this case, none of the coefficients on the treatment indicator were statistically significant, but all are positive. As with the School Lunch program, the effect measured against the other applicants is consistently the largest (although the difference is less marked), and all coefficients are positive. Overall, the estimated effect provides evidence of a 1.7 to 2.2 percent increase. While this is modest, and the results are not statistically significant, again it is important to note the low statistical power due to the modest sample size, thus leading to the suggestion that there might be some modest positive effect.

Table 11: Fixed Effects Estimation for National School Lunch Program

	(1) All	(2) Applied	(3) All	(4) Applied	(5) All	(6) Applied	(7) All	(8) Applied
Grant	6.2189**	6.2189**	2.2971	4.2526	2.1758	3.7938	2.2953	4.2430
	(3.0387)	(3.0598)	(3.3442)	(3.1283)	(3.3418)	(2.9908)	(3.3409)	(3.1432)
Poverty(%)					-0.1528	-0.2547	-0.0677	0.0794
					(0.1483)	(0.3256)	(0.1598)	(0.3260)
Median HH Income			0.0002	0.0009			0.0002	0.0009
			(0.0002)	(0.0006)			(0.0002)	(0.0007)
Unemployment(%)			0.2908	0.0663	0.2998	0.0453	0.3019	0.0533
			(0.1884)	(0.2814)	(0.1944)	(0.2637)	(0.1944)	(0.2732)
Population			0.0004	0.0003***	0.0004	0.0004***	0.0004	0.0003***
			(0.0003)	(0.0001)	(0.0003)	(0.0001)	(0.0003)	(0.0001)
Greater than HS(%)			0.8034***	0.3153	0.8767***	0.5781*	0.8146***	0.3076
			(0.2092)	(0.4137)	(0.2000)	(0.3415)	(0.2100)	(0.4169)
Black population			-0.0111***	-0.0009	-0.0111***	-0.0008	-0.0111***	-0.0008
			(0.0017)	(0.0014)	(0.0017)	(0.0013)	(0.0017)	(0.0013)
_cons	77.1927***	78.9996***	82.7122***	22.9135	89.0920***	35.4412	84.8549***	19.7246
	(0.0498)	(0.2394)	(20.9936)	(31.3183)	(21.3351)	(33.6126)	(21.7071)	(34.4728)
N	1952	409	1952	409	1952	409	1952	409
Counties	320	67	320	67	320	67	320	67

Notes: Standard errors in parentheses. Standard errors clustered at county level. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Fixed Effects Estimation for National School Breakfast Program

	(1) All	(2) Applied	(3) All	(4) Applied	(5) All	(6) Applied	(7) All	(8) Applied
Grant	2.1584	2.1584	1.7664	2.1261	2.0896	2.2007	1.7660	2.0873
	(5.9752)	(6.0459)	(6.7404)	(6.8403)	(6.5457)	(6.4876)	(6.6504)	(6.6650)
Poverty(%)					0.5557**	0.6577	0.3348	0.5763
					(0.2213)	(0.6113)	(0.2792)	(0.6452)
Median HH Income			-0.0007*	-0.0006			-0.0005	-0.0002
			(0.0004)	(0.0008)			(0.0004)	(0.0009)
Unemployment(%)			-0.4183	0.3543	-0.4647	0.2471	-0.4711	0.2588
			(0.4193)	(0.9480)	(0.4274)	(0.9931)	(0.4249)	(1.0124)
Population			-0.0006**	-0.0001	-0.0007**	-0.0001	-0.0006**	-0.0001
			(0.0003)	(0.0001)	(0.0003)	(0.0001)	(0.0003)	(0.0001)
Greater than HS(%)			1.4265***	0.8142	1.2819***	0.7463	1.3952***	0.8042
			(0.3526)	(0.8799)	(0.3284)	(0.7315)	(0.3517)	(0.8690)
Black population			0.0136***	0.0003	0.0137***	0.0005	0.0136***	0.0005
			(0.0009)	(0.0025)	(0.0009)	(0.0024)	(0.0009)	(0.0025)
_cons	52.7016***	57.2826***	-99.9885***	16.2568	-125.0724***	-15.8005	-112.3333***	-12.2640
	(0.1029)	(0.5921)	(25.9633)	(66.3049)	(28.5668)	(70.7576)	(29.0210)	(67.9005)
N	1103	194	1103	194	1103	194	1103	194
Counties	233	43	233	43	233	43	233	43

Notes: Standard errors in parentheses. Standard errors are clustered at the county level. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Fixed Effects Estimation for SNAP

	(1) All	(2) Applied	(3) All	(4) Applied	(5) All	(6) Applied	(7) All	(8) Applied
Grant	1.3389***	1.3389***	0.3836	0.4114	0.3528	0.2843	0.3616	0.4064
	(0.4696)	(0.4728)	(0.4217)	(0.4386)	(0.3988)	(0.4044)	(0.4002)	(0.4320)
Poverty(%)					0.2176***	0.2181***	0.2247***	0.3027***
					(0.0415)	(0.0625)	(0.0489)	(0.0779)
Median HH Income			-0.0001**	0.0000			0.0000	0.0002*
			(0.0000)	(0.0001)			(0.0001)	(0.0001)
Unemployment(%)			0.2402***	0.2983***	0.1946***	0.2556***	0.1945***	0.2600***
			(0.0461)	(0.0755)	(0.0438)	(0.0683)	(0.0437)	(0.0642)
Population			0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
			(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Greater than HS(%)			0.2730***	0.2227*	0.2403***	0.2499**	0.2347***	0.1727
			(0.0421)	(0.1190)	(0.0389)	(0.1013)	(0.0428)	(0.1174)
Black population			-0.0000	-0.0010	-0.0000	-0.0009*	-0.0000	-0.0009*
			(0.0000)	(0.0006)	(0.0000)	(0.0006)	(0.0000)	(0.0005)
_cons	23.4846***	25.5187***	3.9902	14.6970	-2.5461	7.0320	-2.8903	3.3386
	(0.0038)	(0.0179)	(2.9586)	(11.6231)	(2.9999)	(11.1570)	(3.1931)	(10.4672)
N	2254	476	1932	408	1932	408	1932	408
Counties	322	68	322	68	322	68	322	68

Notes: Standard errors in parentheses. Standard errors clustered at the county level. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13 examines the impact on the SNAP program. Since the interventions were nearly all geared primarily toward School Lunch or Breakfast type programs, there was no expectation that the SNAP program would have a large impact. While columns 1 and 2 show a 1.3 percent increase in participation (statistically significant), the remaining columns show less than ½ percent change. It is important to note that all specifications show a positive impact on participation, the impact itself is economically small, and did not reach statistical significance.

