**Report on the Evaluation of Ohio’s Wage Pathways Program**

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We thank the staff at ODJFS for their advice, guidance, unstinting cooperation and hard work in making a great deal of administrative data available to the evaluation. We have no doubt that without the data they provided, the statistical power of the analysis would not be sufficient to detect the program’s impact.

The Ohio Longitudinal Data Archive is a project of the Ohio Education Research Center (oerc.osu.edu) and provides researchers with centralized access to administrative data. The OLDA is managed by The Ohio State University's CHRR (chrr.osu.edu) in collaboration with Ohio's state workforce and education agencies (ohioanalytics.gov), with those agencies providing oversight and funding. For information on OLDA sponsors, see http://chrr.osu.edu .

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# Executive Summary

**The quantitative analysis of the Ohio Wage Pathways program detects an economically and statistically significant program effect on earnings**. We use 2nd Quarter 2018 through 1st Quarter 2019 as our post-onset period, allowing time for the selected counties (Cuyahoga, Ashtabula, Ottawa and Summit) to get Wage Pathways operating and for the program effect on earnings to be manifest. We estimate the program increases the earnings of eligible CCMEP clients by about $500/year, even after controlling for demographic variables. From the outset, we designed this evaluation to compare outcomes for eligible persons versus ineligible persons, where county of residence determines eligibility. This leaves the evaluation unaffected by any tendency of case workers to route more “promising” clients to receive the intervention – a problem known as “creaming.”

Wage Pathways is a “conditional cash transfer” program that provides incentives for youths to do that which is arguably in their own interests. We find that, for CCMEP youths early in their careers, one more year of work experience increases earnings about 25% versus about 4% for one more year of education. As youths become established, the return to experience falls whereas the return to education and training grows. For many youths, incentives to find and hold a job align with their lack of interest in education and training, at least early on. It appears the work skills gained on the first few jobs kick-start the youth’s earning power, and this likely underlies the findings here of a cost-effective program.

**The analysis is a “difference-in-difference” evaluation**, using each person’s labor force outcomes in the year before Wage Pathways started (pre-onset) as the “control” for their outcomes subsequent to program start-up (post-onset). We compared this change from the pre-onset period (2nd Quarter 2016 through 1st Quarter 2017) to the post-onset period for each person. We then compared this change for CCMEP clients in counties with Wage Pathways (experimental counties) to the change in counties without Wage Pathways (control counties), hence the name for this style of analysis “difference-in-differences.”

This approach “nets out” both observed and unobserved differences between the pre- and post-onset periods for both “experimentals” and “controls,” greatly reducing the risk of bias due to differences between those eligible for Wage Pathways and those who were ineligible. **About 20% of the CCMEP cases used in this evaluation were in Wage Pathways counties**. We also allowed for a number of demographic factors to influence earnings growth between the two periods. We have more confidence in our estimate of program effects on earnings than our estimate of how the program changes operating costs in the counties. This reflects the power of the administrative data we used. Those data allowed us to measure weeks of experience with great accuracy, **revealing a large rate of return to experience early in the work career**. This large return to experience, which early in the career is larger than the return to schooling for this population, may be driving the ability of a conditional cash transfer strategy to jump-start careers. It is possible the results here reflect, in part, the strong labor market the economy continues to enjoy. Perhaps the Wage Pathways program was the right program at the right time.

**The Wage Pathways experiment could not employ random assignment**, so a weakness is the possibility that experimental counties faced different labor market conditions from the other 84 “control” counties. However, we used extensive data from Ohio’s Unemployment Insurance Earnings database to construct labor market indicators that we used as control factors in the estimation. Those labor market indicators did not materially affect the results, although some were statistically significant factors in explaining the change in earnings for our sample of approximately 15,000 in-scope CCMEP entrants. Aside from a higher proportion of Blacks in the experimental counties, youths in the control counties are an excellent match.

# Introduction

This report evaluates Ohio’s Wage Pathways experiment, funded by the U.S. Department of Labor through a Workforce Innovation Fund grant. This evaluation effort leans heavily on administrative data, especially Unemployment Insurance Earnings data (hereinafter UI Earnings data). The Ohio Department of Job and Family Services (ODJFS) deposits this and other data with the Ohio Longitudinal Data Archive (OLDA) and the evaluation effort uses the data in the OLDA for much of its analysis. The Ohio State University (OSU) is the evaluator and host of the OLDA, which is a cooperative relationship between OSU and several agencies of the State of Ohio.

**We find the Wage Pathways program appears to make positive earnings impacts that are economically and statistically significant. Our evaluation does not use true random assignment of subject and treatment and, while we do what we can to control for the fact that eligibility is defined by county and not random assignment within county, the lack of true random assignment is a clear and unavoidable weakness.** Quantitative results compare CCMEP youth eligible for WP with youth who are ineligible. Because county of residence determines eligibility, the results are not due to county staff assigning youth more likely to be successful to wage pathway programs. **People often refer to the tendency to assign better prospects to a program as “creaming”; an implementation practice that severely compromises any evaluation. Because county of residence determines eligibility, the evaluation here avoids the “creaming” bias.**

The findings here **may be limited by the possibility that this program was the right program at the right time.** Wage Pathways started up when the labor market was undeniably strong and that continues as of this writing. Whether the impacts we find here would have been found in a less favorable labor market is open to question.

# Project Description

## The Wage Pathways Intervention

The Ohio Department of Job and Family Services (hereinafter ODJFS) undertook a significant restructuring of its workforce and support programs funded with Federal support. ODJFS has labelled these restructured programs as the **Comprehensive Case Management and Employment Program (hereinafter CCMEP).** The Wage Pathways (WP) project offers additional incentives and participant support over and above the CCMEP program. The WP incentives provide payments for continued employment, progress in securing a higher rate of pay, and payments for participants working their way into “in demand” jobs as defined by the state based on considerable input from employers. For the reader to understand Wage Pathways, we must first describe the CCMEP program that provides the overall framework within which the WP experiment fits.

## Comprehensive Case Management and Employment Program (CCMEP)

CCMEP began July 1, 2016 as an innovative approach to addressing both youth underemployment and barriers to jobs or skills attainment. The program combines income support from Temporary Assistance for Needy Families (TANF) with job and skill training from the Workforce Innovation and Opportunity Act (WIOA). CCMEP was implemented statewide, in all counties, by statute.[[2]](#footnote-2) The state allocated over $114 million in its fiscal year 2017 budget (covering July 2016 – June 2017) to ensure the success of CCMEP. The experience Ohio had in implementing CCMEP (and Wage Pathways) has implications for how we evaluate the program, so we start with a discussion of the larger CCMEP program and its implementation.

While many of the services the state and counties deliver to youths remain the same, more than half the counties saw the patterns of service delivery change. The Workforce Innovation and Opportunity Act (WIOA) provides funding to assist youth and adults 14 and over as well as dislocated workers to gain training for entry or reentry to the workforce as well as career services. In addition, counties use funds from the Temporary Assistance for Needy Families (TANF) program to support CCMEP. CCMEP allows counties to combine these two funding streams and integrate the collective training, career services and support activities into an integrated approach for helping eligible youth 16-24 accrue the skills and training they need to find and hold jobs. In the 2017-2018 program year, CCMEP also served youths 14-15, but Wage Pathways is only for youths 18-24. Simultaneously, the integrated CCMEP approach provides other support recipients may need to deal with the problems of everyday life, lest those problems—housing, transportation, medical, or other basic needs--prevent them from holding down a job.

Under CCMEP, counties need to deliver wrap-around services under WIOA, TANF and the Supplemental Nutrition Assistance Program (SNAP) in a holistic manner rather than piecemeal[[3]](#footnote-3). While many states centrally administer their programs, Ohio’s counties (and groups of counties for some programs like WIOA) play a significant role in administering these programs. With 88 counties in Ohio, the largest counties have almost 100 times the population of the smallest, and this scale difference necessitates different service delivery models among the counties.

In addition to evaluating Wage Pathways, the larger team[[4]](#footnote-4) at Ohio State will also evaluate CCMEP through a project with ODJFS, funded by the Laura and John Arnold Foundation. The CCMEP evaluation includes an Implementation Study[[5]](#footnote-5) to identify CCMEP implementation practices used by county and regional agencies in year one. To determine how this implementation worked, the Ohio Education Research Center (OERC) conducted a two-part study regarding the practices employed at the county level. The first part used an online survey to collect data from County Departments of Job and Family Services, Workforce Development Agencies and Workforce Development Boards throughout the state. The second part relied on in-depth focus groups with eleven counties.

Did the advent of CCMEP change the way counties, workforce development agencies and workforce development boards interacted with their clientele? At the outset, about half the counties and workforce development organizations reviewed their practices in terms of their appropriateness for the new CCMEP approach. In about 40% of the counties, policies for serving youth changed to either a great or very great extent. This resulted in structural changes to the agency in about 25% of the cases, and a great or very great change in the operational approach to serving youth in about a third of the counties and over half of the workforce development boards or agencies.

In 75% of the counties and nearly all the workforce development organizations, officials changed how they used the traditional workforce experience program to assign participants individualized activities based on a comprehensive assessment of their situation. This evaluation of participant situations used an extensive questionnaire administered to clients who presented themselves for possible receipt of CCMEP services. The evaluation has access to these questionnaires, which we refer to as the CCMEP enrollment data. Based on information received at intake, over 80% of the counties provide youth with paid workforce experience opportunities funded through TANF subsidized employment.

CCMEP implementation saw some rough spots. The statewide data system needed revision. Integrating work activities undertaken within CCMEP with the reporting system created difficulties for over half the counties. Half the counties had problems recruiting youth for the program, although counties could more easily recruit WIOA eligible youth than TANF youth. Early on, counties also had trouble getting state guidance on WIOA, TANF and Ohio Works First (OWF) program guidelines. Focus groups revealed some counties had problems with maintaining seamless case management, writing policies, and implementing policies and guidelines at the local level. Counties had better experiences in their ability to meet the needs of CCMEP participants and only about 25% reported staff motivation was a moderate or great challenge.

Survey and focus group information reveals a complex and sometimes difficult process of implementing the CCMEP program. With Wage Pathways being an experimental component of CCMEP, one would reasonably expect implementation difficulties with CCMEP would be reflected in WP. Given this “learning by doing” aspect of CCMEP, the WP program started out unevenly, depending on the particular county, with program administration becoming stronger as time passed. With the program phasing in during the second calendar quarter of 2017, that quarter and the quarters immediately after may not have had a fully-functioning CCMEP or WP program. As we discuss below, our approach uses a difference-in-differences analysis comparing outcomes before the onset of Wage Pathways to outcomes after the onset of Wage Pathways. With the implementation of CCMEP and WP varying in smoothness across counties, one might reasonably expect the program effects to start out small, suggesting a strategic choice of pre-onset and post-onset time periods to generate an empirically sharper distinction in the two periods. Below, we discuss how and why we selected our time periods for the difference-in-difference analysis.

## Wage Pathways Program Outline

The Wage Pathways program, being a component of CCMEP, formally began in July 2016 with the program to end September 30, 2019. Only a subset of counties offered Wage Pathways benefits – Ashtabula (extreme northwest corner of Ohio), Cuyahoga (Cleveland area), Ottawa (north central Ohio on Lake Erie and about 15 miles southeast of Toledo, but does not contain Toledo), Summit (Akron area) and Hamilton (Cincinnati area). The entry point to WP was through CCMEP, and it took most counties about a year to implement CCMEP and to phase in WP.[[6]](#footnote-6) As a result, the WP program did not begin until roughly the second quarter of 2017. Funding for WP came from a $6 million workforce innovation fund grant from the U.S. Department of Labor to ODJFS.

Due to administrative delays, the program began enrolling participants in May 2017. Hamilton County was added later in 2018.

The term ‘wage pathway’ is not defined in the original grant materials, but contextually it refers to a sequence of jobs, each with increasingly greater compensation. The qualifications for participation were that individuals must be served by the CCMEP program and be deemed “work ready” by site administrators. Sites used a variety of methods to select participants, which we discuss below.

The major WP program components for the youths include:

1. Comprehensive case management and barrier removal to help participants become work ready so they can gain employment
2. Personal finance and budgeting knowledge to make the youth more resilient to financial instability that can divert the youth’s attention from their jobs
3. Knowledge about navigating the labor market and its opportunities
4. Developing work habits, skills and experience
5. Extended post-placement job coaching
6. Short-term education and training opportunities
7. Work-related financial incentives that encourage employment retention, wage progression and placement in in-demand jobs.

On the caseworker side, the WP program seeks to have the counties supply job coaches and job managers with a long-term outlook on employment retention, wage progression and eventual placement in an in-demand job.

The program’s intent is to promote a route to immediate employment for participating individuals and align ongoing services after initial job attainment to support the earnings advancement of participants. The incentive structure is viewed as the principal differentiating element intended to motivate individuals to strive for career advancement milestones. Many design elements were left to the pilot sites to determine. For example, participant selection processes, plans and processes for assigning caseloads to case managers, frequency and content of post-placement participant interactions, the form and function of post-placement services, and collaboration with employers were determined by pilot sites in their efforts on the project.

### Description of Cash Incentives

The financial incentives that WP offers the participating youths are:

1. Employment retention – working 120 hours in a 30-day period earns a $250 incentive. Participants can earn up to $1000 for achieving four retention incentives.
2. Wage progression – earning a $1/hour or 10% increase from their highest rate of pay and working 240 hours in 60 days earns a $500 incentive. Participants can earn up to two wage progression incentives.
3. In-demand job – to earn the first $500 in-demand incentive, the participant must gain an ODJFS-defined in-demand job paying less than $14/hour and work 360 hours over a 90-day period. To earn the second in-demand incentive, the participant must gain an in-demand job paying $14/hour or more and work 360 hours over a 90-day period. If a participant meets the requirements for the first in-demand incentive with a job that pays $14/hour or more, they will receive a $1000 incentive, as if they had earned both in-demand incentives but only needing to work 360 hours over a single 90-day period instead of having to work 360 hours in each of two 90-day periods.

