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Predictive Analytics Supporting Labor Market Success: A Career Explorer for Job Seekers and Workforce Professionals in Michigan

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ABSTRACT

Career Explorer provides customized career exploration tools for workforce development staff and job seekers in Michigan. There are separate Career Explorer modules for mediated staff services and self-service by job seekers. The system was developed by the Michigan Center for Data and Analytics in collaboration with the W.E. Upjohn Institute for Employment Research and Michigan Works! Southwest. It was funded by the U.S. Department of Labor’s Office of Workforce Investment and the Schmidt Futures foundation’s Data for the American Dream (D4AD) project. In this paper, we describe specifications of the models behind the frontline-staff-mediated version of Career Explorer, which are based on program administrative data, applying data-science methods for predictive analytics. We also describe the self-service Career Explorer, which provides customized labor market information based on published Bureau of Labor Statistics data. Career Explorer became an active feature of Michigan’s online reemployment-services system in June 2021.

JEL Classification Codes: J65, J68, H76

Key Words: dislocated workers, disadvantaged adults, Workforce Innovation and Opportunity Act (WIOA), labor market information, career exploration, reemployment services, occupational choice, occupational mix of employment, industrial mix of employment, workforce areas

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INTRODUCTION

Job seekers often want to know what kinds of employment opportunities they can expect if they remain in their previous field, pursue a different line of work, or undertake training. Likewise, workforce professionals would benefit from being able to share these types of information with job seekers. Yet the sheer variety of options makes it difficult to navigate such information. Moreover, the employment effects of pursuing a particular occupation or training opportunity are likely to vary by factors such as an individual's work history, barriers to work, and geographic location. With so much complexity to manage, it appears that job seekers could benefit from tools that generate predictions tailored to their specific circumstances. This is precisely the purpose of Career Explorer.

Career Explorer is a set of online tools that provides personalized career information for job seekers in Michigan and for the workforce professionals who advise them. Launched in 2021, it applies machine-learning techniques to data from multiple administrative sources to predict employment, income, and training outcomes for individual customers of Workforce Innovation and Opportunity Act (WIOA) programs. While there have been pilot studies applying similar principles, to our knowledge, Career Explorer is the first set of workforce tools to offer individually customized labor market information (LMI) at such a fine-grained level of detail in regular program operations.¹

There are two operational versions of Career Explorer. The first is designed for Michigan workforce professionals to use as they work with job seekers, especially those who may be

¹ Eberts and O'Leary (2002) developed and pilot-tested a frontline-decision support system in Georgia workforce centers, and Behncke, Frölich, and Lechner (2009) conducted randomized controlled trials of individualized service referrals in Swiss public employment centers, but neither of these efforts resulted in operational programs. See also Frölich, Lechner, and Steiger (2003).

eligible for assistance with training programs through the Workforce Innovation and Opportunity Act (WIOA). Accessible directly through the main computing platform used by frontline staff in Michigan Works! local offices, the staff-mediated version of Career Explorer provides estimates of likely outcomes on five measures of labor market success. These predictions are based on administrative data representing the experiences of recent prior program participants who have interacted with the Michigan career centers. The goal is to offer job seekers tailored information to help them make decisions about which occupations to pursue and whether to seek training.

A second, simplified version of Career Explorer is available to clients for self-service use through Pure Michigan Talent Connect (PMTTC), an online virtual job market. PMTC users are given direct access to customized local labor market information (LMI) and career exploration–related views of LMI relevant to their own recent work experience and skills. This information is based on labor market information from the Bureau of Labor Statistics. While this LMI is not as personalized as the information available in the staff-mediated version of Career Explorer, the self-service tools are freely available to anyone who signs up for a PMTC account. In this paper, for the sake of clarity, we refer to the staff-mediated version as “Career Explorer” and to the self-service version as “Career Explorer Companion.”

The Michigan Career Explorer system was developed with funding from the U.S. Department of Labor and Schmidt Futures program Data for the American Dream (D4AD).² Our paper explains our data-science methods for system development, provides summary statistics on system usage, and reports subjective evaluations of the system from workforce professionals and job seekers. Career Explorer is a package of services that all states can implement in their online

² The D4AD grant to Michigan was administered by the National Center for Higher Education Management Systems, <https://nchems.org/>.

workforce development systems to be used in every local one-stop center, by all workforce development professionals, and by every job seeker.

DATA USED TO BUILD CAREER EXPLORER

Career Explorer was built on administrative data from several workforce programs, including unemployment insurance (UI), Workforce Innovation and Opportunities Act (WIOA) training programs, Wagner-Peyser (WP) employment services, and labor market information (LMI) data from the Michigan LMI Bureau and the U.S. Bureau of Labor Statistics (BLS). These worker data include individual histories of quarterly earnings, occupation and industry of prior jobs, records of employment services delivered, job training received, demographic characteristics, geographic location of Michigan residence, and household structure.