Table 14 presents results for participation in the WIC program. In all specifications, grantees appear to have reduced WIC program participation more than the control groups (noting that in general participation declined). The estimated effect is between -1.02 and -2.25 percent, depending on the sample and specification. The largest effects were found in columns one and two, where no control variables were included. In models where control variables were included, the effects are smaller and not statistically significant.

Tables 15 and 16 present the effects of the grant on SSO and SFSP programs, respectively. In the case of both programs, like the School Breakfast Program, the coefficients for the treatment indicator are not statistically significant, although positive for all the specification. The estimations for the SSO program range from 0.55 to 0.04 percent increases and for SFSP program, the changes range from 0.19 to 0.02 percent increases. While these results show a very small increase that did not reach statistical significance, the low power due to small sample size combined with some limitations of the availability of data raises the possibility that there may be some positive programmatic effects.

Table 17 presents all propensity score matching results. The results only include the equivalent of the coefficient on grant and thus are comparable to the first row of the previous regression tables. Propensity score, unlike fixed effects, does not address unobserved heterogeneity. When using the full sample comparison, results are qualitatively similar to those found in regression models. The NSLP and SNAP programs showed positive impacts of the grant project, although only the impact on NSLP was statistically significant. Consistent with findings from regressions, the WIC program showed a statistically significant decline in participation rates for the grant recipients. In contrast, however, when using the applied counties, the impact on participation in the grant project was negative for all programs except SNAP, although none of the negative effects were statistically significant. The estimate for the SNAP program remained positive and was significant and slightly smaller. Possible explanations for this are that the selected counties were different in important but unobservable ways (hence the fixed effect estimates would be preferred) or that the project impact was highly variable depending on important controls; it is also possible that in simple regression models, one type of grant approach was dominating (in which case the propensity score estimates are preferred). The most likely scenario is that the fixed effects estimates are more indicative of the impact of the grant project. Unobserved heterogeneity is likely to be critically crucially important in participation rates, especially given the relatively limited list of control variables used in the propensity score.

Table 14: Fixed Effects Estimation for WIC – Total Participation

	(1) All	(2) Applied	(3) All	(4) Applied	(5) All	(6) Applied	(7) All	(8) Applied
Grant	-2.2524*	-2.2524*	-1.0434	-2.2391	-1.0171	-2.1432	-1.0421	-2.2096
	(1.2869)	(1.3017)	(1.5040)	(1.6787)	(1.4918)	(1.6180)	(1.4986)	(1.6236)
Poverty(%)					-0.0210	-0.0565	-0.0469	-0.1412
					(0.1315)	(0.1766)	(0.1972)	(0.1782)
Median HH Income			-0.0000	-0.0001			-0.0001	-0.0002*
			(0.0002)	(0.0001)			(0.0002)	(0.0001)
Unemployment(%)			-0.0996	-0.1159	-0.0902	-0.0945	-0.0888	-0.0738
			(0.1165)	(0.1687)	(0.1174)	(0.1167)	(0.1193)	(0.1172)
Population			-0.0000	-0.0001**	-0.0000	-0.0001**	-0.0000	-0.0001*
			(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Greater than HS(%)			-0.5420***	-0.0079	-0.5524***	-0.0475	-0.5318***	0.0231
			(0.1204)	(0.0769)	(0.1163)	(0.0948)	(0.1468)	(0.1050)
Black population			0.0001	0.0007	0.0001	0.0007	0.0001	0.0007
			(0.0001)	(0.0004)	(0.0001)	(0.0005)	(0.0001)	(0.0004)
_cons	16.3694***	11.3557***	59.4465***	11.4493	59.2198***	12.4144*	60.4902***	14.7389**
	(0.0190)	(0.0692)	(8.4915)	(7.4123)	(7.7278)	(6.2168)	(9.2149)	(5.7703)
N	744	207	744	207	744	207	744	207
Counties	152	39	152	39	152	39	152	39

Notes: Standard errors in parentheses. Standard errors clustered at the county level. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15: Fixed Effects Estimation for SSO

	(1) All	(2) Applied	(3) All	(4) Applied	(5) All	(6) Applied	(7) All	(8) Applied
Grant	0.3054	0.3054	0.2662	0.1750	0.0417	0.2193	0.3181	0.5517
	(0.3260)	(0.3416)	(0.6355)	(0.5788)	(0.5231)	(0.4699)	(0.6448)	(0.6562)
Poverty(%)					0.0160	0.1951	0.0981	0.3376
					(0.0676)	(0.1835)	(0.0901)	(0.2863)
Median HH Income			0.0002	0.0001			0.0002	0.0004
			(0.0001)	(0.0002)			(0.0002)	(0.0004)
Unemployment(%)			0.1562	-0.0481	0.1235	-0.0517	0.1427	-0.0729
			(0.1107)	(0.2261)	(0.1157)	(0.2650)	(0.1116)	(0.2677)
Population			-0.0000	-0.0000	-0.0000	0.0000	-0.0000	-0.0000
			(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Greater than HS(%)			0.2358**	0.0585	0.3009**	-0.0555	0.2307**	-0.1127
			(0.1147)	(0.2280)	(0.1298)	(0.1910)	(0.1135)	(0.1959)
Black population			-0.0000	0.0003	-0.0001	0.0004*	-0.0000	0.0009
			(0.0001)	(0.0004)	(0.0001)	(0.0002)	(0.0001)	(0.0007)
_cons	3.4573***	2.8775***	-20.6087**	-6.9949	-20.0075**	-3.6136	-24.4880**	-16.0823
	(0.0043)	(0.0342)	(9.4538)	(19.0100)	(9.1166)	(13.7147)	(10.7674)	(22.7694)
N	379	50	379	50	379	50	379	50
Counties	86	12	86	12	86	12	86	12

Notes: Standard errors in parentheses. Standard errors clustered at the county level. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 16: Fixed Effects Estimation for SFSP