These incentives can be “stacked”; **a participant is allowed to earn all three incentives and may concurrently satisfy more than one incentive**.

### The Timing of Program Launch

Summit County, which includes Akron, and Cuyahoga County, which includes Cleveland, were central in developing the initial proposal to USDOL. We can characterize these counties as having urban population density with pockets of significant poverty. At the time of project conception, Summit and Cuyahoga counties ran an initiative called Skills-Based Hiring that relied on the WorkKeys assessment as a focal tool in engaging business in the matching and labor force attachment process. The leaders from these counties envisioned the Wage Pathways program as an extension of the Skills-Based Hiring initiative. At the time, the Skills-Based Hiring initiative was the focal element of the program, and cash incentives were not a focal design element. However, once the grant was funded, the main design elements of the program were changed to focus on cash incentives. This resulted in a need for the state and these counties to negotiate the scope of work, which resulted in a delayed launch of the program. The delay motivated the state to bring new counties into the program, with the added component that at least one rural county would be chosen, and that the implementation would be kept in the northern part of the state. Ashtabula and Ottawa Counties volunteered to participate, with leaders indicating that they thought cash incentives would benefit their clients. Ashtabula and Ottawa began enrolling participants in May 2017. Cuyahoga and Summit began enrolling participants in October 2017.

A transition occurred in July 2018 in Ottawa County when the originally contracted CCMEP service provider did not succeed in its bid to continue providing services for the county and was replaced by another service provider. Following the transition, almost no new participants were enrolled in Ottawa County through mid-2019.

Later, Hamilton County, which includes Cincinnati, was added in response to overall lagging WP participant numbers statewide. Hamilton began enrolling participants in July 2018. This late start, for practical purposes, made Hamilton County a “control county” as its CCMEP clients did not receive as much exposure to WP as the other four counties. One might expect including Hamilton as a control county would tend to understate the true impact of WP insofar as whether Hamilton County clients benefited at all from exposure to the WP program. However, as it turned out, whether Hamilton County was in or out of the analysis data file, the estimated effect of the program changed little.

# Evaluation of the Wage Pathways Program Implementation

## Overview of the Implementation Evaluation

The implementation evaluation had two overarching goals: (1) document fidelity to the intended design, and (2) assess whether design elements effectively promoted job placement and retention and earnings advancement for participants. We used qualitative methods including interviews, focus groups, onsite observation, and participant file review to investigate how sites implemented project activities. Evaluation topics were framed around the defining elements of the program.

* Are intake and assessment methods effective in identifying individuals who are work ready and best served by immediate employment and cash incentives?
* Are cash incentives effectively integrated with career counseling and other workforce services to support job attainment, retention, and advancement?
* Does post-placement engagement with participants promote job retention and earnings advancement to complement cash incentives?
* Are cash incentives an effective tool for promoting job retention and wage advancement among participants?
* How, and in what ways, were employers engaged in the Wage Pathways program?

## Selection of Participants

Counties selected Wage Pathways participants from their overall CCMEP service population. CCMEP guides employment and training services for individuals based on a comprehensive assessment of employment and training needs, as well as a basic skills assessment. CCMEP participants develop an Individual Opportunity Plan (IOP), which may include plans to obtain a high school diploma, job placement, work experience, and establishes plans for supportive services such as childcare, and transportation. Case managers work closely with CCMEP participants, with participants asked to commit to a minimum of 20 hours per week for participating in activities outlined in their IOP. Wage Pathways was introduced to individuals in the context of CCMEP case management discussions and IOP development. The state did not prescribe how the site would deliver the Wage Pathways overview to potential participants. Generally, an individual is considered to have completed the CCMEP program when they have successfully obtained employment, begun post-secondary education, and/or enlisted in the military. However, individuals enrolled in Wage Pathways are retained in the CCMEP program for up to two years. This allows time for participants to receive extended services and achieve the incentives with a goal of achieving earnings increases. Potential participants were invited to participate in a Wage Pathways orientation session, which provided a deeper explanation of the program’s goals and incentives. Individuals could self-select to become participants following the orientation.

Each county had a slightly different strategy to recruit participants. Typically, case managers did the recruiting with several commenting in interviews that they made determinations whether to introduce the program to an individual based on their assessment of an individual’s work readiness. In many cases, case managers had worked with participants in other programs and felt confident they could predict which individuals would persist in the Wage Pathways program. Participant word of mouth was another prominent source of recruitment. Two counties held workshops and orientations regularly, open to any residents, which introduced the Wage Pathways program alongside other programs. Other recruitment activities included individual mailings/emails, direct outreach or phone calls to targeted individuals, and through industry partners. Three out of four sites had relationships with at least one local industry partner to recruit Wage Pathways participants. In these situations, employers introduced new hires to the Wage Pathways program and if an employee was interested and met baseline qualifications, employers began a discussion process with a case manager. In one county, an employer advertised the Wage Pathways program as part of their recruitment strategy.

Central evaluation questions are: 1) Did the availability of incentives, as the focal element of the program, impact Wage Pathways participants’ job attainment or earnings advancement outcomes? and 2) How did programs select participants?. In interviews, we asked Wage Pathways case management staff at each site if selection processes were designed to identify and enroll individuals who were more likely to achieve successful outcomes as a result of the availability of cash incentives. Case managers did not have a common theory how to identify ideal candidates for the program. Approximately half of those interviewed thought individuals who were accomplishing the Wage Pathways milestones likely would have achieved the milestones even without the incentives. However, they had numerous anecdotes about individuals using incentives to address critical barriers such as car repairs, tuition payments, testing fees, or challenging housing situations. They agreed that individuals ready and motivated to work could use the incentives to overcome barriers or advance further faster if the incentives were used by the participants for barrier removal or career advancement purposes.

At this point, we emphasize that the quantitative evaluation of Wage Pathways compared before versus after outcomes for persons in counties offering Wage Pathways to persons in counties not offering Wage Pathways. Our implementation study revealed a tendency for clients more likely to benefit from Wage Pathways to be guided toward the program. In a quantitative evaluation comparing participants versus non-participants, this guidance of certain clients toward Wage Pathways would have resulted in an overstatement of the efficacy of the program. Our evaluation does not suffer from this bias, as we compare clients who were eligible for WP to clients who were ineligible (as determined by county of residence) rather than participants versus non-participants. Our finding of positive program impacts is not biased by how case managers directed clients toward Wage Pathways. We designed our evaluation strategy anticipating that case managers would direct clients with better prospects toward Wage Pathways.

All counties adhered to the intake guidelines as provided by ODJFS; however, determination of work readiness varied across sites. In all four counties, if someone is eligible or participating in CCMEP and ready for work or currently employed, the individual is a potential Wage Pathways participant. Largely, these individuals were already in CCMEP and participating in another program (e.g. a summer employment program or other youth-serving workforce development initiative). In a large majority of cases, the case managers were familiar with the potential participants and their career plans, goals, and barriers, and this familiarity helped case managers make their own assessments of each individual’s work readiness – usually based on a track record of reliable attendance with no disciplinary actions. One county reported they had so many potential participants under these criteria, they prioritized individuals dealing with homelessness, exiting foster care, or not in school. One county required individuals to obtain employment as a demonstration of work readiness, and individuals did not become participants until they started working. Another county conducted recruitment from the pool of individuals that had completed an 8-week work readiness course prior to Wage Pathways.

All counties reported that if an individual’s IOP goal was more focused on education, this individual was excluded from the potential participant pool. All of the case managers agreed that Wage Pathways fits better with individuals who do not have barriers that will prevent work.

## Integrating Wage Pathways with Other Workforce Development Programs and Services

The Wage Pathways intervention, as described by the ODJFS, included several elements that were intended to enhance the utilization of cash incentives.

Figure 1: Wage Pathways Participant Flow

Eligibility Determination

* WIOA-eligible
* TANF co-enrollment encouraged
* 18-24 years old

CCMEP Participation

* Assessment
* Individual Opportunity Plan (IOP)
* Barrier removal

Wage Pathway Selection

* Interested and able for immediate work, 120 hours per month

Wage Pathway Intervention

* Prioritize Work - 120 hours per month
* Availability of Wage Pathway Tool
* Financial Learning and Budget Calculator Tool
* Advancement coaching and intensive follow-up
* Short-term training possibilities
* Cash incentives

Once individuals became participants, case managers had the option to utilize a career coaching tool called the Wage Pathways Tool to guide conversations with participants. The Wage Pathways Tool provided clickable and searchable occupational and career pathway information including wages, educational requirements, job openings and trends, and advancement pathways for each in-demand occupation. Additionally, ODJFS provides a Financial Learning and Budget Calculation Tool that case managers can use to help individuals learn about financial management alongside occupational data. These tools are intended to enhance career counseling to help individuals plan pathways to reach successively higher-paying jobs. Other services included support for resume development, familiarization with job search tools, and interview practice. Other programs and services provided by ODJFS may be accessed by the individual as determined in the IOP, TANF and WIOA Title I-B Youth Programs.

All case managers agreed that the Wage Pathways incentives need to be bundled with other services and programs because the Wage Pathways program does not offer training or barrier mitigation services. However, with a notable exception in Cuyahoga County, there was little evidence of systematic or consistent approaches for career pathway planning and the purposeful integration of incentives. Many participants had received cash assistance, food assistance, job readiness workshops, education or training assistance, childcare, or transportation services through other programs. The evaluation team observed that the additional Wage Pathways cash incentives intended to encourage career and earnings advancement were not typically accompanied by a plan with specific steps to achieve advancement.

The evaluation team queried case managers about the nature and extent of career coaching conversations with individuals about longer-term, multiple-step career pathways, including the use of tools to aid conversations. Additionally, during site visits, the evaluation team reviewed Wage Pathways participant case files looking for career pathway planning. While not entirely unused, the majority of case managers in all counties indicated that they did not regularly use the Wage Pathways Tool or Financial Management and Budget Calculation Tool. The most frequently cited reason for not using the tools was that participants were dealing with basic needs and barriers that were fundamental, such as rent and transportation, and rarely were prepared to develop career plans other than for the purposes of basic subsistence. Similarly, case files typically included general career goals such as “get a job” or “earn more money” without specific pathways mapped. Case managers sometimes used other tools such as the OhioMeansJobs website to obtain labor market and occupational information.

Cuyahoga County provided a notable exception. The county delivers CCMEP and WIOA Youth programming in collaboration with two contracted service provider organizations, Towards Employment and Guidestone. Both organizations required individuals to engage in multi-week work readiness coursework and barrier removal services prior to engaging in Wage Pathways. The work readiness course and extended case management provided individuals the opportunity to develop specific, multi-step career pathways plans.

## Post-Placement Participant Engagement

Generally, post-placement engagement of participants was highly individualized depending on each participant’s situation. There were no programmatic requirements at any of the sites for participants to remain engaged other than for the purposes of documenting and transacting incentives. Primarily, postplacement engagement served an administrative accounting purpose, although case managers were open to discussions of barrier mitigation or career coaching. Participants who indicated a need for new employment, career coaching, or services were invited to re-engage with the agency. Several case managers described their efforts in terms of working to maintain or strengthen a pre-existing relationship with the participants so they would feel comfortable reengaging, if needed.

Following placement, case managers reported that many participants had unclear career or advancement plans for the future. Relatedly, there was reported uncertainty among many participants about pursing training and/or education for the purposes of advancement. Case managers typically followed up monthly, or bi-weekly, with participants via email, text, or phone call in an effort to remain in communication.

## Effectiveness of Incentives

There was a unanimous belief among case managers that most participants were using incentives for positive purposes. Positive examples included paying for children’s school supplies, health bills, college tuition, utility bills, rent, gas, car payments, legal fees, and industry certification testing fees. Negative examples included using incentives for tattoos, video games, and bar tabs. Case managers were united in expressing the opinion that the process for incentive documentation and receipt made participants much more willing and accessible to communicate with staff following job placement.

Six out of the ten participants interviewed indicated the incentives motivated them to continue working to achieve a retention incentive. Although ten out of ten participants believed they would have achieved the milestones they achieved with or without the incentives, case manager opinions varied on whether incentives effectively encouraged job attainment, retention, or advancement. Several case managers reported that participants were likely to stay in an initial job if they did not have significant issues with wages or their managers even if an advancement incentive was available. Case managers believed that participants who had previous working experience, at least a high school degree or GED, and reliable transportation were most likely to achieve retention and advancement incentives. In the case of one participant, the individual hesitated to make more money for concern of losing cash welfare benefits.[[7]](#footnote-7)

Counties were not uniform in their incentive processing speeds. For example, one county could process incentive payments within two weeks of receiving documentation of hours worked, whereas another required four months. All case managers believed that longer processing times lessened the impact of the incentive. There was no prescribed processing time requirement for the sites, so the slower sites were still in compliance with program guidelines.

## Engagement with Employers

Employer engagement practices varied among the counties. In all counties, case management staff communicated with many employers to document hours worked for incentive payout. Generally, employers were not engaged in the strategy, design, or delivery of the Wage Pathways program unless they were already participating in another program in collaboration with the site. For example, in one county, service providers had packaged services in another initiative to focus on post-placement job retention and advancement, including barrier mitigation leading to job retention and skills training leading to advancement. In that county, the Wage Pathways incentives were integrated into this framework. In one county, individuals were placed in jobs prior to enrolling in the Wage Pathways program, and case managers communicated directly with the employer and the participant with a goal of achieving internal promotion. In another county, case managers received regular and structured feedback from one employer on the participants’ workplace performance to help guide the supportive services provided by case managers.

## Summary of the Implementation Evaluation

County staff implemented Wage Pathways with fidelity to its intended design. All sites complied with the requirements of the model designed the Ohio Department of Job and Family Services, which are listed in Figure 1, above.