We extracted the data used to estimate models for Career Explorer from two main sources: 1) Michigan's One-Stop Management Information System (OSMIS) database for workforce programs and 2) the unemployment insurance (UI) wage record system. The OSMIS database contains data on all Michigan residents who apply for and receive any employment assistance from the state workforce system, which operates through a network of Michigan Works! employment centers—known as American Job Centers (AJCs) in states around the country. The programs administered through OSMIS include the following:

- Workforce Innovation and Opportunity Act (WIOA) programs for disadvantaged adults and dislocated workers
- Wagner-Peyser Act–funded employment service (ES)
- Employment and training for Temporary Assistance for Needy Families (TANF) cash public-assistance recipients, a program that in Michigan is called Partnership Accountability Training and Hope (PATH)

- Employment and training for the Supplementary Nutrition Assistance Program (SNAP), formerly known as food stamps, which is called SNAP-E&T (for SNAP Employment and Training)
- Trade Adjustment Assistance (TAA)

Applications to all these different employment programs provide data on demographic characteristics. These data are either entered directly to OSMIS by the customer, or by a caseworker during an interview with the customer.

The UI wage-record database is populated by quarterly reports from Michigan employers on wages paid to all their employees. These reports are the basis for employer UI tax computations and for monetary eligibility assessments by UI applicants if they become unemployed. These wage-record data also include the Federal Employer Identification Number (FEIN) and the employer's industry code (North American Industry Classification System, or NAICS). Data on county unemployment rates by month come from the U.S. Bureau of Labor Statistics (BLS) and its Local Area Unemployment Statistics (LAUS) program.

These data sources have several limitations that affect the availability and quality of variables for analysis, and those limitations may ultimately affect the performance of the decision-support algorithms used in this project. To begin with, several of the variables in the OSMIS database are self-reported and not mandatory, and therefore have high proportions of missing values. Additionally, other variables are inconsistently recorded by customers and staff in local Michigan Works! offices across the state. This may result from the fact that Michigan Works! offices have some local discretion in how they collect and enter data to OSMIS.

The UI wage records data suffer from some inconsistencies because employers have discretion in self-selecting the industry for their business activities and in assigning occupation codes to workers they employ. Furthermore, the UI wage record provides only data for individuals employed in Michigan. Thus, when a job seeker from Michigan finds a job in another

state, or a job seeker from another state enters Michigan's system, that job seeker's reemployment is not directly measurable using only Michigan wage records.

Because of these limitations, it was not possible to account for many theoretically interesting concepts (e.g., some service activities) that likely influence job market outcomes. Nonetheless, this study was able to use several dozen variables constructed from program administrative and wage record data. These data are discussed in more detail below, where we list the dependent and independent variables used to build models for the mediated Career Explorer. We list all means and variances for variables used to estimate the WIOA adult and dislocated worker tools in Appendix A.

The unit of analysis for the model-development sample is registration for services with WIOA by an individual with an employment program. That is, when an individual seeks reemployment assistance from the State of Michigan, that individual receives a registration identification number (ID number) for each program into which he or she is enrolled (e.g., WIOA Adult, WIOA Dislocated Worker, or PATH). Thus, a single person can appear multiple times in the data if he or she was registered in more than one program during a contact with employment services or he or she entered services multiple times during the period studied. We estimated the models below based on observations from one program at a time (e.g., WIOA Adult or WIOA Dislocated Worker), and thus, ultimately, there were very few cases in which a single person appeared more than once in the data for model estimation.

The administrative data used for this study included both a registration-for-services date and a program-exit date. We used these dates as indicators of when an individual took part in the workforce program. We discarded observations with entry dates before the 2017 program year. To avoid working with data collected during the pandemic, we also removed those with exit

dates after June 30, 2019. Estimation samples for models underlying tools in the mediated Career Explorer are based on customers who registered for WIOA services after July 1, 2016, and exited the program by June 30, 2019—that is, Program Years (PY) 2017 and 2018. This yielded 11,852 observations for estimation of the WIOA Adult models and 2,509 for estimating the WIOA Dislocated Worker models.³

We list means based on data in the two estimation samples on selected variables in Table 1.⁴ Tests for differences in means suggest the two samples are significantly different in many ways. Dislocated workers had a much longer lag between registration with the Wagner-Peyser employment service and registration with the WIOA program. They were also twice as likely to be military veterans compared to disadvantaged adults. Dislocated workers also had steadier prior work histories and average quarterly-earnings histories that were double the average level for disadvantaged adults. Dislocated workers were also more likely to have worked in production occupations and less likely to have worked in health care or food service occupations compared to disadvantaged adults. Finally, dislocated workers were more likely to have worked in manufacturing and to have been involved with the UI program, and less likely to have worked in hospitality, than disadvantaged adults.