	(1) All	(2) Applied	(3) All	(4) Applied	(5) All	(6) Applied	(7) All	(8) Applied
Grant	0.1040	0.1040	0.1976	0.0924	0.1873	0.0355	0.1831	0.0242
	(0.2492)	(0.2571)	(0.2339)	(0.1859)	(0.2510)	(0.2751)	(0.2448)	(0.2400)
Poverty(%)					0.0961***	0.1997**	0.0905**	0.1654
					(0.0289)	(0.0906)	(0.0348)	(0.1059)
Median HH Income			-0.0001	-0.0001**			-0.0000	-0.0001
			(0.0000)	(0.0001)			(0.0000)	(0.0001)
Unemployment(%)			0.0595	-0.0444	0.0377	-0.1385	0.0388	-0.1171
			(0.0402)	(0.0836)	(0.0375)	(0.1152)	(0.0378)	(0.1335)
Population			-0.0000*	0.0000	-0.0000*	0.0000	-0.0000	0.0000
			(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Greater than HS(%)			0.0379	0.0909	0.0186	0.0654	0.0235	0.1078
			(0.0471)	(0.1390)	(0.0453)	(0.0977)	(0.0464)	(0.1267)
Black population			0.0000	-0.0008	0.0000	-0.0006	0.0000	-0.0005
			(0.0000)	(0.0009)	(0.0000)	(0.0007)	(0.0000)	(0.0008)
_cons	2.9615***	2.3985***	1.7102	6.4797	-0.9823	-1.6392	-0.7533	-1.8289
	(0.0037)	(0.0257)	(3.3503)	(12.7466)	(3.2422)	(9.7565)	(3.4096)	(10.0562)
N	543	80	543	80	543	80	543	80
Counties	119	17	119	17	119	17	119	17

Notes: Standard errors in parentheses. Standard errors clustered at the county level. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 17: Propensity Score Match Estimate (Controls, Income, and Poverty)

Program Participation	NSLP	NSBP	SNAP	WIC	SFSP	SSO
All Counties	4.9246**	-0.3502	2.4294	-8.1334***	-0.8745	-0.4684
	(2.3654)	(2.0293)	(2.1799)	(2.4170)	(0.5973)	(1.1982)
Applied Counties	-1.0932	-0.2587	3.4160**	-3.3228	-0.2479	-0.4139
	(4.1072)	(1.9674)	(1.5380)	(2.5003)	(0.2278)	(0.7911)
Matches	3	3	3	3	3	3
Counties	409	43	68	39	17	12

Notes: Standard errors in parentheses. Standard errors are clustered at the county level.
Propensity score matches made using lagged values of median household income, poverty, Unemployment rate, population, percent high school graduate or higher, total African American population, and time trend. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

VI. Conclusions

The present investigation examined the effectiveness of a quasi-experimental project designed to provide support and training to community groups in order to improve the use of safety net food programs. It was hypothesized that the provision of support and training at the community level to these outreach organizations would positively impact and improve participation rates when compared to business-as-usual counties or populations. Study findings provide evidence of largely nonsignificant effects with some limitations. Therefore, there appears to be only weak evidence that the project had an impact on the counties. Importantly, survey data showed an initial decline that was larger than the one observed in national trends. Potential explanations of these observed differences might be explained by differences in economic conditions, thus undermining potential conclusions of programmatic effects. The subsequent rise in 2018 as compared to a larger decline in the CPS data suggests that the project had very little effect, or alternatively, that the initial effect quickly wore off. As previously noted, numerous issues and threats to conclusion validity exist when considering the comparison between the project survey data and comparisons to CPS data, further undermining the potential clue conclusion of programmatic impact and effects. This is further complicated by the fact that the study did not have adequate statistical power to test a number of the models. County level analyses do provide some evidence and indication of potentially positive effects by the intervention. The grant project had a modest positive impact on participation rates for the two school meal programs and SNAP, but a modestly negative impact on participation for WIC.

In conclusion, although the goal of the project was to improve access to safety net food programs, underlying this approach was the goal to simply build infrastructure. Thus, the project sought to build community assets through partnerships that would generate positive effects reducing food insecurity over the longer term. Given the relatively brief assessment framework to measure project effectiveness, these longer-term goals and potential returns might've been largely masked. Due to the subsequent Covid pandemic, it was very challenging to measure potential long-term effects. It should also be noted that the project itself was relatively modest in magnitude where grants were typically around $50,000 over the course of three years. If one expects a dose response, this modest amount might simply not be detectable. Therefore, an important conclusion from the present work is that future projects seeking to build infrastructure in order to support the reduction of food insecurity would be completed using both larger samples as well as longer evaluation periods.

References

Blundell, R., & Pistaferri, L. 2003. Income volatility and household consumption: The impact of food assistance programs. *Journal of Human resources*, vol. 38, pp.1032-1050.

Callaway, Brantly, and Pedro HC Sant'Anna. 2021. Difference-in-differences with multiple time periods. *Journal of Econometrics,* vol. 225, no. 2, pp. 200-230.

Coleman-Jensen, A., Rabbitt, M., Gregory, C., & Singh, A. 2017. Household food security in the United States in 2016. ERR-256, U.S. Department of Agriculture, Economic Research Service.

Coleman-Jensen, A., Rabbitt, M., Gregory, C., & Singh, A. 2018. Household food security in the United States in 2017. ERR-256, U.S. Department of Agriculture, Economic Research Service.

Coleman-Jensen, A., Rabbitt, M.P., Gregory, C.A. and Singh, A., 2022. Household food security in the United States in 2021. vol. 51. Washington, DC: United States Department of Agriculture Economic Research Service, pp.1-3.

Figlio, D. N., & Winicki, J. 2005. Food for thought: the effects of school accountability plans on school nutrition. *Journal of public Economics*, vol. *89* no.2-3, pp.381-394.

Farrigan, Tracy. 2018. Child Poverty Heavily Concentrated in Rural Mississippi, Even More So Than Before the Great Recession. Amber Waves https://www.ers.usda.gov/amber-waves/2018/july/child-poverty-heavily-concentrated-in-rural-mississippi-even-more-so-than-before-the-great-recession/

Farnham, K. 2017. Evaluating Nonresponse Bias in the 2015 Food Security Supplement to the Current Population Survey. Memorandum for U.S. Department of Agriculture, Economic Research Service, Food Assistance Branch, from U.S. Bureau of the Census Demographic Statistical Methods Division.

Gregory, C.A., M.P. Rabbitt, and D.C. Ribar. 2015. The Supplemental Nutrition Assistance Program and Food Insecurity. in SNAP Matters: How Food Stamps Affect Health and Well-Being. J. Bartfeld, C. Gundersen, T.M. Smeeding, and J.P. Ziliak (eds.), pp. 74–106, Stanford University Press.

Gregory, C.A. 2020. Are We Underestimating Food Insecurity? Partial Identification With a Bayesian 4-Parameter IRT Model. *Journal of Classification* vol. 37, pp. 632–655.