We devoted much of the implementation evaluation to seeking a unifying theory for which characteristics, program elements, and contexts were most associated with successful job attainment, retention, and advancement. Statewide, case managers had varying opinions about who is best served by a cash incentives program, who is most likely to achieve the intended outcomes, and which contextual services are most supportive.

In general, participants, in collaboration with case managers, developed vague IOPs that did not provide clear goals or routes for career advancement. For example, “get a job” or “earn more money” were common goals listed in IOPs. Several case managers commented that the development of specific IOPs, which require participants to conceptualize a longer-term vision, was challenging in a short time frame because individuals were often focused on solving immediate challenges. Two organizations, Towards Employment and Guidestone, required Wage Pathways participants to engage in multi-week job readiness programming prior to becoming eligible to receive incentives through the Wage Pathways program. These organizations were able to dedicate additional time to helping participants envision longer-term pathways in their IOPs.

Another weakness in the implementation was that while ODJFS provided the counties with training on how to provide career coaching to the counties’ clients, this training did not appear to get translated into the coaching the clients actually received. In part, this reflected the focus of clients on the more immediate problems in their lives as opposed to longer-term considerations. This would tend to reduce the long-term impacts of WP.

Case managers were fairly unanimous that the individuals most likely to successfully earn cash incentives for job retention and earnings advancement were those that had previously demonstrated an example of reliability and motivation to work prior to Wage Pathways. For example, several case managers believed individuals who had completed some form of workforce training, already had a job, or had a history of workplace reliability were more likely to earn cash incentives. However, only two counties had operationalized approaches for selecting program participants based on previous demonstration of this type of behavior. Towards Employment and Guidestone in Cuyahoga County required participants to complete multi-week work readiness courses, and Ashtabula County required individuals to find jobs prior to enrolling in Wage Pathways.

Case managers believed that the majority of participants were using cash incentives for intended purposes such as bill payments, car repairs, tuition, healthcare, etc. While many case managers were able to cite examples of misused cash incentives, there was not a strong overall belief that incentives were misused.

# The Quantitative Evaluation

## The Targeted Population and its Relation to Ohio’s New Service Delivery System

The Wage Pathways experiment targets youths 18-24 who are eligible for services either through WIOA or TANF. Reentrants from incarceration may receive CCMEP and WP services. Any age-eligible youth eligible for CCMEP is, in principle, eligible for WP. WP focuses on low-income, low-skill young adults who are disconnected from the workforce due to employment barriers (such as legal entanglements, disabilities, lack of credentials or financial instability) that make it difficult for the youth to stay on a long-term occupational path or participate in educational and training programs that lead to credentials and skills with an economic payoff.

However, CCMEP enrollees get screened by staff in the county’s Job and Family Services agency to determine whether they are age-eligible as well as “work ready.” “Work ready” means they can commit to working at least 120 hours per month. Counties may not have sufficient funds to enroll all youth eligible for the program, so county personnel may selectively enroll youths in the program. This introduces a subjective evaluation of county staff into the process of placing youths into WP. “Creaming” or selecting the possibly participants who are most likely to succeed in a program creates serious problems for the evaluator. One cannot be sure whether positive impacts for the participants reflects an ability of the program to produce better outcomes for the disadvantage or reflects the ability of program staff to channel participants who are more likely to succeed into the program.

By using the random assignment of subject and treatment, or a “randomized controlled trial,” evaluation efforts can avoid the confounding of “creaming.” Being a statutory program, the state and counties felt random assignment of CCMEP benefits at the individual level would be politically unacceptable, even for the non-statutory Wage Pathways component. The compromise the state and counties made was to allow counties to opt into the WP experiment, making all their CCMEP enrollees eligible (in principle) for this 15th CCMEP benefit. The evaluation team knew randomization at the person level was unacceptable and designed the analysis strategy with this in mind. The late adoption by Hamilton County (Cincinnati) surprised us and we modified our analysis strategy to account for Hamilton being out of cycle with the other “experimental” counties. The state initially had some difficulties persuading counties to offer the WP component. However, over time, counties became more supportive of the program and that may have contributed to Hamilton County deciding to become an experimental county, albeit late in the process. We did not know whether, and in which direction, the selection of the experimental counties might bias the results. We constructed a set of labor market indicators in an attempt to control for statewide differences in labor market conditions.

## The Objectives

This evaluation seeks an answer to the question whether the Wage Pathways experiment, if implemented state-wide, would contribute to young people becoming economically self-sufficient in a cost-effective manner. The Wage Pathways incentives encourage young people to behave in ways that enhance their earnings prospects and we bear that in mind in designing the statistical tests. Specifically, while the null hypothesis is that WP has no effect on behavior, the alternative hypothesis is that WP has a positive effect. If we find WP has a negative effect on earnings, we will take that finding as evidence there is no effect rather than evidence of an (illogical) negative effect. Having a one-sided alternative hypothesis makes one-sided tests generically most powerful.[[8]](#footnote-8)

## Data Sources

We use a variety of data sources for the quantitative evaluation, chiefly administrative data. We decided that evaluating WP (and CCMEP) using bespoke survey data was an inferior approach because survey methods have high costs and non-response has become a serious problem.[[9]](#footnote-9) Legal complications can make it difficult to use administrative data for evaluations, as use of these data falls under regulatory restrictions imposed by various state and Federal agencies. For example, ODJFS controls access to UI Earnings data because of their responsibility to administer the unemployment compensation program. On the other hand, TANF and SNAP data, while in the custody of ODJFS, have their access restricted by the US Department of Health and Human Services. Obtaining administrative data, especially when one needs personal identifiers to link across databases, requires time, patience, and considerable paper work. Fortuitously, OSU and several Ohio agencies have, for the past decade, been constructing the Ohio Longitudinal Data Archive (OLDA). Over several years, OSU and these agencies have negotiated data sharing agreements and instituted a governance structure to facilitate data sharing among agencies. Without the OLDA framework and the network of institutional connections OLDA created, we could not have assembled the administrative data necessary to evaluate WP (or CCMEP) within the necessary time frame.

It takes time for ODJFS to process the data streams that feed its data holdings and, after processing those data, ODJFS needs to forward those data to OSU and the OLDA for editing, re-shaping, documenting and loading into the OLDA data structure. Consequently, the evaluators have access to the newest installment of quarterly administrative data about two quarters after the close of a quarter. The Wage Pathways (WP) program, including funding for its evaluation, ends September 30, 2019. This lag in data availability limits the period we must choose as the post-onset period. As we will see below, the employment data have a strong seasonal component and this required us to select pre- and post-onset periods of 4 quarters to avoid seasonality contaminating the analysis. Data from 2nd Quarter 2019 arrived too late to include in the evaluation. The narrative here conveys the approach taken in the quantitative evaluation and our explanation of the strengths and weaknesses of that analysis.

While we also collected survey data for this evaluation, the survey effort focused on those metrics we could not obtain from administrative data; namely, wage rates, hours worked and occupation. Thanks to our ability to draw on administrative data, including the intake data collected from youths seeking to enroll in CCMEP, we assembled a comprehensive data set to support the evaluation. The next section details those data resources.

### Administrative Data

UI Earnings Data – Starting in 2002, CHRR at The Ohio State University archived Ohio’s UI Earnings data, as well as the Quarterly Census of Employment and Wages[[10]](#footnote-10). CHRR re-configured the quarterly UI Earnings reports into a file with each person being a logical record with that person’s earnings for the five employers that paid him/her the most in that quarter (as well as the scrambled EIN for each employer), weeks worked for each employer, the dollar amount of earnings with each employer, the number of weeks the person worked for that employer in the quarter, the industry code that matches the employer’s EIN, and total UI-covered earnings in the quarter for that person.[[11]](#footnote-11) These data go back to 1995, covering about 15 million persons in at least one quarter. The data do not include earnings for Federal workers, the self-employed (which would include independent contractors), certain farm workers and members of the military.[[12]](#footnote-12) For this population the omission of farm work and the possibility of free-lance, episodic earnings are the most likely gaps in data coverage. We use a scrambled, pseudo-SSN to identify people in this file as well as most other data records in the OLDA. Data analysts do not have access to SSNs or any other Personal Identifying Information (PII).

While we use the UI Earnings data primarily to measure earnings of the CCMEP enrollees, we also use these data to assess labor markets more generally throughout Ohio. Using earnings outcomes for youths not in CCMEP but who have strong similarities to their CCMEP peers can provide a useful, albeit imperfect, comparison group for assessing labor market conditions. We return to this topic below, first in our discussion of the Bureau of Motor Vehicles (BMV) data, and again in the Methods section where we discuss the econometric approach.

CCMEP Enrollment Data – When youths seek to enroll in the CCMEP program, they complete an assessment that collects data concerning education, barriers to employment, work experience, military experience, legal entanglements, personal well-being and interests. This form included the youth’s phone number (primarily a cell phone) that CHRR survey specialists used to issue invitations to complete our survey (see below). The CCMEP enrollment assessment collects data on hourly rate of pay and hours worked at the time the youth completed their entrance assessment, as well as for any job prior to the one they reported as their current job at enrollment. We made an effort to interview twice anyone[[13]](#footnote-13) who enrolled in CCMEP so, in the best case, we would have four observations on wage rates and hours. As noted above, to participate in WP a youth must enroll in CCMEP and live in a county that offers WP so WP youth are a subset of all CCMEP youth. The CCMEP enrollment database contains youths who are either eligible or ineligible for WP depending on their county of residence. The enrollment data, as of the Fall of 2018, contains data on 25,178 youths. Starting with these 25,178 individuals, we match data from the UI Earnings database (above) and other administrative and survey data (below) to constitute the data on eligibles and ineligibles for the analysis.

TANF/SNAP Data – Among CCMEP enrollees, personal situations vary. However, TANF/SNAP data allow us to measure enrollees’ cumulative disadvantage as revealed by the number of months during their lifetime they received benefits from those two programs, either directly as the “prime beneficiary” or payee or indirectly as the member of a household or assistance unit receiving benefits under either or both programs. We limited our data request for these data to a few basic data fields. While the TANF/SNAP data contain some additional demographic variables, such as citizenship, we did not use demographics only contained in the TANF/SNAP data to avoid the substantial missing data problems that would result from not having such variables for over half of the enrollees.

To illustrate, Table 1 shows the prevalence of TANF recipiency among enrollees and Table 2[[14]](#footnote-14) does the same for SNAP.

Table 1

Months of TANF Receipt by CCMEP Enrollees[[15]](#footnote-15)

| Count | Cell Description |
| --- | --- |
| 100 | None |
| 1225 | 1-6 months |
| 1230 | 7-12 months |
| 2015 | over one through two years |
| 1699 | over two through three years |
| 2010 | over three through five years |
| 1186 | over five through eight years |
| 1720 | over eight years through fifteen years |
| 509 | over fifteen years |
| 11694 | Total |

Table 2

Months of SNAP Receipt by CCMEP Enrollees

|  |  |
| --- | --- |
| Count | Cell Description |
| 53 | None |
| 389 | 1-6 months |
| 433 | 7-12 months |
| 662 | over one through two years |
| 570 | over two through three years |
| 1126 | over three through five years |
| 1615 | over five through eight years |
| 4405 | over eight years through fifteen years |
| 2441 | over fifteen years |
| 11694 | Total |

As one would expect, these two measures of cumulative disadvantage are highly correlated.

PIRL Data – The WIOA Participant Individual Record Layout (PIRL) data set contains data on various program participants. ODJFS uses these data to report to the U.S. Department of Labor. They contain data on race as well as certain key program participation dates. All CCMEP participants have records in the PIRL.

Bureau of Motor Vehicles Data – This data set contains data on everyone holding an Ohio driver’s license plus those holding a state-issued ID. The Bureau of Motor Vehicles (BMV) issues both these IDs. This file contains data for about 11.7 million people and contains information on month and year of birth,[[16]](#footnote-16) gender, county of residence, issue date and the most recent date the person updated their ID. When we first proposed the evaluation of the Wage Pathways project, OLDA did not hold the BMV ID data. Nearly all of our CCMEP enrollees match to the BMV data. Oddly, the enrollment data do not contain gender or county of residence, making the BMV data very useful.

Ancillary Data – Only five counties in Ohio offered the Wage Pathways program to their CCMEP enrollees: Ashtabula (the extreme northeast corner of the state), Cuyahoga (Cleveland area bordering Lake Erie), Ottawa (north central Ohio along Lake Erie), Summit (Akron area, just south of Cuyahoga) and Hamilton (in the extreme southwest corner of the state – the Cincinnati area).[[17]](#footnote-17) Hamilton phased in the WP program in the fall of 2018, about a year after the other four counties. This lag makes it somewhat ambiguous whether Hamilton should be included with the other four counties as an experimental site for evaluation purposes. The danger of having the four counties that adopted WP in 2017 all in the same part of the state is that we may confound locational differences with program effect differences.[[18]](#footnote-18) The evaluation must analyze the program data as they come to us. This geographic clustering of the experimental counties led us to explore whether we could measure local labor market conditions and use those to control for differences in labor demand across the various parts of Ohio where WP ineligibles live. To do this, we merged the UI Earnings data with the BMV data, so for everyone in the UI Earnings data we have their month and year of birth, gender and county of residence. The OLDA also holds Ohio Department of Higher Education data for state-supported post-secondary education and training programs.

CCMEP enrollees mostly have high school degrees or less (see the codebook page in Table 3); only 3.3% have educational or training attainment beyond a high school diploma or GED. We linked the OLDA data on state-supported post-secondary education and training to the merged UI Earnings and BMV data, and then removed all youths in the CCMEP age cohort who also appear in the higher education file to make the set of non-CCMEP peers more closely resemble our CCMEP enrollees. While this is an imperfect comparison group, we believe the labor market experiences of this synthetic cohort should be indicative of labor market conditions around Ohio for less-educated youths in the CCMEP age bands.