³ While the estimation samples are limited by the availability of covariates, very few observations were lost by this restriction. In Program Year 2019 (July 2018–June 2019), a total of 12,140 disadvantaged adults and 2,955 dislocated workers were enrolled in Michigan WIOA programs. Nationwide, the WIOA program garners a significant share of federal funding for active labor programs, but annual participant totals nationwide are not big in absolute terms. Nationwide in Program Year 2019, WIOA enrolled 640,822 in the Adult program and 413,948 in the Dislocated Worker program. Average per-participant expenditures in Fiscal Year 2019 were \$1,319 and \$3,048 in the Adult and Dislocated Worker programs, respectively. Holzer (2023) says these funding levels are not sufficient to offer meaningful job training, and he quotes the Government Accountability Office as saying that total federal expenditure on job training is less than 0.1 percent of gross domestic product.

⁴ We give tests of means across all variables in both estimation samples in Appendix Table A.1.

Table 1 Descriptive Statistics on Predictor Variables in WIOA Adult and Dislocated Worker Samples

Variables	Adult N = 11,852		Dislocated Worker N = 2,509		WIOA Dislocated Worker minus WIOA Adult mean	
	Mean	Std dev	Mean	Std dev	Difference	t-stat
Prior employment and earnings						
Average quarterly earnings	4,166	4,987	8,726	7,129	4,560	30.50
Variance in quarterly earnings (\$000s)	7,698	298,827	25,917	330,710	18,220	2.55
Proportion of quarters employed ^a	0.502	0.351	0.652	0.300	0.150	22.00
Count of quarters unemployed ^b	1.923	3.180	0.669	2.039	-1.254	-25.03
Proportion qtrs w/ multiple employers	0.132	0.206	0.099	0.175	-0.033	-8.31
Consecutive quarters at same employer	2.782	2.404	4.018	2.289	1.236	24.35
Count of quarters employer changed	1.249	1.218	1.057	0.949	-0.192	-8.73
Educational attainment						
GED	0.117	0.321	0.083	0.276	-0.034	-5.44
Bachelor's degree	0.097	0.296	0.181	0.385	0.084	10.30
High school diploma	0.403	0.491	0.346	0.476	-0.057	-5.42
Occupation of prior employment						
Health-Care Support	0.135	0.341	0.044	0.205	-0.091	-17.66
Food Preparation and Serving Related	0.080	0.271	0.025	0.155	-0.055	-13.85
Production	0.162	0.368	0.189	0.392	0.027	3.17
Industry of prior employment						
Accommodation	0.112	0.315	0.043	0.203	-0.069	-13.86
Health Care	0.156	0.363	0.103	0.304	-0.053	-7.65
Manufacturing	0.099	0.299	0.193	0.395	0.094	11.26
Unemployment insurance (UI)						
Beneficiary referred by WPRS	0.006	0.077	0.043	0.202	0.037	9.04
UI exhaustee	0.014	0.117	0.093	0.290	0.079	13.42
Employed at registration	0.367	0.482	0.045	0.208	-0.322	-53.05
Michigan workforce area						
Detroit Employment Solutions	0.441	0.497	0.080	0.272	-0.361	-50.89
GST Michigan Works!	0.102	0.303	0.159	0.366	0.057	7.29
Southwest Michigan Works!	0.015	0.123	0.077	0.266	0.062	11.42
Other variables						
County unemployment rate	4.887	1.184	4.940	1.424	0.053	1.74
Number of employment barriers	1.463	1.025	1.279	0.979	-0.184	-8.48
Days between WP and WIOA registrations	11.941	35.471	34.362	48.534	22.421	21.93
Participated in multiple WIOA programs	0.024	0.153	0.069	0.253	0.045	8.58
Military veteran	0.031	0.173	0.069	0.253	0.038	7.18
Number of family members	2.133	1.497	2.042	1.363	-0.091	-2.98

NOTE: Based on quarterly earnings in the eight calendar quarters preceding application for services. ^aMost have eight quarters with earnings. Four quarters is the fewest. ^bThese are consecutive quarters. This table lists only subsets of variables in each category. The full list of predictor variables is given in Appendix Table A.1, along with means and *t*-tests for significant differences between WIOA adult and dislocated workers in the estimation samples.

SOURCE: Appendix Table A.1 (computations based on Michigan program administrative data).