Gundersen, C., Kreider, B., & Pepper, J. 2012. The impact of the National School Lunch Program on child health: A nonparametric bounds analysis. *Journal of Econometrics*, vol.*166,* no. 1, pp. 79-91.

Gundersen, C., B. Krieder, and J. Pepper. 2017. Partial Identification Methods for Evaluating Food Assistance Programs: A Case Study of the Causal Effect of SNAP on Food Insecurity. *American Journal of Agricultural Economics* vol. 99 no. 4, pp.875–893.

Herman, D. R., Harrison, G. G., Afifi, A. A., & Jenks, E. 2004. The effect of the WIC program on food security status of pregnant, first-time participants. *Family Economics and Nutrition Review*, vol. *16,* no.1, p. 21.

Hoop, R., J. Hatch, E. Hood, and Farber, J. 2022. Evaluating Nonresponse Bias in the 2020 Food Security Supplement to the Current Population Survey. Memorandum for U.S. Department of Agriculture, Economic Research Service, Food Assistance Branch, from U.S. Bureau of the Census Demographic Statistical Methods Division.

Hoynes, H. W., & Schanzenbach, D. W. 2009. Consumption responses to in-kind transfers: Evidence from the introduction of the food stamp program. *American Economic Journal: Applied Economics*, vol. 1, no.4, pp.109-39.

Kabbani, N. S., & Kmeid, M. Y. 2005. The role of food assistance in helping food insecure households escape hunger. *Review of Agricultural Economics*, vol. 27, no.3, pp.439-445.

Kreider, B., Pepper, J. V., Gundersen, C., & Jolliffe, D. 2012. Identifying the effects of SNAP (food stamps) on child health outcomes when participation is endogenous and misreported. *Journal of the American Statistical Association*, vol. 107, no. 499, pp. 958-975.

Kreider, B., Pepper, J. V., & Roy, M. 2012. Identifying the effect of WIC on very low food security among infants and children. University of Kentucky Center for Poverty Research Discussion Paper Series. Paper 23.

McGranahan, David. 2015. Understanding the Geography of Growth in Rural Child Poverty Amber Waves. https://www.ers.usda.gov/amber-waves/2015/july/understanding-the-geography-of-growth-in-rural-child-poverty/

Millimet, D.J., I.K. McDonough, and T.B. Fomby. 2018. Financial Capability and Food Security in Extremely Vulnerable Households, *America Journal of Agricultural Economics* vol. 100, no. 4, pp.1224–1249.

Ratcliffe, C., McKernan, S. M., & Zhang, S. 2011. How much does the Supplemental Nutrition Assistance Program reduce food insecurity? *American Journal of Agricultural Economics*, vol. 93, no. 4, pp.1082-1098.

Tiehen, L., C. Newman, and J. Kirlin. 2017. The Food Spending Patterns of SNAP Households: Findings From the National Food Acquisition and Purchase Survey Data. EIB-176, U.S. Department of Agriculture, Economic Research Service.

Wauchope, Barbara and Shattuck, Anne, 2010. Federal child nutrition programs are important to rural households. The Carsey Institute at the Scholars' Repository. Paper 94. http://scholars.unh.edu/carsey/94

Appendix

Details of Participation Collection

Our data for National School Lunch Program (NSLP) for 322 poorest counties are derived from the counties corresponding state's Department of Education. The national school lunch participation data was available on the state agencies online portal. Some data was available at the school level, some at the school district level and some at the county level. Data that was available at the school and school district level was aggregated to the county level.

In 2015 Shannon County in South Dakota was renamed to Oglala Lakota County. Being unaware of this transition we missed including data on this county. Hence our poorest county count declined to 322. Participation rate in the National School Lunch Program for most counties for most years is calculated as the number of student's in a county enrolled in the free or reduced lunch program divided by the total number of a county's student population. In case of some counties there were some problems encountered during these calculations. School Enrollment data for some counties in Texas and West Virginia unavailable for some of the years leading to gaps in the participation rates of School Lunch Program as well as School Breakfast Program in these counties. Counties in Tennessee for the entire duration does not have enrollment data, however for 2010 to 2014 these counties report the participation rates. Data for Issaquena, MS and Buffalo, SD is missing for the entire period from the source files that we received from their respective state agencies. Final Lunch data available to us is an unbalanced panel of 320 counties between 2011 and 2017 with some gaps in the data.

Except for counties in Texas our data for School Breakfast Program (SBP) derived from the corresponding state's Department of Education. Data for Texan counties was provided by the department of Agriculture. Similar to the National School Lunch program data, some data was at the county level and some was at the school district level. Data at the school district level was aggregated to the county level. The data that we have for School Breakfast Program is the total number of meals served and for some counties we have the number of school days in a given year. The participation rate is calculated by dividing the average daily participation in a county to the total number of the county's student population. The average daily participation is the number of meals served divide by the average number of school days. Since, data for number of school days in a year is not available for all of the counties, I calculate the average school days for the available counties and use this average value to calculate average daily participation for each of the counties.

We have no data for any of the nineteen counties of Alabama, since we received no response from the responsible agencies. We received data for New Mexico counties, however we are unsure whether the data is count of students enrolled in the program or the number of meals served. It looks like it may be the number of students enrolled in the program. If that is indeed the case, then another reason to not include this data is that it would introduce inconsistencies in the measure of participation rate. Data for Missouri is available from 2012 to 2015. Updated data for the counties in Missouri was made available to us as a county of students enrolled in the program. Including this would introduce the same inconsistency in the measure as data for counties in New Mexico. Data for counties in Arkansas, Oklahoma, and South Carolina, is available for a period of 2012 – 2015. We did not receive data for the updated years (2016, 2017). There are gaps in the data for several counties in Georgia. Final Breakfast data is available for 233 counties spanning from 2012 to 2017 with several gaps in the data.

SNAP participation rate along with other demographic data like median household income, poverty rate, unemployment rate, population, percent of population with greater than high school education, and the count of the Black or African American population in the county used in the analysis are derived from 2016 American Community Survey's 5-year estimate. This data is a balanced panel of 322 counties between 2012 and 2016.

Data for Women, Infants, and Children (WIC) program is gathered from the counties corresponding state's Department of Health. Participation rate is calculated by dividing the total number of WIC participants in a county to the county's total population. Data for WIC is available for counties in Alabama, Arkansas, Louisiana, Missouri, North Carolina, Oklahoma, South Carolina, Tennessee, and Texas. Final WIC data is an unbalanced panel of 152 counties from 2011 to 2017.