The desire to measure local labor market conditions in Ohio raises the question of just what are the labor markets in Ohio. Rather than attempting to define labor markets in Ohio, we choose to accept the labor market taxonomy developed by ODJFS as our guide. In Figure 2, we show the ODJFS-defined labor markets for Ohio. Note that one labor market (market B in northeast Ohio) contains three of the experimental counties that offer the Wage Pathways program, with Ottawa County being nearby.

For Highest Grade Completed, we edited and re-coded the data from the enrollment database. We applied the following edits:

* Anyone reporting a GED who does not report a HS diploma or GED certificate we code 11 years completed. If a person reports 12 or fewer years completed but reports a HS diploma or GED certificate we code as 12 years completed.
* If a person reports they are in high school but does not report a highest grade completed, we assign them 9 years completed.
* If a person is not in high school and does not report a highest grade completed and does not report NONE for highest grade completed we assign a highest grade of 0.
* Anyone claiming an Associate’s degree we assign 14 years completed. All those claiming Associate’s degrees have HS degrees. Anyone claiming a Bachelor’s degree we assign 16 years completed.
* Anyone reporting some number of years of college without claiming a Bachelor’s degree we assign that number of years completed up to a maximum of 15.
* People reporting VOC\_TECH for highest grade completed we assign 13 years. These VOC\_TECH claimants all report a HS degree. Similarly, all reporting a PSDC (post-secondary degree or certificate) we assign 13 years; they all have HS degrees. Those reporting MASTER we assign 18 years.
* Those reporting HS who also report HS diploma or GED certificate, we assign 12 years. Those reporting HS who do not report HS graduation we assign 11 years.
* Those reporting GED who also report HS graduation, we assign 12 years. Those reporting GED who do not report HS graduation we assign 11 years.
* Anyone who claims less than the 12th grade completed but nonetheless reports a HS degree or a GED certificate, we assign 12 years completed.
* We suppress counts for cells with from one to nine people

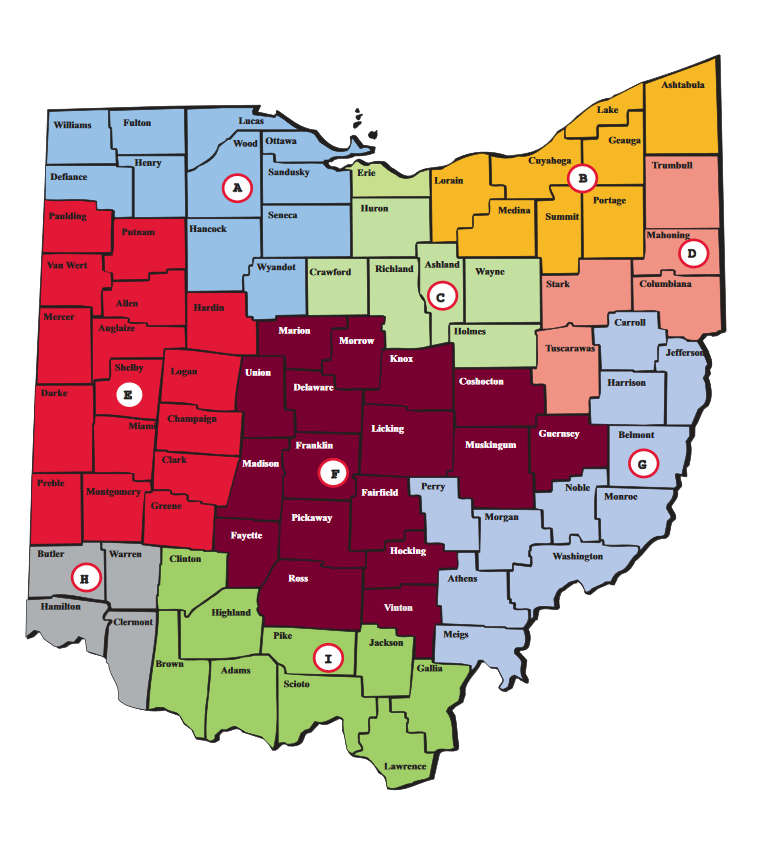
Table 3

Highest Grade Completed by CCMEP Enrollees

| Count | Cell Description |
| --- | --- |
| 864 | None |
| suppressed | First grade |
| suppressed | Second grade |
| suppressed | Third grade |
| suppressed | Fourth grade |
| suppressed | Fifth grade |
| 11 | Sixth grade |
| 85 | Seventh grade |
| 230 | Eighth grade |
| 11209 | Ninth grade |
| 1110 | Tenth grade |
| 2710 | Eleventh grade |
| 8114 | Twelfth grade |
| 525 | 13th |
| 209 | 14th |
| 65 | 15th |
| 28 | Bachelor's degree |
| suppressed | Master's degree |
| suppressed | 19 years |
| 25178 | Total |

Figure 2

Labor Markets in Ohio – ODJFS Definition



#### Age and Time Periods for Administrative Data

Our experimental counties can only assign youths 18-24 to Wage Pathways.[[19]](#footnote-19) So, to construct a comparison group we must select persons, in the time period under consideration, who are in, or close to, this 18 – 24 age range. Ashtabula, Cuyahoga, Ottawa and Summit Counties started Wage Pathways in May, October, May and October (all in 2017), respectively. Hamilton County started WP in July 2018. Administrative data arrive with a lag, so we have a limited ability to observe Hamilton County outcomes after implementation.

Besides the staggered startup for WP, we also need to account for pronounced seasonality in the employment data. In the Appendix, we examine both seasonality and temporal trends in the data. Because we found seasonality, when we aggregate data over time, we select four consecutive quarters to aggregate earnings. While the chosen periods do not start in the same quarter of the year, using four consecutive quarters avoids problems that would be created by having one interval containing unequal numbers of the four quarters.

For the four sites in northern Ohio, WP was active from 4th Quarter 2017 on, so tracking eligible clients through the 3rd quarter of 2018 will give us four quarters of data when WP was active. We will not have enough time to evaluate their WP outcomes for the two years through 3rd Quarter 2019 due to the time required to release the UI Earnings data and program end September 30, 2019. Since we cannot look at two years of WP outcomes in northern Ohio, our best alternative, given we need to look at the data in four quarter blocks, is to pick our four quarter period post-implementation as late as possible. This gives clients more exposure to the WP program, earn incentives, and improve their earnings relative to controls should the program be effective.

We will use the quarterly UI Earnings data extensively and will treat the quarters before the second quarter of 2017 as pre-onset quarters. We will use the four quarters from 2nd Quarter 2018 through 1st Quarter 2019 as post-onset, and 2nd Quarter 2016 through 1stQuarter 2017 as pre-onset for WP, provided the person was 18 on 31 December 2017. The most recent quarter for which we have data is 1st Quarter 2019. Because it took time to phase in WP, we use the latest possible four-quarter interval as post-onset to give the program more time to work. If we had enough data after the program was fully phased-in, we would have picked eight consecutive quarters as the post-onset period. For the differences-in-differences analysis, we select people with birth years from 1994 through 2000 to stay close to the 18-24 age range set by the program.[[20]](#footnote-20)

### Survey Data

The administrative data described above have a great deal of detail; only exploring the metadata on the OLDA web site will convey the scope of the data we have access to. An important part of this evaluation centers on three factors: the rate of pay, hours worked, and occupation. The Wage Pathways program (and CCMEP more generally) aims to help young workers establish careers that lead to self-sufficiency, hence the focus on wages and hours. In addition, Ohio has a major focus on training programs outside the traditional college degree track. WP has an incentive tied to “in demand” jobs. However, the major administrative data resource on employees – the UI Earnings file – does not measure wage rates, hours worked or occupation. The UI Earnings file records quarterly earnings for each worker’s employer and the number of weeks worked in the quarter for that employer, but not hours worked, rate of pay or occupation. That left it to the evaluation team to collect those data independently.

For the survey, operations staff at CHRR used the respondent’s phone number (predominantly a mobile phone) from the enrollment form completed upon registering for CCMEP. We provided a link the respondents could tap on and that took them to the survey. We texted the youths a message inviting them to do the survey, promising it would be short, confidential and they would get a $10 incentive. We encrypted all data transfers. For respondents who did not break-off and subsequently re-start the interview, average time for survey completion was a little under three minutes.

To collect data on wages and hours, we used a simplified form of the questions used in the Current Population Survey and the National Longitudinal Surveys. Collecting data on occupation presents problems, especially because the survey was self-administered on a mobile phone. Usually surveys use trained interviewers to collect occupation data, but that would have made the survey effort prohibitively expensive. Instead, we used *O\*NET-SOC AutoCoder* from R.M. Wilson Consulting. This Web application uses as inputs the person’s education level, their industry[[21]](#footnote-21), and a verbatim description of their job title and responsibilities. We took respondent education from the CCMEP enrollment form and industry from the most recent employer in the UI Earnings file. This avoided having to ask the respondent these questions; asking about industry would have been a speculative exercise in any event. The *AutoCoder* software took this information and generated up to four[[22]](#footnote-22) occupation matches to the verbatims and pre-loaded education and industry data. If the *AutoCoder* could not generate any match, the survey asked the respondent to add more detail. It was rare the *AutoCoder* could not provide tentative matches; we only needed to probe for an additional verbatim in 58 cases, or less than 5% of the time. The survey then presented the respondent with the *AutoCoder*’s best occupation matches and asked the respondent which was the best match. After reviewing the verbatims and the respondent’s chosen occupational match, we were very satisfied with the performance of the *AutoCoder* software and our algorithm. Table 4 shows the distribution of occupation within broad occupational “families” for the first survey wave[[23]](#footnote-23). Of the 2255 first-wave respondents, 1104 worked in the last week and another 230 worked in the last 30 days, but not in the last week. Of these 1334 respondents who had worked in the last 30 days, the algorithm resulted in 1310 coded occupations.

Winter 2018/19 – After initial experimentation with using a lottery as a respondent incentive, we offered respondents a $10 incentive for doing the survey. We gave respondents three choices of how to receive that incentive: an Amazon gift “card”[[24]](#footnote-24), a Walmart gift card or a McDonald’s gift card. These choices reflected our judgement that Amazon would be popular with younger persons and Walmart and McDonalds were accessible to lower income people.

Table 4

Wave 1 Survey Occupation of CCMEP Respondents

| Count | Cell Description |
| --- | --- |
| 20 | Management |
| suppressed | Business and Financial Operations |
| suppressed | Computer and Mathematical |
| suppressed | Architecture and Engineering Occupations |
| suppressed | Life, Physical and Social Science |
| 15 | Community and Social Service |
| 34 | Education, Training and Library |
| 10 | Arts, Design, Entertainment, Sports and Media |
| 28 | Healthcare Practitioners and Technical |
| 102 | Healthcare Support |
| 17 | Protective Service |
| 299 | Food Preparation and Serving |
| 122 | Building and Grounds Cleaning and Maintenance |
| 98 | Personal Care and Service |
| 156 | Sales and Related |
| 144 | Office and Administrative Support |
| suppressed | Farming, Fishing and Forestry |
| 22 | Construction and Extraction |
| 31 | Installation, Maintenance and Repair |
| 88 | Production |
| 101 | Transportation and Material Moving |
| suppressed | Military Specific |
| 1310 | Total |

Spring 2019 – The Spring wave began in May and ended in August. We only made small changes in the questionnaire. We asked all respondents who were working in the last week how many employers they had and, for those working for more than one employer, asked how many hours the respondent worked at all jobs taken together. We did not offer a McDonald’s gift card as that card was difficult to procure and only 10% of respondents requested it.

Table 5

Wave 2 Survey Occupation of CCMEP Respondents

|  |  |
| --- | --- |
| Count | Cell Description |
| suppressed | Management |
| suppressed | Business and Financial Operations |
| suppressed | Computer and Mathematical |
| suppressed | Architecture and Engineering Occupations |
| suppressed | Life, Physical and Social Science |
| 13 | Community and Social Service |
| suppressed | Legal |
| 24 | Education, Training and Library |
| suppressed | Arts, Design, Entertainment, Sports and Media |
| 28 | Healthcare Practitioners and Technical |
| 77 | Healthcare Support |
| 11 | Protective Service |
| 177 | Food Preparation and Serving |
| 96 | Building and Grounds Cleaning and Maintenance |
| 80 | Personal Care and Service |
| 90 | Sales and Related |
| 115 | Office and Administrative Support |
| suppressed | Farming, Fishing and Forestry |
| 14 | Construction and Extraction |
| 16 | Installation, Maintenance and Repair |
| 45 | Production |
| 72 | Transportation and Material Moving |
| suppressed | Military Specific |
| 905 | Total |

Our quantitative evaluation leans very heavily on the administrative data, chiefly the UI earnings data. As discussed above, those data are a powerful asset for the evaluation. However, from the outset, we identified three lacunae with the UI data. They do not measure hours worked, rates of pay and occupation. The tables above show the major occupational breakdown for CCMEP youths eligible for Wage Pathways. One notable finding is that, over an interval of about six months, these youths move away from Food Preparation and Serving occupations. Those occupations have long been a gateway to the labor market, with youths learning the ways of the world of work and, in the case of wait-staff, experiencing the direct connection between compensation and having a positive customer (and employer) orientation. In Table 6 below we show how employment rates, wage rates and hours worked change over a six month interval for WP eligible youths.

Table 6

Findings from Two Respondent Survey Waves

|  |  |  |
| --- | --- | --- |
|  | Wave 1 | Wave 2 |
|  | Oct 2018 - Feb 2019 | May - Aug 2019 |
| Worked last week | 48.9% | 62.3% |
| Worked last 30 days | 59.2% | 83.8% |
| Hrs/wk major job | 25.8 | 29.4 |
| Paid Hourly Major Job | 90.6% | 88.7% |
| Hourly Rate of Pay | $11.57 | $12.28 |
| Weekly earnings if not paid by hour | $233.80 | $294.27 |

Seasonality makes it difficult to compare the two waves although Wave 1 includes the busy holiday season, Wave 2 includes a large part of the summer that is usually favorable to younger workers. Even so, over this rather short time span, hourly rate of pay went up by 6%, hours per week went up 14%, and employment increased substantially. The findings on the hourly rate of pay foreshadow a key finding below – the rapidity with which earnings for young workers expand early in their work careers.