Summer Food Service Program (SFSP) data is gathered from the counties corresponding state's Department of Education or Department of Health and Seamless Summer Option (SSO) is made available by Department of Education. SSO is a part of NSLP, however data for this program unlike NSLP is not available for all 322 counties. Participation rate is calculated by dividing the average daily participation in a county to the county's total population. The average daily participation is the number of meals served divide by the number of days summer meals were served. Since, data for number of days summer meals are served in a year is not available for all counties, I use number of days in June and July (61 days) as the number of days summer meals served. Final SSO data is an unbalanced panel of 80 counties and SFSP data is an unbalanced panel of 118 counties from 2011 to 2017.

A. Appendix Tables and Figures

Table A1: Linear Probability regressions on Household Food Insecurity Indicator with Weights

	Base	Income	Demographics	Full
Year 2017	-0.074	-0.027	-0.068	-0.022
	(1.38)	(0.65)	(1.36)	(0.55)
Year 2018	-0.062	-0.005	-0.055	-0.008
	(1.20)	(0.12)	(1.07)	(0.19)
Below Federal Poverty		0.607		0.548
		(13.23)**		(9.98)**
100% to 133% Poverty		0.483		0.433
		(8.74)**		(7.77)**
133% to 150% Poverty		0.206		0.195
		(4.56)**		(4.51)**
Age/100			-0.118	0.079
			(0.84)	(0.63)
African American			0.047	0.057
			(0.99)	(1.39)
Native American			0.144	0.069
			(2.22)*	(1.10)
Other Race			0.002	0.021
			(0.04)	(0.34)
Less than High School			0.318	0.212
			(4.93)**	(2.82)**
Trade School			0.028	0.070
			(0.38)	(1.30)
Associates Degree			-0.216	0.006
			(3.12)**	(0.10)
Bachelors Degree plus			-0.314	-0.026
			(5.78)**	(0.49)
Male			-0.039	-0.036
			(0.96)	(0.97)
Hispanic			0.048	0.004
			(0.67)	(0.06)
Intercept	0.342	0.092	0.530	0.055
	(8.31)**	(2.76)**	(4.86)**	(0.55)

Notes: Dependent variable = 1 if food insecure; n=1,633, robust standard errors, significance * $p<0.05$; ** $p<0.01$.

Table A2: Linear Probability Regressions on Child Food Insecurity Indicator Survey Analysis Sample with Weights

	Base	Income	Demographics	Full
Year 2017	-0.118	-0.004	-0.086	-0.003
	(1.69)	(0.08)	(1.21)	(0.06)
Year 2018	-0.029	0.016	-0.039	0.005
	(0.42)	(0.29)	(0.55)	(0.09)
Below Federal Poverty		0.545		0.502
		(10.09)**		(6.89)**
100% to 133% Poverty		0.368		0.324
		(6.22)**		(4.69)**
133% to 150% Poverty		0.175		0.149
		(3.73)**		(2.98)**
Age/100			-0.138	0.007
			(0.62)	(0.04)
African American			-0.067	-0.032
			(1.22)	(0.71)
Native American			0.055	-0.005
			(0.62)	(0.05)
Other Race			-0.018	0.024
			(0.23)	(0.30)
Less than High School			0.339	0.293
			(3.45)**	(2.95)**
Trade School			0.086	0.037
			(0.96)	(0.44)
Associates Degree			-0.129	0.066
			(1.40)	(0.78)
Bachelors Degree plus			-0.290	-0.028
			(4.09)**	(0.37)
Male			-0.026	0.003
			(0.50)	(0.07)
Hispanic			-0.042	-0.122
			(0.45)	(1.36)
Intercept	0.345	0.054	0.529	0.072
	(6.08)**	(1.42)	(3.49)**	(0.51)

Notes: Dependent variable = 1 if food insecure; n=1,633, robust standard errors, significance * $p<0.05$; ** $p<0.01$.

Table A3: Marginal Effects from Probit Regressions on Household Food Insecurity Indicator

VARIABLES	Base	Income	Demographics	Full
Year 2017	-0.0530*	-0.0517**	-0.0536*	-0.0496*
	(0.0295)	(0.0256)	(0.0274)	(0.0258)
Year 2018	0.0142	0.0303	0.0144	0.0307
	(0.0300)	(0.0264)	(0.0282)	(0.0256)
Age/100			-0.171*	0.00588
			(0.0880)	(0.0837)
African American			0.0699**	0.0121
			(0.0288)	(0.0273)
Native American			0.116**	0.0670
			(0.0468)	(0.0430)
Other Race			0.0764**	0.0507
			(0.0367)	(0.0336)
Less than High School			0.133***	0.0767*
			(0.0433)	(0.0402)
Trade School			-0.0904**	-0.0500
			(0.0358)	(0.0329)
Associates Degree			-0.167***	-0.0353
			(0.0352)	(0.0348)
Bachelors Degree plus			-0.331***	-0.112***
			(0.0261)	(0.0310)
Male			-0.0355	-0.0264
			(0.0319)	(0.0313)
Hispanic			0.0414	0.0263
			(0.0410)	(0.0371)
Below Federal Poverty		0.550***		0.465***
		(0.0200)		(0.0297)
100% to 133% Poverty		0.455***		0.397***
		(0.0284)		(0.0322)
133% to 150% Poverty		0.282***		0.250***
		(0.0327)		(0.0339)
Observations	1,633	1,633	1,633	1,633

Table A4: Marginal Effects from Probit Regressions on Child Food Insecurity Indicator

VARIABLES	Base	Income	Demographics	Full
Year 2017	-0.0677*	-0.0374	-0.0614*	-0.0394
	(0.0363)	(0.0331)	(0.0340)	(0.0330)
Year 2018	-0.00344	0.0265	0.00825	0.0265
	(0.0367)	(0.0337)	(0.0350)	(0.0328)
Age/100			0.154	0.169
			(0.141)	(0.137)
African American			0.00948	-0.0281
			(0.0372)	(0.0353)
Native American			0.0923	0.0529
			(0.0614)	(0.0584)
Other Race			0.0376	0.0263
			(0.0468)	(0.0456)
Less than High School			0.174***	0.145***
			(0.0505)	(0.0486)
Trade School			-0.0965**	-0.0701*
			(0.0425)	(0.0400)
Associates Degree			-0.187***	-0.0824*
			(0.0442)	(0.0450)
Bachelors Degree plus			-0.337***	-0.165***
			(0.0349)	(0.0403)
Male			0.000119	0.00650
			(0.0407)	(0.0398)
Hispanic			-0.000489	-0.0139
			(0.0490)	(0.0484)
Below Federal Poverty		0.556***		0.449***
		(0.0384)		(0.0473)
100% to 133% Poverty		0.461***		0.394***
		(0.0468)		(0.0498)
133% to 150% Poverty		0.286***		0.253***
		(0.0518)		(0.0526)
Observations	1,060	1,060	1,060	1,060

Table A5: Base Linear Model for Household Food Insecurity across Samples

	Any	FI complete	Dem Complete	Complete All
Year 2017	-0.039	-0.043	-0.049	-0.053
	(1.56)	(1.68)	(1.83)	(1.79)
Year 2018	0.028	0.011	0.004	0.014
	(1.10)	(0.42)	(0.13)	(0.47)
Intercept	0.447	0.454	0.455	0.443
	(25.53)**	(25.38)**	(24.28)**	(21.20)**
N	2,283	2,186	2,021	1,633

Table A6: Demographics Linear Model for Household Food Insecurity across Samples

	Any	FI complete	Dem Complete	Complete All
Year 2017	-0.050	-0.051	-0.051	-0.057
	(2.02)*	(2.01)*	(2.01)*	(2.05)*
Year 2018	0.005	-0.002	-0.002	0.015
	(0.22)	(0.07)	(0.07)	(0.53)
Age/100	-0.130	-0.142	-0.142	-0.173
	(1.68)	(1.81)	(1.81)	(1.96)
African American	0.079	0.074	0.074	0.068
	(2.98)**	(2.77)**	(2.77)**	(2.32)*
Native American	0.159	0.172	0.172	0.118
	(3.60)**	(3.84)**	(3.84)**	(2.39)*
Other Race	0.082	0.081	0.081	0.074
	(2.52)*	(2.47)*	(2.47)*	(2.05)*
Less than High School	0.197	0.204	0.204	0.141
	(5.69)**	(5.83)**	(5.83)**	(3.25)**
Trade School	-0.067	-0.057	-0.057	-0.102
	(1.86)	(1.57)	(1.57)	(2.53)*
Associates Degree	-0.160	-0.158	-0.158	-0.188
	(4.58)**	(4.44)**	(4.44)**	(4.81)**
Bachelors Plus	-0.318	-0.317	-0.317	-0.346
	(12.08)**	(11.88)**	(11.88)**	(11.86)**
Male	-0.015	-0.015	-0.015	-0.035
	(0.51)	(0.51)	(0.51)	(1.07)
Hispanic	0.033	0.031	0.031	0.045
	(0.93)	(0.86)	(0.86)	(1.09)
Intercept	0.549	0.556	0.556	0.601
	(12.01)**	(12.00)**	(12.00)**	(11.66)**
N	2,083	2,021	2,021	1,633

Table A7: Full Linear Model for Household Food Insecurity across Samples

	Any	FI complete	Dem complete	Complete all
Year 2017	-0.055	-0.055	-0.055	-0.055
	(2.08)*	(2.08)*	(2.08)*	(2.08)*
Year 2018	0.032	0.030	0.030	0.030
	(1.24)	(1.17)	(1.17)	(1.17)
Age/100	-0.002	0.008	0.008	0.008
	(0.02)	(0.10)	(0.10)	(0.10)
African American	0.012	0.008	0.008	0.008
	(0.45)	(0.30)	(0.30)	(0.30)
Native American	0.067	0.070	0.070	0.070
	(1.51)	(1.57)	(1.57)	(1.57)
Other Race	0.049	0.048	0.048	0.048
	(1.47)	(1.42)	(1.42)	(1.42)
Less than High School	0.088	0.088	0.088	0.088
	(2.05)*	(2.02)*	(2.02)*	(2.02)*
Trade School	-0.052	-0.055	-0.055	-0.055
	(1.36)	(1.43)	(1.43)	(1.43)
Associates Degree	-0.041	-0.042	-0.042	-0.042
	(1.06)	(1.09)	(1.09)	(1.09)
Bachelors Plus	-0.112	-0.112	-0.112	-0.112
	(3.37)**	(3.35)**	(3.35)**	(3.35)**
Male	-0.021	-0.027	-0.027	-0.027
	(0.68)	(0.85)	(0.85)	(0.85)
Hispanic	0.023	0.028	0.028	0.028
	(0.60)	(0.72)	(0.72)	(0.72)
Below Federal Poverty	0.490	0.493	0.493	0.493
	(14.77)**	(14.76)**	(14.76)**	(14.76)**
100% to 133% Poverty	0.401	0.406	0.406	0.406
	(11.21)**	(11.27)**	(11.27)**	(11.27)**
133% to 150% Poverty	0.217	0.218	0.218	0.218
	(6.73)**	(6.72)**	(6.72)**	(6.72)**
Intercept	0.172	0.169	0.169	0.169
	(3.07)**	(3.01)**	(3.01)**	(3.01)**
N	1,657	1,633	1,633	1,633

Table A8: Base Linear Model for Child Food Insecurity across Samples

	Any	FI complete	Dem Complete	Complete All
Year 2017	-0.048	-0.047	-0.061	-0.067
	(1.54)	(1.51)	(1.87)	(1.86)
Year 2018	0.006	0.010	-0.013	-0.003
	(0.18)	(0.32)	(0.39)	(0.09)
Intercept	0.418	0.417	0.424	0.428
	(19.33)**	(19.23)**	(18.57)**	(16.76)**
N	1,453	1,437	1,319	1,060

Table A9: Demographics Linear Model for Child Food Insecurity across Samples

	Any	FI complete	Dem Complete	Complete All
Year 2017	-0.057	-0.055	-0.052	-0.066
	(1.80)	(1.74)	(1.66)	(1.88)
Year 2018	0.011	0.011	0.005	0.009
	(0.35)	(0.37)	(0.16)	(0.27)
Age/100	0.338	0.338	0.302	0.168
	(2.52)*	(2.52)*	(2.23)*	(1.12)
African American	0.020	0.016	0.012	0.007
	(0.60)	(0.48)	(0.36)	(0.18)
Native American	0.156	0.155	0.160	0.094
	(2.79)**	(2.77)**	(2.86)**	(1.46)
Other Race	0.011	0.008	0.005	0.034
	(0.25)	(0.18)	(0.12)	(0.71)
Less than High School	0.184	0.184	0.188	0.190
	(4.20)**	(4.21)**	(4.23)**	(3.64)**
Trade School	-0.063	-0.067	-0.061	-0.110
	(1.48)	(1.55)	(1.42)	(2.29)*
Associates Degree	-0.187	-0.191	-0.193	-0.209
	(4.33)**	(4.43)**	(4.46)**	(4.32)**
Bachelors Plus	-0.309	-0.308	-0.311	-0.343
	(9.28)**	(9.25)**	(9.33)**	(9.35)**
Male	0.010	0.004	0.007	0.000
	(0.26)	(0.09)	(0.17)	(0.00)
Hispanic	0.056	0.062	0.054	0.001
	(1.18)	(1.29)	(1.12)	(0.01)
Intercept	0.344	0.345	0.362	0.460
	(5.27)**	(5.28)**	(5.51)**	(6.37)**
N	1,338	1,332	1,319	1,060