## The Outcome Study

### Research Design

We built our design of the outcome study around two major factors: 1) the availability of extensive administrative data, especially earnings data, in the OLDA starting in the early 2000s; and 2) the fact that ODJFS and its affiliated county departments[[25]](#footnote-25) of Job and Family Services would find an evaluation built around random assignment of subject and treatment was politically unacceptable in their counties. In addition, the operation of the WP program gave considerable discretion to program staff in the local offices, so which clients ended up being participants and which became non-participants could very easily reflect “creaming” in the local offices; picking the best prospects to put into the WP program, resulting in a significant overstatement of the efficacy of the WP program. What ODJFS wanted to learn was whether adding WP as a statutory component of the new (statutory) CCMEP program would be cost effective. As evaluators, the quantitative outcome study aims to measure the costs of adding the WP component in all counties as well as the benefits that accrue to the CCMEP clients in the state because of this addition. The political process will determine whether the estimated costs versus benefits make the program an attractive addition to the overarching CCMEP program.

*Context* - Being a part of the State of Ohio’s new Comprehensive Case Management and Employment Program, the WP evaluation takes CCMEP as a given. While some of the same people who are evaluating WP will evaluate CCMEP and the two evaluation efforts share most of the same data elements, the differences in how the state implemented the two programs produce significant differences in their evaluations. Most notably, while WP does not employ random assignment at the individual level, it does employ quasi-random assignment at the county level. Counties had to volunteer to be WP implementation sites; the state did not randomly select counties to host WP implementations.

From the point of view of clients in the 88 counties of Ohio, the availability of the WP treatment in their county did not reflect their individual-specific differences in their willingness to work or participate in the program. It very well could be the case that more forward-looking and aggressive counties adopted WP and these counties would more likely produce more positive results than the average outcome that would result in the event the program were instituted state-wide. While the quantitative analysis cannot answer the question of whether the counties that chose to offer WP were or were not unusual in their ability to generate good results, the qualitative analysis that focuses on procedures, activities and motivations within the counties may illuminate this matter.

*Logic Mode*l - The logic model for the Wage Pathways program begins with screening CCMEP participants for suitability for WP. WP is a conditional cash transfer program that emphasizes employment as the major program priority. Youths from disadvantaged backgrounds and with few marketable skills nonetheless need to support themselves, typically in conjunction with other transfer and social support programs such as TANF, SNAP, housing assistance and Prevention, Retention and Contingency (PRC) programs at ODJFS.[[26]](#footnote-26)

The first step for Wage Pathways is having county case workers determine whether the presenting client is “work ready”, that is, is ready and willing to work 120 hours per month and participate in WP. It is at this stage where “creaming,” if it happens, will manifest itself.

The second step is for one (or more) of the following activities to take place to ready the client for work. These are:

1. The case worker designs an approach for the client to overcome barriers to work.
2. The youth gets short-term education or training.
3. The youth gets job coaching and long-term guidance.
4. The youth gets social support to enable work continuity.

The third step involves incentive payments that encourage job retention, wage growth and employment in in-demand occupations. These three steps will, it is hoped, help the youth attain self-sufficiency and stability.

The four supporting actions in the second step aim to enhance the employment prospects of the client, ranging from skill accretion to support and services that allow the client to continue to hold his or her job(s).[[27]](#footnote-27) These key activities only include those unique to WP. The CCMEP participants from which county caseworkers recruit WP participants receive more services under CCMEP. One may think of CCMEP as a *wrap-around* program in that it combines WIOA and TANF benefits with the caseworker handling both programs for the client. For evaluation purposes, we investigate the extent to which the WP program improves outcomes relative to CCMEP alone. The evaluation of CCMEP as mentioned will proceed on its own although the two evaluations will share many elements. We may characterize this second column as program activities that directly impact the youth’s capabilities in the labor market – directing him or her toward short-term training, providing support so unfortunate events don’t force the youth to stop working, and providing coaching and mentoring to help the youth negotiate the labor market so they can build on what they have learned by working and direct that knowledge toward moving ahead in the labor market.

The third step is the *incentive input* to the WP process, namely the cash awards participants can earn by meeting benchmark goals for the WP program.[[28]](#footnote-28) We may characterize this third step as program features that provide the youth with incentives to do things that move them ahead in the labor market. Finally, the fourth column shows the outcome or impact of the program. The time frame of WP is rather short, so one can hardly look at outcomes after only a year as evidence of self-sufficiency and stability. We use data on earnings after Wage Pathways has started as evidence for or against the youth moving toward self-sufficiency and stability. If WP results in eligible youths having greater earnings than ineligible youths, we take that as a sign the program is helping youths move toward self-sufficiency and stability.

### Measures of Education and Experience

The WP program does not feature extensive education or training for the client; rather, it uses incentive payments to encourage the youth to take actions that will move them toward self-sufficiency. This approach emphasizes helping youths find and keep a job as the pathway toward self-sufficiency. The efficacy of encouraging youths to take a job and work their way up as an alternative to education and training depends upon the rate of return to experience. As a minor digression, let us look at a bit of evidence on this matter using the administrative data we have assembled for Ohio.

We will explore two ways to investigate the rate of return to experience. First, we will merge the BMV data with the UI Earnings data so our earnings data have age and gender. Currently, we have no way to match in educational attainment to the UI Earnings data except for ways that would systematically exclude youths like those in CCMEP[[29]](#footnote-29). Extracting data for everyone in the merged Ohio UI data born 1994-2000, we have 391,443 observations. Our regression of the log of earnings on experience (Exp – this variable is implemented using age) and gender (1 for male, 2 for female) yields

LnEarn = 8.750 + 0.223Exp - 0.182Gender

(2137.05) (371.50) (88.44)

R2 = 0.2753

The numbers below the coefficients are the t-statistics. The estimates are significant at any conventional significance level. A return to a year of experience of 22% is more than twice as large as the typical estimated return to a year of education. This is the Mincerean return[[30]](#footnote-30) to experience, capturing the sum of the returns to employer-specific experience and the returns to general experience. As a check on this number, we computed the return to experience in a second way. Again looking at youths born 1994-2000, we focused on those youths who worked for the same employer for 13 weeks in both of two consecutive quarters and computed the rate of change in earnings with that employer from one quarter to the next. We did this calculation for four consecutive quarters[[31]](#footnote-31) to avoid seasonality. Over the four quarters from 2nd Quarter 2016 through 1st Quarter 2017, the estimated rate of return to employer-specific experience was 14%.

With either measure, it appears young workers enjoy a substantial return to experience, making the use of incentives to encourage youths to find and hold a job a viable short-term strategy to move toward self-sufficiency. We suspect a longer-term look at these data will show these high rates of return to experience will not persist. In addition, we suspect the return to experience will also be an increasing function of education. In the longer term, a high return to experience in the teens and early twenties will not dominate the well-known earnings premium that inures to more education.

#### Methods

##### Pseudo Randomization

At various points above in this report, we have discussed the chosen strategy of pseudo-randomization by selecting a limited number of counties to host WP rather than randomizing at the individual level. While randomizing at the individual level would have been the better strategy from an econometric perspective, we have tried to incorporate features into the analysis that would attenuate that disadvantage.

##### Controlling for Labor Market Differences

One of our major concerns with the strategy of pseudo randomization by county was that it resulted in four of the WP counties being in the northern part of the state, three of whom were in the same ODJFS-defined labor market. The fifth WP county (Hamilton in southeast Ohio) started its implementation of WP so late that by the time the evaluation report was due we would not have time to observe earnings on the WP eligibles in Hamilton County for at least four quarters post-onset. Given the serious seasonality in the administrative data, the short post-onset period could confound the analysis.

If labor market conditions differ markedly for CCMEP youths in WP-eligible versus WP-ineligible counties, we could misattribute the effect of these differences labor market conditions to the effect of the WP program. To attenuate this possible source of error, we used the statewide administrative data to attempt to determine whether there were differences in the labor market conditions facing youths across the nine ODJFS-defined labor markets and, if there were, use these as regressors in our difference-in-difference estimation to take these differences into account.

To investigate labor market differences faced by youths, we merged the UI Earnings data with the BMV records so that, for each UI Earnings record, we had month and year of birth, gender and county of residence. From this universe, we discarded everyone not born 1994-2000, everyone who had enrolled in CCMEP[[32]](#footnote-32), and everyone who had a record in the OLDA Higher Education file. We made this latter exclusion because, as Table 3 above shows, CCMEP enrollees mostly have a high school diploma or less.

Using this synthetic comparison group, we constructed three measures. First, we computed the return to firm-specific experience for youths who had worked for the same employer for 13 weeks for both of two consecutive quarters, averaged over the period from 2nd Quarter 2016 through 1st Quarter 2017. Second, we examined, for each labor market, the prevalence of youths working in industries that employ most youths to determine whether opportunities in those industries varies. In Table 7, below, we compare the industry of employment using data from CCMEP youth taking our survey versus the industry for the primary employers of all UI covered workers. This illustrates the disproportionate role some industries play in employing youths.

Table 7

Relative Concentration of Youth in Eight Industries

| NAICS Code | Description | CCMEP Survey | UI Data  (All Ages) |
| --- | --- | --- | --- |
| 561 | Admin. & Support | 15.3% | 6.7% |
| 624 | Social Assistance | 10.9% | 3.3% |
| 722 | Food & Drink Estab. | 16.2% | 8.6% |
| 813 | Religious, Grantmaking, Civic & other organizations[[33]](#footnote-33) | 3.9% | 0.7% |
| 445 | Food & Bev. Stores | 1.7% | 2.2% |
| 447 | Gas Stations | 1.2% | 0.7% |
| 452 | Gen. Merch. Stores | 1.9% | 2.3% |
| 453 | Misc. Store Retail | 1.3% | 0.5% |
|  | Total | 52.4% | 25.0% |

Third, for each county, we computed the fraction of youths born 1994-2000 who had ever held a UI covered job as a percent of youths in the BMV database for that county. We can think of this as an “ever employed” rate for youths.[[34]](#footnote-34) In Table 8, we show these metrics along with data on population by labor market.

Table 8

Selected Characteristics of Ohio Labor Markets

(See Figure 2 for Market Definitions)

| Measure | A  Northwest  Near  Sandusky | B  Northeast near Cuyahoga  & Akron | C  North Central  Near  Ashland | D  Stark-Mahoning  Around  Canton &  Youngstown | E  West Central  Near Dayton  Springfield | F  Central near  Columbus | G  Appalachia  Carroll  to Meigs | H  Southwest  Cincinnati | I  Appalachia  Gallia to  Clinton |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Population | 961,614 | 2,864,784 | 510,652 | 1,006,586 | 1,466,374 | 2,395,015 | 408,621 | 1,610,439 | 385,671 |
| Number of youths ever in UI & born 1994 - 2000 | 82,642 | 237,162 | 44,435 | 82,457 | 125,364 | 205,860 | 27,484 | 142,110 | 28,520 |
| Number of youths in BMV born 1994-2000 | 91,893 | 267,535 | 48,026 | 93,452 | 139,097 | 230,646 | 33,692 | 157,640 | 35,111 |
| Ratio of youths in BMV to total population | 9.56% | 9.34% | 9.40% | 9.28% | 9.49% | 9.63% | 8.25% | 9.79% | 9.10% |
| Ratio of youth in UI to youth in BMV | 89.93% | 88.65% | 92.52% | 88.23% | 90.13% | 89.25% | 81.57% | 90.15% | 81.23% |
| % in Youth Intensive Industries Q2 2016 - Q1 2017 | 51.18% | 48.94% | 46.65% | 49.31% | 51.48% | 51.59% | 41.82% | 49.44% | 45.79% |
| Return to experience  - same employer | 13.47% | 14.20% | 16.06% | 13.19% | 14.97% | 15.64% | 13.11% | 14.36% | 13.06% |

For over half a century, many commentators have discussed the labor market problems in Appalachia. The labor market measures in Table 6 reinforce the standard view of Appalachia. The rate of return to staying with an employer is 2-3% lower than we see in the very strong labor markets elsewhere in Ohio. The northern branch of Appalachian counties show a remarkable weakness in the lack of opportunities in the industries that provide significant employment for youths. The band of counties along the Ohio River from Carroll to Meigs have a lot of shale and gas (see Figure 3).

Figure 3

Marcellus Shale in Ohio

https://www.sourcewatch.org/images/3/31/OhioShaleMap.jpg

Marcellus foundation runs along Ohio's eastern border to Washington county.  Utica structure is west of Marcellus going south to Pickaway county east by southeast to Meigs county.

While important economically, once fracking moves out of the drilling phase, the production work requires more skilled workers. **Finally, looking at the fraction of youths born 1994-2000 who have ever worked, we see the Appalachian counties have “ever employed” rates about ten percentage points less than elsewhere in Ohio. This suggests the positive effects of fracking have not overcome the historical disadvantages of Ohio’s Appalachian region.**

We will use these three metrics for labor market conditions in Ohio as regressors in our difference-in-difference equations to quantify the degree to which labor market conditions differ across Ohio. We will use these regressors to determine whether differences in labor market conditions explain variation in career advancement. This will attempt to control for labor market conditions that may differentiate outcome for WP counties versus counties that do not offer WP. If we find that local labor market conditions do not explain variation in the difference-in-difference regressions, or their presence in the earnings regression does not affect the estimated impact of WP, we can take that as evidence suggesting the clustering of the WP counties in the northern part of Ohio is less of a problem than one might have feared.