Table A10: Full Linear Model for Child Food Insecurity across Samples

	Any	FI complete	Dem complete	Complete all
Year 2017	-0.045	-0.044	-0.046	-0.046
	(1.33)	(1.32)	(1.35)	(1.35)
Year 2018	0.033	0.033	0.030	0.030
	(0.99)	(0.99)	(0.91)	(0.91)
Age/100	0.198	0.201	0.202	0.202
	(1.39)	(1.40)	(1.41)	(1.41)
African American	-0.026	-0.031	-0.033	-0.033
	(0.76)	(0.89)	(0.94)	(0.94)
Native American	0.054	0.051	0.055	0.055
	(0.88)	(0.84)	(0.90)	(0.90)
Other Race	0.026	0.023	0.023	0.023
	(0.57)	(0.50)	(0.50)	(0.50)
Less than High School	0.170	0.169	0.166	0.166
	(3.27)**	(3.24)**	(3.17)**	(3.17)**
Trade School	-0.079	-0.083	-0.080	-0.080
	(1.70)	(1.78)	(1.71)	(1.71)
Associates Degree	-0.102	-0.100	-0.100	-0.100
	(2.11)*	(2.07)*	(2.07)*	(2.07)*
Bachelors Plus	-0.165	-0.161	-0.165	-0.165
	(3.93)**	(3.82)**	(3.92)**	(3.92)**
Male	0.020	0.011	0.011	0.011
	(0.51)	(0.26)	(0.28)	(0.28)
Hispanic	-0.012	-0.007	-0.013	-0.013
	(0.23)	(0.13)	(0.26)	(0.26)
Below Federal Poverty	0.403	0.409	0.408	0.408
	(10.01)**	(10.11)**	(10.07)**	(10.07)**
100% to 133% Poverty	0.339	0.339	0.335	0.335
	(7.86)**	(7.85)**	(7.75)**	(7.75)**
133% to 150% Poverty	0.177	0.175	0.172	0.172
	(4.62)**	(4.59)**	(4.49)**	(4.49)**
Intercept	0.118	0.117	0.121	0.121
	(1.53)	(1.52)	(1.57)	(1.57)
N	1,071	1,066	1,060	1,060

Table A11: Unweighted CPS Estimates of Household Food Insecurity Models

	Base	Income	Demographics	Full
Year 2017	-0.004	-0.003	-0.003	-0.002
	(0.92)	(0.60)	(0.66)	(0.40)
Year 2018	-0.019	-0.012	-0.014	-0.010
	(4.23)**	(2.88)**	(3.30)**	(2.45)*
Below Federal Poverty		0.306		0.255
		(43.47)**		(34.52)**
100% to 133% Poverty		0.210		0.172
		(19.86)**		(16.16)**
133% to 150% Poverty		0.176		0.149
		(16.93)**		(14.28)**
Age/100			-0.187	-0.152
			(18.53)**	(15.29)**
African American			0.091	0.060
			(15.40)**	(10.48)**
Native American			0.119	0.077
			(6.67)**	(4.42)**
Other Race			0.114	0.089
			(6.01)**	(4.86)**
Less than High School			0.114	0.052
			(15.29)**	(7.06)**
Trade School			-0.028	-0.006
			(3.35)**	(0.77)
Associates Degree			-0.023	-0.0004
			(2.81)**	(0.05)
Bachelors Degree plus			-0.109	-0.068
			(31.48)**	(20.16)**
Male			-0.049	-0.029
			(13.92)**	(8.44)**
Hispanic			0.016	0.002
			(2.31)*	(0.24)
Intercept	0.145	0.081	0.268	0.187
	(46.60)**	(27.70)**	(36.00)**	(25.53)**
N	36,161	36,161	36,161	36,161

Table A12: Unweighted CPS Estimates of Child Food Insecurity Models

	Base	Income	Demographics	Full
Year 2017	-0.002	-0.002	-0.003	-0.002
	(0.22)	(0.21)	(0.30)	(0.27)
Year 2018	-0.022	-0.015	-0.017	-0.013
	(2.44)*	(1.78)	(1.89)	(1.54)
Below Federal Poverty		0.326		0.272
		(27.25)**		(20.67)**
100% to 133% Poverty		0.221		0.185
		(13.11)**		(10.71)**
133% to 150% Poverty		0.209		0.170
		(8.84)**		(7.13)**
Age/100			-0.027	0.016
			(0.78)	(0.47)
African American			0.087	0.044
			(7.46)**	(3.83)**
Native American			0.131	0.086
			(4.43)**	(3.05)**
Other Race			0.129	0.108
			(3.69)**	(3.15)**
Less than High School			0.097	0.033
			(6.42)**	(2.20)*
Trade School			-0.045	-0.016
			(2.82)**	(1.04)
Associates Degree			-0.016	0.011
			(0.99)	(0.70)
Bachelors Degree plus			-0.138	-0.076
			(18.44)**	(10.37)**
Male			-0.084	-0.054
			(11.61)**	(7.71)**
Hispanic			0.012	-0.010
			(1.09)	(0.87)
Intercept	0.187	0.102	0.247	0.143
	(29.68)**	(17.16)**	(15.16)**	(8.92)**
R^2	0.00	0.12	0.07	0.14
N	10,453	10,453	10,453	10,453

Notes: States in the Applied category. Dependent variable = 1 if household is food insecure; t-statistics in parenthesis based on robust standard errors, * $p<0.05$; ** $p<0.01$.