##### Econometric Theory and Control vs Experimental

In difference-in-difference evaluations, we look at the change in outcomes before and after the treatment for both people who received, or were eligible to receive, the treatment versus people (in the same or comparable periods) who were ineligible for the treatment.[[35]](#footnote-35) When we speak of outcomes, we primarily mean quarterly UI earnings. We collected secondary outcomes in a separate survey effort. Those secondary outcomes are hourly rate of pay and usual hours per week. We consider these secondary outcomes because, unlike the administrative data that will be complete for virtually all experimental and control cases, not all CCMEP enrollees cooperated with the survey effort.

Consider a simple model where we observe, for each person i, an outcome Y at times t and t+1: the “before” and “after” program onset periods, respectively. CCMEP participants in Cuyahoga, Summit, Ottawa and Ashtabula who entered WP started doing so in May (Ashtabula and Ottawa Counties) or October (Cuyahoga and Summit Counties). Our post-onset period needs to be four (or eight) quarters long to avoid seasonality and we would like the post-onset period to end as late as possible to give the program more time to have an impact. We did not have enough data to cover eight post-onset quarters, so we used the four quarters from 2nd Quarter 2018 through 1st Quarter 2019 as our post-onset interval. The pre-onset period extends from 2nd Quarter 2016 to 1st Quarter 2017.

The primary data for the outcome analysis is the quarterly UI earnings. Each person has a set of characteristics Xi that do not change from t to t+1. Examples of such variables are race, sex, education on entering CCMEP, whether the person had prior involvement in the criminal justice system, and so forth. At intake to CCMEP, each client answers an extensive set of questions about their circumstances that we can use to adjust for differences between controls and experimentals, although the difference-in-difference method removes time-invariant characteristics j that only impact the level of Y. We allow for the possibility that the time-invariant X variables affect the *trend* in Y by including as a regressor tXiso that X can change the rate at which Y changes over time. The WP program focuses on earnings growth, and we want robustness to the possibility that the characteristics of youths affect not only the *level* of their earnings, but also the rate at which those earnings grow. In addition, each person has a set of characteristics Zi,t that may change over time. The Xs and Zs may be characteristics of the person or the person’s location.

Equation 1) expresses pre-onset earnings (or another outcome) as a function of time-invariant and time-varying regressors. Equation 2) is our post-onset regression.

Yi,t = Xi+ tXi+ Zi,t1 + itXi1it+ Zi,t2it + ui,t 1)

Yi,t+1 = Xi+ (t+1)Xi+ Zi,t+11 + it+1Xi1it+1+ Zi,t+12it+1 + ui,t+1 2)

We use t as an indicator of whether person i was eligible to receive the “treatment” in period t. In the control (or ineligible) group, t = t+1 = 0. For experimentals (or eligibles), t = 0 and t+1 = 1.[[36]](#footnote-36) measures the simple additive effect of the treatment; 1 allows the treatment effect to interact with the time invariant characteristics Xi and 2 allows the treatment effect to interact with the time varying Zi .

For control cases (for which we use the superscript c), the “after” outcome minus the “before” outcome change is

Yc = Xi+ Zc1 + uc. 3)

Where Y is Yi,t+1 - Yi,t and similarly for other variables.

For experimental cases (for which we use the superscript e), the corresponding change in outcome is

Ye = Xi+ Ze1 + + XieZi,t+1e2 + ue. 4)

If we “stack” 3) and 4), pooling observations for both experimentals and controls, using t as a zero-one indicator for the two groups as above, the pooled regression is, again dropping the i subscript,

Y = X+ Z1 + t+ tXtZt+12 + u. 5)

This model is just identified in that there five parameters (or parameter vectors) to be estimated (1, and 2) and five regressors (or regressor vectors) (XZ,t, tX and tZ,t+1), giving just identification[[37]](#footnote-37). The effect of time-invariant characteristics on the levels of earnings has dropped out as a consequence of differencing the data. That is, the model uses the level for X and change in the Zs for both groups, the level of X interacted with the eligibility indicator for the experimentals, and the “after” value of Z for the experimentals.

In the event the program effect does not interact with regressors and there is a simple additive effect, equation 5) simplifies to the level for the Xs, the additive program effect plus a term reflecting the change in Z. Using age as a time varying variable will, after differencing, result in an intercept term in the differences regression. Testing out a variety of demographic variables in the difference-in-differences equation avoids misattributing different earnings growth for eligibles vs ineligibles to program effects when the difference is due to differences in characteristics that have an effect on earnings growth.

The primary question we want to answer is whether the intervention has an overall impact. It is not essential to determine whether the program impact differs by demographic characteristic.

Sometimes people raise a concern over missing data and the possibility the observed data points differ systematically from the unobserved data points. The primary data for the outcome evaluation are administrative data from the UI earnings file, the CCMEP enrollment process, and TANF and SNAP program data. These administrative files mean our observations on CCMEP people cover that universe, not a sample. Not having an earnings record in the UI file means that, apart from informal work, the person has no regular employment earnings.[[38]](#footnote-38) We also collected survey data on wage rates, occupation and hours worked. The scope for selection bias in the survey earnings data is small. The reason the scope for being misled by selection on the survey collected is highly limited is that we have high-quality earnings data from the UI insurance program. The essence of the selection problem is that the missing data may disproportionately come from one tail or the other of the earnings distribution. While wages and hours may be missing, earnings will always be observed.

Factors that are time invariant and do not differentially modify the program effect are differenced out of the analysis. Thus interpersonal differences (whether observable or not), so long as they do not affect how the program functions or the extent to which earnings grow, are inessential. We see below that time-invariant characteristics survive in the difference-in-difference earnings model (as well as regressions for the change in weeks and the change in number of employers). Measures of disadvantage don’t simply explain a different *level* in labor market outcomes but explain variation in how these outcomes change over time.

##### Universe vs Sampling; Completeness of Data

Program evaluations that depend upon survey data suffer from nonresponse, which plagues all survey efforts, not just those used to support evaluation research. Our efforts here take a different approach. We have used administrative data for all youths presenting for the CCMEP program and have used data on these persons from TANF and SNAP, UI Earnings data (including jobs held and weeks worked on various jobs), background data from their program application, demographics from Ohio Driver’s License and State ID data, PIRL data reported to the U.S. Department of Labor and, finally, constructed labor market indicators computed based on UI Earnings data for youths not in CCMEP and, who like the great majority of CCMEP youth, have had not post-secondary education or training.

As a consequence, these data will be very complete although not perfect. We will not lose observations because of sampling, although there are occasional missing data due to minor incompleteness in the administrative data.

##### Data and Results

In Table 9, we list the variables we use in the difference-in-difference regressions. None of the variables varies over time within the limits of our measurement.

Table 9

Variables in the Analysis

| Variable | Explanation |
| --- | --- |
| Earnings | Based on UI data. We use four consecutive quarters for both the pre- and post-onset periods. When using the log of earnings, we discard observations with zeroes. |
| Weeks Worked | Based on UI data. This variable will be very accurate for persons with a single employer during a quarter. For multiple job-holders during a quarter, the number is the maximum number of weeks the person could have worked. We also use four consecutive quarters for this variable. |
| Number of Employers | Based on UI data. This variable is very accurate for covered employment. In the analysis we sum this number for four consecutive quarters, giving the number of employer-quarters during the pre- and post-onset periods. |
| Number Months TANF | Based on TANF/SNAP data. This variable is very accurate, coming from payments data. It shows the number of months the person either directly received TANF payments or counted as an assistance group member and thereby increased payments for the actual payee. We take this as a measure of cumulative disadvantage. |
| Number Months SNAP | Based on TANF/SNAP data. This variable is very accurate, coming from payments data. It shows the number of months the person either directly received Food Stamp or SNAP payments or counted as an assistance member and thereby increasing payments for the actual payee. We take this as a measure of cumulative disadvantage. This variable and the TANF variable above are highly correlated, so their coefficients are negatively correlated. |
| Gender | Based on BMV data. This variable is very accurate. 1=male, 2= female. |
| County | Based on BMV data. This variable is accurate, but subject to error when people move. When we have evidence a person moved out of Ohio, we drop the observation. |
| Education | Based on CCMEP enrollment data, which is self-reported. The variable is fairly accurate; we edited the data so it shows highest grade completed. Anyone without a diploma or GED will not be coded 12. The edit rules appear in the on-line metadata codebook. |
| RTExp | This is a created labor market descriptor. It is the rate of change in earnings for those who worked 13 weeks in both the current and previous quarter. We sum this quarterly rate of change over the four consecutive in the pre-onset period (2nd Quarter 2016 through 1st Quarter 2017). This is computed for youths statewide born 1994-2000 who are not in CCMEP and have not appeared in the state Higher Education database. County measures for this variable exhibit modest variation. |
| KIFirms | This is a created labor market descriptor. It is the number of youths working for industries that employ most youth (see Table 5 above) divided by the population in that labor market. As with the variable above, we compute this metric using peers not in CCMEP or in the Higher Education database. The county measures for this variable exhibit modest variation. |
| EverEmpR | This is a created labor market descriptor. It is the fraction of youths in a labor market who held any job in the UI data during the pre-onset period. As with the variables above, we compute this metric using peers not in CCMEP or in the Higher Education database. The county measures for this variable exhibit modest variation. |
| IEP | Based on self-reported Enrollment data. Indicates whether youth had ever had an IEP in school. |
| Transp | Based on self-reported Enrollment data. Indicates whether youth has reliable transportation. |
| JuvCT | Based on self-reported Enrollment data. Indicates whether youth has ever been involved with juvenile court. |
| Age | Age in 2000; ranges from zero to six. |
| Yrs\_ExpX | Number of weeks person has worked from Q1 2010 through Q1 2016 divided by 52. We use this variable in the difference-in-difference regressions to avoid simultaneity, as experience in our pre-onset “before” period is jointly determined with the observed labor market outcomes in the pre- and post-onset periods. |
| Yrs\_ExpY | Number of weeks person has worked from Q1 2010 through Q4 2017 divided by 52. We use this variable in the post-onset levels regressions to avoid simultaneity, as experience in the post-onset period is jointly determined with the observed labor market outcomes in the post-onset period. |
| Black | Indicator based on Participant Individual Record Layout from report to U.S. Department of Labor |
| Hispanic | Indicator based on Participant Individual Record Layout from report to U.S. Department of Labor |

Table 10, below, shows our results for the difference-in-difference estimation for earnings, weeks worked and number of employers. The reference periods for pre- and post-onset are four quarters, the former starting 2nd Quarter 2016 and the latter 1st Quarter 2018. Absolute values of t-statistics are below the coefficients.

The eligibility indicator is the central variable, but the regressions include indicators of local labor market conditions as well as characteristics of the youth. With the regressions being based on differencing outcomes over time, the variable coefficients reveal the variables’ effect on earnings growth as well as on changes in hours and number of employers. The majority of labor supply and wage equations look at *levels* rather than changes. As noted early on in this report, the central issue here is earnings growth, so changes are the right metric. When we show the regressions for levels in earnings, the results will look more familiar. We also caution the reader that these regressions represent people at the outset of their working lives and the results for these growth regressions will not endure deeper into their careers.

Table 10

Difference-in-Difference Labor Market Outcome Regressions

| Variable | Earnings | Weeks | #Employers | Regressor Mean |
| --- | --- | --- | --- | --- |
| Eligible for WP | 493.2  (4.33) | 1.66  (5.04) | 0.078  (6.22) | 0.190 |
| Age in 2000 | -516.2  (18.59) | -1.61  (19.9) | -0.087  (28.49) | 2.69 |
| County Return to Firm Exp | -146.3  (2.55) | -0.03  (0.20) | -0.020  (3.11) | 14.326 |
| County %Youth in youth-intensive Ind | 188.8  (0.83) | 1.01  (1.53) | 0.042  (1.65) | 4.120 |
| County %Youth ever Employed | -19.6  (0.55) | -0.33  (3.18) | -0.001  (2.09) | 88.491 |
| Gender | -846.0  (7.93) | -2.69  (8.70) | -0.082  (6.97) | 1.659 |
| #Months SNAP | -2.3  (2.62) | -0.003  (1.14) | -0.0004  (3.68) | 48.59 |
| #Months TANF | 3.88  (2.93) | 0.01  (2.87) | 0.0006  (4.11) | 21.93 |
| Highest Grade Completed | -123.1  4.46 | -0.83  (10.36) | -0.036  (11.83) | 10.40 |
| Had IEP in School | 227.2  (2.32) | 1.54  (5.43) | 0.53  (4.88) | 0.249 |
| Has Reliable Transportation | -153.8  (1.25) | -1.19  (3.32) | -0.049  (3.56) | 0.865 |
| Juvenile Court Involvement | -154.4  (1.37) | -0.26  (0.8) | -0.037  (3.00) | 0.171 |
| Has Minor Children | -858.4  (3.78) | -1.95  (2.96) | -0.050  (1.98) | 0.380 |
| Female x Has Minor Children | 813.00  (3.36) | 3.16  (4.50) | 0.095  (3.57) | 0.332 |
| Hispanic | 541.3  (2.31) | 1.74  (2.57) | 0.056  (2.16) | 0.035 |
| Black | -207.0  (2.18) | -0.57  (2.09) | -0.026  (2.48) | 0.535 |

N= 14,829

In Table 11, we provide regressions for the levels of the outcome variables in the post-onset period (calendar year 2018): (log of) earnings[[39]](#footnote-39), weeks worked[[40]](#footnote-40) and number of employers[[41]](#footnote-41). The log earnings equation is similar to a wage equation much-used in the labor supply literature except that inasmuch as the administrative data do not measure hours worked, we must settle for earnings rather than wages.

Table 11

Levels Regressions for Labor Market Outcomes 2018

| Variable | Log Earnings | Weeks Worked | #Employers |
| --- | --- | --- | --- |
| Eligible for WP | 0.053  (1.69) | 1.39  (4.12) | -0.004  (0.33) |
| Age in 2000 | 0.004  (0.54) | -0.837  (9.43) | -0.032  (9.28) |
| Yrs\_ExpY (Q1 2010 – Q4-2017) | 0.328  (27.01) | 6.449  (48.06) | 0.221  (41.98) |
| County Return to Firm Exp | 0.003  (0.19) | -0.132  (0.77) | 0.006  (0.85) |
| County %Youth in youth-intensive Ind | 0.109  (1.70) | 0.250  (0.37) | 0.104  (3.91) |
| County %Youth ever Employed | -0.028  (2.74) | 0.246  (2.32) | 0.006  (1.53) |
| Gender | -0.114  (6.55) | 1.091  (3.44) | 0.064  (5.18) |
| #Months SNAP | -0.002  (6.55) | -0.015  (5.74) | -0.0002  (2.58) |
| #Months TANF | 0.000  (0.15) | 0.004  (0.89) | 0.0001  (0.66) |
| Highest Grade Completed | 0.037  4.89 | 0.309  (3.74) | 0.010  (3.05) |
| Had IEP in School | -0.156  (5.59) | -1.055  (3.60) | -0.034  (2.99) |
| Has Reliable Transportation | 0.1470  (4.232) | 0.912  (2.48) | 0.028  (1.93) |
| Juvenile Court Involvement | -0.199  (6.26) | -2.827  (8.42) | -0.005  (0.40) |
| Has Minor Children | -0.081  (1.29) | -1.202  (1.68) | 0.062  (2.34) |
| Female x Has Minor Children | -0.152  (2.28) | -1.202  (1.68) | -0.118  (4.20) |
| Hispanic | 0.159  (2.49) | 1.911  (2.75) | 0.047  (1.74) |
| Black | -0.067  (2.58) | -0.174  (0.62) | 0.116  (10.58) |

N = 14,829 except log earnings regression that has 12,225 observations with positive earnings

The central variable is eligibility for Wage Pathways, and we find it has a positive, significant impact on earnings. Our point estimate of the effect of eligibility on earnings is $500/year. Our sample has 14,829 persons of whom 19% were eligible, or 2,818 eligible persons. For all of 2018, these eligible people, in aggregate, earned roughly $1.4 million more due to being eligible for WP. We suspect the earnings gain after the first year would decline, but we must await more data to assess total income gains over several years. Those data will be readily available in the UI earnings file, making it relatively straightforward to measure longer-term outcomes.

As noted above, our primary concern centered on eligibility being defined by county rather than via random assignment within county, creating the possibility we misattribute different labor market conditions in the various Ohio labor markets to WP program effects. The three constructed labor market metric variables we constructed using a synthetic “peer” group of the same age and a lack of post-secondary education, while sometimes significant, do not contribute to the finding on a WP effect. This implies the clustering of the experimental counties in the northeast of Ohio has not biased our estimators of program impacts.

The WP program encourages youths to hold a job, stressing work experience over additional formal education, the latter of which many CCMEP youth are likely ill-disposed to obtain. What do the education versus experience coefficients tell us about this strategy? Education, of course, has a positive impact. In the log earnings equation using post-onset earnings, one more year of education raises earnings by 3.7%. In the post-onset log earnings equation, the return to an additional year of experience (using detail on weeks the youth has worked, was about 33%. This suggests that, in the short-run, youths in this particular group holding a job for an additional year would likely see their earnings increase more than their peers who had instead completed one more grade in secondary school. For new workers, the high rate of return to experience will not continue and the returns to education, especially if they obtain a high school degree, will increase and last for a lifetime.

Ohio’s high school graduation rate is about 85%. Those without high school degrees are more likely to be in the CCMEP population than their graduating peers. For those at the bottom of the educational distribution who, for one reason or another, are unlikely to get a high school degree or its equivalent, getting and holding a job can get their career moving forward more quickly than commonly thought given the large initial return to experience estimated here. Carefully tracking the workforce behavior of CCMEP clients will help us understand the longer-term impacts of programs like CCMEP.

WP stresses overcoming barriers. We see that the variables that reflect the presence of these barriers still act to reduce earnings, so WP does not overcome those barriers so much as it appears to mitigate the effect of those barriers, in aggregate, benefit CCMEP clients eligible for Wage Pathways regardless of barriers. Few would have expected the program to erase completely the effects of the cumulative disadvantage to which these vulnerable youths have been exposed.

## Summary of the Quantitative Evaluation and Threats to Validity

The estimated effect of having Wage Pathways available in a county is to raise average earnings for CCMEP clients who were age eligible by between $300 and $700 per year. With 3,000 youths in the four “experimental” counties age-eligible for WP, that is an aggregate earnings increase of between $0.9 and $2.1 million. If a state-wide program for 100% rather than 20% of younger CCMEP clients were in place and the other counties could achieve the same impacts, these younger CCMEP clients in aggregate would have their earnings increase by between $4.5 and $10.5 million. With our short follow-up period, we cannot yet estimate the extent to which such gains might persist over the longer run. Longer-run impacts would, of course, increase the average earnings benefit to eligibles.

The quantitative evaluation leaned heavily on the availability of administrative data. These data provided data on about 15,000 CCMEP clients who, if they were in a Wage Pathways county, would have been age-eligible for the intervention. This sample size provided sufficient statistical power to measure the effect of the program. Even if the program impact were only to increase earnings of eligibles by $200, we could have detected that. Our findings are not an artifact of program staff assigning the best prospects to WP. We designed the evaluation to avoid the bias “creaming” creates if one were to compare program participants to non-participants. Because Wage Pathways focused on “work ready” clients, having staff select the best candidates for Wage Pathways reflected the counties being faithful to the design of the program.

The major threat to validity for these findings is having eligibles defined by county rather than true random assignment. As noted above, this reflects the political constraints under which CCMEP and all program must operate. We have tried to attenuate this threat by constructing labor market indicators to control for the difference in labor market conditions of eligible versus ineligible counties. Those indicators have significant effects in our outcome regressions, yet their presence does not materially affect the estimated effect of eligibility. We do not claim that this proves that our impacts do not, to some degree, confound county differences and program effects. However, the positive measured impacts and the fact that the intervention covered 20% of age-eligible CCMEP clients give reason to be quite hopeful.

In Table 12, we show the means for key variables for the counties not offering WP (Control Counties) versus the four counties offering WP (Experimental Counties). The only notable departure (other than the change in earnings) is a greater prevalence of Black CCMEP clients in the experimental counties.

Table 12

Means for Control vs Experimental Counties

| Variable | Control Counties | Experimental Counties |
| --- | --- | --- |
| Difference in Earnings | -126.99 | 290.39 |
| Age in 2000 using BMV data | 2.60 | 2.65 |
| Rate of Return firm-specific Experience in County | 14.36 | 14.20 |
| Youth in youth-intensive industries as % of pop | 4.10 | 4.05 |
| Fraction youth ever employed | 88.20 | 88.65 |
| Gender (2=female) | 1.64 | 1.64 |
| Months FS Recipiency | 46.21 | 44.32 |
| Months TANF Recipiency | 20.79 | 19.24 |
| Highest Grade Completed | 10.38 | 10.18 |
| Had IEP In School | 0.25 | 0.24 |
| R Has Reliable Transportation | 0.85 | 0.89 |
| Ever in Juvenile Court? | 0.17 | 0.15 |
| Has Minor Children | 0.37 | 0.31 |
| Female with minor children | 0.32 | 0.27 |
| Hispanic | 0.03 | 0.05 |
| Black | 0.44 | 0.75 |

Another important threat to validity comes from the fact that the period for our study is rather unusual. The post-onset period overlaps with a time when the labor market has been more favorable to workers, and especially unskilled workers, than any other time in over a decade. This leads to the question whether this a good program or is it the right program for the times? With job openings outnumbering the unemployed and casual empiricism revealing Help Wanted signs seemingly everywhere, it could easily be the case that Wage Pathways is riding the crest of this job market wave. Would we see the same results if the program were instituted during the period from 2009-2014 when the recovery was weak and there were many discouraged workers? We do not and cannot know. Even if the evidence suggests a successful program with the right features at the right time, this does not mean the evidence here supports the proposition that this is the right program for disadvantaged youths in all labor market conditions.

We believe the results of the quantitative evaluation are reliable and the program has a positive impact that is economically and statistically significant.

# Cost Study

Project staff received cost data from the sites with costs reported in broad categories. We did not audit or otherwise verify their reported costs. Table 13 reports those costs. We do not include space charges in those costs as Wage Pathways did not change aggregate space requirements.

When considering the likely costs of a statewide implementation on a continuing basis, we want to focus on variable costs that will likely scale up with the number of eligibles. Incentive payments averaged about $150 per eligible client, reflecting about 20% of eligibles being judged “work ready” and choosing to participating in WP. The low faction of eligibles participating reflects low participation in the late-starting Hamilton County program. We include under incentive payments costs counties incurred to provide payments to participants to help them get started working.

Wage Pathway costs average $390 per eligible person – about $100 less than the one-year increase in earnings we estimate for Wage Pathways in the northern tier of experimental counties. ODJFS felt Hamilton County ran the Wage Pathways program very close to ODJFS’ original intention. Cuyahoga and Hamilton counties appear to exhibit scale economies, relative to the other three counties.suggesting a statewide implementation would have favorable cost metrics in other metro areas where CCMEP cases cluster.

Table 13

Wage Pathways Costs in the Four Experimental Counties

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| |  |  |  |  |  |  |  | | --- | --- | --- | --- | --- | --- | --- | |  | **Cuyahoga** | **Summit** | **Ashtabula** | **Hamilton** | **Ottawa** | **Total** | | Incentive Payments | $303,555 | $25,000 | $100,000 | $219,812 | $9,000 | $657,367 | | Personnel-Admin | $82,500 | $134,496 | $1,035 | $27,606 | $0 | $245,637 | | sub-awards | $326,425 | $0 | $350,000 | $170,650 | $35,000 | $882,075 | | Misc. costs | $0 | $0 | $20,000 | $0 | $0 | $20,000 | | **Total** | $712,480 | $159,496 | $471,035 | $418,068 | $44,000 | $1,805,079 | | Eligibles | 2283 | 323 | 360 | $1,618 | 45 | 4629 | | **# WP participants** | 529 | 47 | 111 | 169 | 22 | 878 | | **WP participants per eligible** | 23.2% | 14.6% | 30.8% | 10.4% | 48.9% | 19.0% | | **Incentives/participant** | $573.83 | $531.91 | $900.90 | $1,300.66 | $409.09 | $748.71 | | **Incentives/eligible** | $132.96 | $77.40 | $277.78 | $135.85 | $200.00 | $142.01 | | **Cost/Eligible** | $312 | $494 | $1,308 | $258 | $978 | $390 | |  |  |  |  |  |  |
|  |  |  |  |  |  |  |

ODJFS instructed the county staff charged with implementing WP to support the program within their existing staffing levels and this explains the modest personnel charges. However, the various counties did utilize contractors to counsel youths on establishing careers and moving their terms of employment forward.

## Fixed vs Variable Costs

While incentive costs will clearly vary over time with participation and extending Wage Pathways to more counties will increase incentive costs, some costs are likely one-time start-up costs, which become less significant over time. Some of the personnel, sub-award and miscellaneous costs may reflect costs counties incurred setting up the Wage Pathways program operating in their service area. With or without Ottawa, incentive costs average about $145 per eligible, so variable costs per age-eligible client likely average between $145 and $500.

Organizational cost accounting gets done in different ways by different organizations. For-profit organizations pay careful attention to which costs they should attribute to which activities or product lines. Even so, large companies also allocate fixed charges (such as upper-level management) to activities and product lines absent clear and compelling reasons to make those allocations.

Public sector organizations use fund accounting, focusing on the need to pay for their costs out of a variety of programs for which they have been given money. Some of the non-incentive costs of Wage Pathways may reflect counties using fund allocations for WP to cover salaries and facilities they have incurred and would still need to cover absent the WP program. Administrative costs per eligible person would likely decline as the program lasts longer and county staff have routinized program administration.

## Implications for A Larger Implementation

Looking at cost-benefit for Wage Pathways, we have more confidence in our estimated one-year, short-term benefit of $300 - $700 per eligible than our estimated cost of $145 - $500 per eligible. We measure incentive costs – the central feature of the program – accurately, and incentive costs are clearly less than the earnings benefits the program produces. A longer term, state-wide implementation would allow county staff to reduce ongoing costs after the start-up costs have been paid and counties have regularized their processes. If incentive costs increase that would suggest the program is producing higher earnings for participants, improving the cost-benefit ratio.

# Conclusions from the Evaluation

Wage Pathways has considerable promise. Even if its positive impacts decline in the second and third years, its benefits in the form of higher earnings for the youths will very likely exceed the costs directly attributable to the program. Incentive payments also increase the estimated benefit to the youths, but those incentive payments are a transfer from taxpayers to CCMEP clients and should not be counted as a net societal benefit.

It will not be difficult or costly to estimate the earnings impacts of WP over time given the established analytic framework. The more important questions about the cost/benefit ratio of Wage Pathways lie on the cost side. Insofar as some of the average costs estimated here represent counties covering commitments out of a convenient funding source and the costs of starting a new program, the cost-benefit ratio is more favorable than it appears here. We suspect that once ODJFS measures longer-term impacts and looks more closely at the extent to which offering Wage Pathways would require counties to spend more money after its initial phase-in, the program will be judged favorable on purely cost-benefit grounds. However, there are great many more considerations the state must take into account as well as important political judgements.

# Appendix A – Seasonality in the Administrative Data

We use the quarterly UI Earnings data for some of the most important quantitative analyses. These data have a substantial seasonal component and we must respect that in choosing time periods of the analysis to avoid having seasonality contaminate that analysis. This appendix looks at seasonality as well as key variables over time to show that while there is a seasonal component, the data show a consistent pattern over time and display behavior that reflects long-term trends and business cycles. The data here use the UI Earnings data for all of Ohio and for all ages.