Survey Instrument

Section I

1. Have you heard of the following child food assistant programs?

	Participated myself or one of my family members participated in it	I have known or heard of it	I've never heard of it
National School Lunch Program (NSLP)	☐	☐	☐
School Breakfast Program (SBP)	☐	☐	☐
Summer food service program (SFSP)	☐	☐	☐
Supplemental nutrition assistance program (SNAP) (food stamps)	☐	☐	☐
Child and Adult Care Food Program (CACFP)	☐	☐	☐
Women, Infants, and Children program (WIC)	☐	☐	☐
Food Distribution Program on Indian Reservations (FDPIR)	☐	☐	☐

2. Do you think that any of these statements stop you from applying for child food assistance programs?

	Yes	No
Do not know if I'm eligible	☐	☐
Do not know how or where to apply	☐	☐
Do not like to rely on government assistance/charity	☐	☐
Do not want my peers to know I need help	☐	☐
People treat you badly	☐	☐
Don't feel like it	☐	☐
Had bad experience with food assistant programs	☐	☐
Too much paperwork	☐	☐
Transportation is a problem	☐	☐
Benefit too small for effort required	☐	☐

3. Do you agree with these statements?

	Never	Sometimes	Quite Often	Always	Other
People should be ashamed about being on child food assistant programs	☐	☐	☐	☐	☐
People Should be bothered by being on child food assistant programs	☐	☐	☐	☒	☐

4. Do you know these programs in your area?

	Yes	No
Farmers' Market	☐	☐
Community gardens	☐	☐
Asset development programs	☐	☐
Food-buying cooperatives	☐	☐
Community-supported agriculture programs	☐	☐
Farm-to-school initiatives	☐	☐
Community kitchens	☐	☐
Food Pantries or Food Banks	☐	☐

Section II

5. Do you have a car?
   - ☐ Yes
   - ☐ No

6. Can you use public or community transportation, like buses, to get to places where you get child food assistance programs (like SNAP)?
   - ☐ Yes
   - ☐ No

Section III

7. "We worried whether our food would run out before we got money to buy more." Was that often, sometimes, or never true for you in the last 12 months?
   - ☐ Often true
   - ☐ Sometimes true
   - ☐ Never

8. "The food that we bought just didn't last and we didn't have money to get more." Was that often, sometimes, or never true for you in the last 12 months?

☐ Often true
☐ Sometimes true
☐ Never

9. "We couldn't afford to eat balanced meals." Was that often, sometimes, or never true for you in the last 12 months?
   ☐ Often true
   ☐ Sometimes true
   ☐ Never

10. In the last 12 months, did you or other adults in the household ever cut the size of your meals or skip meals because there wasn't enough money for food?
    ☐ Yes
    ☐ No

11. If you answered yes to question 10, how often did you or other family members cut or skip meals because there was no food?
    ☐ Almost every month
    ☐ Some months but not every month
    ☐ Only 1 or 2 months

12. In the last 12 months, did you ever eat less than you felt you should because there wasn't enough money for food?
    ☐ Yes
    ☐ No

13. In the last 12 months, were you ever hungry, but didn't eat, because there wasn't enough money for food?
    ☐ Yes
    ☐ No

14. In the last 12 months, did you lose weight because there wasn't enough money for food?
    ☐ Yes
    ☐ No

15. In the last 12 months did you or other adults in your household ever not eat for a whole day because there wasn't enough money for food?
    ☐ Yes
    ☐ No

16. How often did you or other adults not eat for a whole day when there was no food?
    ☐ Almost every month
    ☐ Some months but not every month

☐ Only 1 or 2 months

17. Do you have children age 0-17 in your home?
    ☐ Yes
    ☐ No

18. "We relied on only a few kinds of low-cost food to feed our children because we were running out of money to buy food." Was that often, sometimes, or never true for you in the last 12 months?
    ☐ Often true
    ☐ Sometimes true
    ☐ Never

19. "We couldn't feed our children a balanced meal, because we couldn't afford that." Was that often, sometimes, or never true for you in the last 12 months?
    ☐ Often true
    ☐ Sometimes true
    ☐ Never

20. "The children were not eating enough because we just couldn't afford enough food." Was that often, sometimes, or never true for you in the last 12 months?
    ☐ Often true
    ☐ Sometimes true
    ☐ Never

21. In the last 12 months, did you ever cut the size of any of the children's meals because there wasn't enough money for food?
    ☐ Yes
    ☐ No

22. In the last 12 months, were the children ever hungry but you just couldn't afford more food? (Yes/No)
    ☐ Yes
    ☐ No

23. In the last 12 months, did any of the children ever skip a meal because there wasn't enough money for food? (Yes/No)
    ☐ Yes
    ☐ No

24. How often in the last twelve months did the children in your family have to skip a meal because there was no food?
    ☐ Almost every month

☐ Some months but not every month
☐ Only 1 or 2 months

25. In the last 12 months did any of the children ever not eat for a whole day because there wasn't enough money for food?
☐ Yes
☐ No

Section IV

26. What is your age?

____

27. What is your sex?
☐ Male
☐ Female

28. What race/ethnicity do you consider yourself?
☐ African American (black)
☐ American Indian
☐ Asian American
☐ European American
☐ Other

29. Do you consider yourself to be Hispanic or Latino?
☐ Yes
☐ No

30. What is your highest educational level at this point?
☐ Less than high school graduation
☐ High school diploma or GED
☐ Technical or skilled trade training
☐ Associate’s degree
☐ Bachelor’s degree or above

31. How many people are in your household?
☐ 1
☐ 2
☐ 3
☐ 4
☐ 5
☐ 6

☐ 7
☐ 8
☐ 9
☐ 10
☐ Over 10 people

32. How much did your family have in income last month? (Circle the relevant range based on the number of people in your household)

No. of People in your Household	Income			
1	$0 - $990	$991 - $1287	$1288 - $1832	$1833+
2	$0 - $1335	$1336 - $1736	$1737 - $2470	$2471+
3	$0 - $1680	$1681 - $2184	$2185 - $3108	$3109+
4	$0 - $2025	$2026 - $2633	$2634 - $3747	$3748+
5	$0 - $2370	$2371 - $3081	$3082 - $4385	$4386+
6	$0 - $2715	$2716 - $3530	$3531 - $5023	$5024+
7	$0 - $3061	$3062 - $3980	$3981 - $5663	$5664+
8	$0 - $3408	$3509 - $4430	$4431 - $6304	$6305+
9	$0 - $3754	$3755 - $4881	$4882 - $6946	$6947+
10	$0 - $4100	$4101 - $5332	$5333 - $7588	$7589+
Over 10 people	$0 - $4600	$4601 - $5980	$5981 - $8280	$8281+

33. Place of Residence
State

____

County

____

Do you live within city limits?
☐ Yes
☐ No

34. Number of people in the household between the ages of 0 – 17:

____