We start by showing how seasonality impacts the UI Earnings data. In Figure 4, we show data on multiple job holding.[[42]](#footnote-42) The blue line shows the number of jobs held during a quarter. The troughs all fall in the first quarter of the calendar year with the second and third quarters showing recovery. The gray line shows the number of jobs held per person for those who were employed the quarter before; the orange line shows jobs per employed person for those not employed the quarter before. These latter two lines are smoothed using a four-quarter moving average. The seasonal pattern in the blue line is unmistakable. The smoothed lines both show multiple job-holding is pro-cyclical. During contractions, multiple job holding declines whereas during expansions, it increases. This illustrates how the monthly “jobs” number from the Current Employment Statistics (CES) survey can be misleading by overstating good news in expansions and overstating bad news during contractions.[[43]](#footnote-43)

Figure 4

Seasonality in Job Holding

Figure 5 shows the discordance between the BLS estimate of jobs held in Ohio from the CES and data from the UI Earnings file. The UI earnings file will give a higher number of jobs as its reference period is quarterly, whereas the CES uses a monthly reference period.

Figure 5

CES vs UI Job Holding for Ohio

To reduce that reference period distortion, we have taken the highest monthly figure during a quarter for Ohio employment from the CES and used that to adjust the CES monthly data to a quarterly value that should more closely align with the UI data. We used a four-quarter moving average to smooth the CES quarterly data as we did for the UI jobs data. The gap between UI employed and UI jobs held reflects multiple job holding during a quarter.

We also see seasonality in what we call the Earnings Accrual Rate in Figure 6. For this rate, we compute total earnings on all UI jobs for persons gaining employment in a quarter as a percentage of total UI earnings on all jobs for persons who were employed the previous quarter. The Earnings Accrual Rate shows aggregate earnings for persons moving from not employed the previous quarter to being employed in the current quarter as a percentage of total earnings for all workers in the previous quarter. The troughs in the first quarter are unmistakable along with a sharp recovery in the second quarter. This pattern reflects the relatively small accrual of new jobs after the fourth quarter followed by a sharp upturn in the spring.

Figure 6

In Figure 7, we plot the estimated wage growth rate, annualized, with both the nominal and deflated growth rate smoothed along with the deflated wage growth rate that has not been smoothed.

Figure 7

Again, the rather erratic, unsmoothed wage growth rate has a decided seasonal pattern, this time with troughs in the fourth quarter. The smoothed earnings accrual rate shows almost no variation except for a temporary increase as the economy was beginning to recover from the Great Recession.

The figures in this appendix show substantial seasonal variation in the UI earnings data across a variety of dimensions. It is this seasonal variation that dictates that when looking at labor market outcomes for our CCMEP Wage Pathways experimental and control cases (as well as if one were to look at the general population) one should look at outcomes for four consecutive quarters to avoid misleading results driven solely by seasonal variation. So, in our difference-in-difference design, the labor market metrics we use for both the pre- and post-program onset time periods will cover four consecutive quarters. In this way, we avoid the misleading results that could emerge if the reference period were one or another of the “seasons” in the UI Earnings data. Seasonality could affect control and experimental cases differentially if the employer mix in northeast Ohio differed from what is typical in the rest of the state.

After filtering the UI Earnings data with a four-quarter moving average, we obtain a time series measure of the condition of the Ohio labor market over time. Figure 8 shows Ohio’s constant dollar UI earnings, or real wage bill, at an annual rate from 2003 through mid-2018. The official cyclical peak for the business cycle as set by the National Bureau of Economic Research was in the 4th Quarter of 2007. As one can see, UI Earnings in Ohio peaked about two years before the business cycle peaked. Our smoothed UI Earnings data actually show stronger total earnings growth in our pre-onset period for WP (which we define as 2nd Quarter 2016 through 1st Quarter 2017) than the following four quarters. Our difference-in-difference design described in the main text will remove the effects of labor market conditions that have roughly the same impact on eligibles and ineligibles.

Figure 8

Constant Dollar Wages & Salaries in Ohio, Smoothed and Annualized

2003 – 2017, in $1000s

References

Lou, Tian; Zagorsky, Jay L.; Munn, Sunny L. and Hawley, Josh; “How is Ohio’s Comprehensive Case Management and Employment Program (CCMEP) Being Implemented? A View From Around the State,”December, 2017.

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1. Corresponding author. [Olsen.6@osu.edu](mailto:Olsen.6@osu.edu) . "Report on the Evaluation of Ohio’s Wage Pathways Program" by Randall J. Olsen et al is licensed under CC BY 4.0. This report was funded with Federal funds under a grant awarded by the U.S. Department of Labor’s Employment and Training Administration. The content of this publications does not necessarily reflect the views or the policies of the U.S. Department of Labor, nor does mention of trade names, commercial products, or organizations imply any endorsement of same by the U.S. Government. [↑](#footnote-ref-1)
2. Ohio Administrative Code 5101:14-1-02. The statue specified 14 services CCMEP should deliver. Wage Pathways is a 15th, experimental, service not covered by statute. [↑](#footnote-ref-2)
3. The Department of Agriculture funds SNAP. SNAP is not one of the statutory benefits under CCMEP. However, case workers attempt to enroll clients in whatever program will enhance client success. So, while a separate program, from the client’s perspective, SNAP is one of the benefits the CCMEP case manager offers. [↑](#footnote-ref-3)
4. This larger team includes staff at the Center for Human Resource Research (CHRR), the OERC and the John Glenn College of Public Affairs. While nominally housed in different parts of the university, these staff members work closely with one another and jointly manage and maintain the Ohio Longitudinal Data Archive, which houses the administrative data resources that both the WP and CCMEP evaluation efforts use extensively. [↑](#footnote-ref-4)
5. The implementation of the CCMEP program and how counties viewed it differed across Ohio. A report by Lou et al. “How is Ohio’s Comprehensive Case Management and Employment Program (CCMEP) Being Implemented? A View from Around the State”, December, 2017, describes that process and those differences. [↑](#footnote-ref-5)
6. Implementing CCMEP involved systems work, some of which was particular to CCMEP. WP had additional delays because the State of Ohio and Cuyahoga and Summit Counties had to negotiate contracts and the scope of work changed from what the counties originally envisioned. [↑](#footnote-ref-6)
7. Assistance programs often phase out benefits with rising income and often that means that these clients face high implicit tax rates in the vicinity of incomes that require the phasing out of benefits. [↑](#footnote-ref-7)
8. Neyman, J.; Pearson, E. S. (1933-02-16). "IX. On the problem of the most efficient tests of statistical hypotheses". Phil. Trans. R. Soc. Lond. A. **231** (694–706): 289–337. [↑](#footnote-ref-8)
9. National Research Council. 2013. *Nonresponse in Social Science Surveys: A Research Agenda*. Washington, DC: The National Academies Press. [↑](#footnote-ref-9)
10. This data source contains wage payments, not wage rates. [↑](#footnote-ref-10)
11. Restricting earnings detail to only five employers captures the vast majority of covered employment. Because we also include total quarterly earnings as a variable, we track all earnings even if we only identify the five employers that provided the worker the most earnings. Readers can examine the metadata for the UI Earnings file at https://www.chrr.ohio-state.edu/investigator/pages/search.jsp . The study is Ohio Longitudinal Data Archive – Metadata, and the substudy is ODJFS – UI Wages All Quarters Metadata. [↑](#footnote-ref-11)
12. Hotz, V. J., & Scholz, J. K. (2002). Measuring employment and income for low-income populations with administrative and survey data. *Studies of welfare populations: Data collection and research issues*, 275-315. [↑](#footnote-ref-12)
13. Some CCMEP enrollees left Ohio subsequent to their CCMEP enrollment. In the follow-on surveys, we asked the respondents for their address, primarily to send them an incentive for completing the survey. If anyone left Ohio as of the first follow-on survey, we did not request completion of the second follow-on survey. Based on reported addresses at the first follow-on survey, a little more than 1% of CCMEP enrollees left Ohio after their enrollment. [↑](#footnote-ref-13)
14. These tables show the codebook pages in the OLDA for these variables. [↑](#footnote-ref-14)
15. Blanks or absence of a TANF/SNAP record need to result in a value of 0 for this and the following variable. This infilling can only take place after the various data sets are combined with the CCMEP enrollment data or by an action when merging. This duration can include time in a TANF assistance group when youth was a minor. [↑](#footnote-ref-15)
16. OLDA suppresses day of birth to protect confidentiality. [↑](#footnote-ref-16)
17. See Figure 2 for a county map of Ohio. [↑](#footnote-ref-17)
18. While this clustering creates analytical problems, the WP program stresses close coordination between case managers and employers so as to improve job retention, skill advancement and ultimate self-sufficiency. Having WP counties clustered in northeast Ohio made it easier for participating counties collaborate in maintaining a connection with employers who hired WP participants. [↑](#footnote-ref-18)
19. In addition, the youth must be TANF or WIOA-eligible – preconditions of the CCMEP program. TANF or WIOA eligibility is not unique to Wage Pathways eligibles. [↑](#footnote-ref-19)
20. A person born in 1994 would turn 23 sometime in 2017 and hence could have been “treated” in the second half of 2017 and part of 2018. A person born in 1999 would have turned 18 sometime in 2017 and could have been treated in the second half of 2017 through the projected end of the program September 30, 2019. [↑](#footnote-ref-20)
21. It uses as an input the North American Industrial Classification System or NAICS code. [↑](#footnote-ref-21)
22. If the match score for an occupation was relatively poor, we did not present it. [↑](#footnote-ref-22)
23. We suppress counts for cells with from one to nine observations in this and the next table. [↑](#footnote-ref-23)
24. The Amazon gift card was actually a certificate ID we sent to the respondent’s mobile phone. They could use this code towards the purchase of something from Amazon. Some of the respondents did not have a regular address we could mail to, so for those respondents an Amazon card was the only alternative of the three methods for delivering incentives when mailing the incentive was not possible. Of the 2250 respondents in Wave 1, 1093 requested Amazon certificates, 923 Walmart cards and 234 McDonald’s cards. Some respondents requested Walmart or McDonald’s cards, but their address was bad so we needed to replace those cards by texting an Amazon certificate. [↑](#footnote-ref-24)
25. Whereas many states have agencies controlled by their directors with county offices clearly subordinate to state leadership, in Ohio counties have significant autonomy over how they locally administer state programs. For the WP experiment, the state could encourage counties to offer the program but could not direct counties to participate. A pure random assignment approach to eligible versus ineligible clients needed county-level approval. Concern over the optics of otherwise identical clients being offered very different services in the local offices made random assignment unacceptable. The evaluation team focused on creating an evaluation strategy that was as good as possible given these constraints. [↑](#footnote-ref-25)
26. The PRC program provides for non-recurring, short-term, crisis-oriented benefits and services to divert families from cash assistance with short-term help in overcoming acute, as opposed to chronic, factors that threaten to overwhelm the family. Counties can use such services or assistance to help a family member retain their employment. Contingency services aim to meet an emergent need that threatens the safety, health or well-being of one or more family members. [↑](#footnote-ref-26)
27. Many workers hold multiple jobs. Overall, for all Ohio workers, for every 100 persons holding at least one job during a quarter, they collectively hold about 114 jobs. Among those in CCMEP, the latter number is about 110. [↑](#footnote-ref-27)
28. Offering incentive payments to encourage people to do what is in their own self-interest is not a new idea. New York City launched a Conditional Cash Transfer (CCT) program in 2007. With World Bank support, Bangladesh instituted a CCT aimed at girls in grades 6 to 10 who remained in school, got passing grades and remained unmarried. The payments combined a stipend deposited in a bank in the girl’s name, payments to defray the girl’s school expenses, and tuition and other support to the school. [↑](#footnote-ref-28)
29. While we have access to matched post-secondary education and training data provided in state-supported institutions, legal constraints on the state holding Social Security numbers make it impossible to match in K-12 educational data. Very few CCMEP enroll in state-supported post-secondary education and training, so restricting analysis to those with post-secondary education and training would severely limit sample size as well restrict us to an unusual set of CCMEP participants. [↑](#footnote-ref-29)
30. This is not exactly the Mincerian return as we cannot measure education for our merged UI Earnings and BMV data. Moreover, we omit the square of experience as these workers are far from the overtaking age. [↑](#footnote-ref-30)
31. Our estimated return to experience based on quarter-to-quarter earnings changes for the same employee-employer dyad is based on over 83,000 quarterly changes. [↑](#footnote-ref-31)
32. We made this exclusion as we did not want our labor market metrics entangled with any effects of CCMEP or WP. [↑](#footnote-ref-32)
33. Some non-profit and educational organizations can obtain a certificate allowing them to pay 85% of the minimum wage. [↑](#footnote-ref-33)
34. The age distribution of youths within the various labor markets is very similar. [↑](#footnote-ref-34)
35. As mentioned above, in this evaluation, we contrast those CCMEP clients eligible for WP with those who were ineligible, as case workers may have selected eligible participants based on their likelihood of success. [↑](#footnote-ref-35)
36. For this evaluation, our inability to randomly assign the treatment means we are comparing WP experimentals (eligible) to controls (ineligibles), not WP participants to non-participants. [↑](#footnote-ref-36)
37. The identification problem goes back to Frisch and Haavelmo roughly 90 years ago. [↑](#footnote-ref-37)
38. Some employees do not have earnings reported to the Ohio UI system. Federal and military employees, and some small family businesses, non-profits and religious organizations do not report earnings. [↑](#footnote-ref-38)
39. We only estimate the log earnings equation for those with non-zero earnings in 2018. [↑](#footnote-ref-39)
40. Zeroes included. [↑](#footnote-ref-40)
41. Zeroes included. [↑](#footnote-ref-41)
42. This figure uses one in six people in the UI Earning file. This is about 900,000 people for every quarter. [↑](#footnote-ref-42)
43. The CES has doubtful provenance for other reasons. It is a BLS survey of employers, but as small businesses go out of business or start-up, the sampling frame BLS uses cannot be refreshed to reflect these high frequency moves. In addition, the CES does not identify workers who hold more than one job, as the sampled employers cannot provide this information. [↑](#footnote-ref-43)