METHODOLOGY FOR DEVELOPING CAREER EXPLORER

There are two very different versions of Career Explorer. The version available to workforce professionals—to help them counsel dislocated workers and disadvantaged adults about the most appropriate occupational training to build career pathways—contains tools based on statistical models. The other version is a collection of self-service features available to all job seekers in Pure Michigan Talent Connect (PMTTC), which provides customized views of labor market information (LMI) based on published summary statistics. Our discussion of methodology is focused on development of the statistical models behind the staff-mediated version of Career Explorer. We describe the self-service features after our explanation of the statistical models.

Models for Mediated Career Explorer Tools

The Career Explorer system used by professional workforce development staff provides customized information on five job market outcomes that can inform choices about career pathways.⁵ We selected the outcomes based on whether they could be predicted using the available administrative data and whether they best informed crucial career-planning decisions. The system produces estimates of outcomes for individual customers based on statistical models specified through data science methods.

We estimate the following five outcomes, based on the experiences of recent WIOA program participants with similar characteristics:

- Probability of reemployment within six months from program exit
- Time to reemployment from program exit
- Probability of employment after WIOA occupational skills training

⁵ Pure Michigan Talent Connect (2023) documents the system in a staff manual.

- Reemployment earnings after WIOA occupational skills training
- Probability of completing WIOA occupational skills training if started

Each of these outcomes was estimated using statistical prediction models. There are separate sets of models for WIOA dislocated workers and WIOA disadvantaged adults, meaning that 10 models, in total, underlie the system. We estimated two distinct types of models. The probability models all had the general form of Equation (1):

$$(1) \quad p_i = P(B|X), \quad i = 1, \dots, n,$$

where $p_i \in \{0,1\}$ is a binary outcome variable that has the value 1 for success, else 0. The predictor variables in the model are represented by a matrix, X , of data on predictors, and B is a conforming vector of model parameters on the predictors. The outcomes in the group of probability models are the probability of reemployment within two calendar quarters after program exit, the probability of employment after WIOA occupational skills training, and the probability of completing WIOA occupational skills training if started.

The models for continuous outcomes, y , have the general form of Equation (2):

$$(2) \quad y_i = Y(G|X), \quad i = 1, \dots, n,$$

where G is a vector of model parameters, and the set of predictors X is used to model the outcomes y . The continuous outcomes are time to employment and reemployment earnings. The same set of predictor variables, X , is available for both the probability and continuous outcome variables. We select the final X variables in each model to optimize prediction accuracy using data science methods explained below.

Outcome Variables

We measured four of the five outcomes using data from state-required quarterly employer reports on earnings paid to employees—also known as UI wage records. The outcomes based on

wage records include two binary variables (p) and two continuous variables (y). The binary outcomes are 1) reemployment within six months of program exit (or not), as evidenced by earnings in the quarterly wage records (or not), and 2) employment after participating in WIOA occupational skills training (or not), as evidenced by earnings in the quarterly wage records (or not). The continuous outcomes measured with wage records are months to reemployment (counting three months for every quarter with earnings), and the level of quarterly reemployment earnings, as recorded directly in the wage records.

The fifth outcome, completion of WIOA occupational skills training, is a binary variable drawn straight from WIOA administrative records in OSMIS. The binary variable (p) indicating training completion (or not) among those who start WIOA job skills training, is the dependent variable in the probability models for training completion. The training completion data are available in OSMIS, along with data on observable characteristics of training participants and type of training.

Predictor Variables

Like the outcome variables, the predictor variables are based on data drawn from OSMIS, UI wage records, and UI claims administrative files. Summary statistics on the available predictor variables, X , are given in Table 1, which groups variables into six categories.⁶ The categories of variables are 1) prior employment and earnings, 2) educational attainment, 3) prior occupation and industry of employment, 4) involvement with UI, 5) local Michigan workforce area, and 6) selected other variables. The last group includes rate of unemployment in county of residence, number of barriers to employment, time lag in days between registration for job search

⁶ Table 1 lists only a subset of available variables within some categories. The variables listed in Table 1 show mostly significant differences between the WIOA Adult and Dislocated Worker groups on observable characteristics.

and registration with WIOA, number of WIOA programs in which the client is registered, military veteran status, and number of family members. While Table 1 lists only a few variables for some categories (the full set is given in Appendix A), available predictor variables include a full set of 20 industry (North American Industry Classification System, or NAICS) dummy variables, 22 occupation (Standard Occupational Classification, or SOC) dummy variables, 7 educational attainment dummy variables, 16 dummy variables for Michigan workforce areas (the Detroit area was omitted from estimation), and 6 UI variables.

Predictor variables were defined for everyone in the database. The following predictor variables, X , were based on earnings in the eight calendar quarters before application for services:

- Average quarterly earnings across the eight quarters before application for services
- The variance in quarterly earnings across the eight quarters before application for services
- The proportion of quarters employed (where earnings are ≥ 0) among the eight quarters prior to registration for services
- The duration of unemployment (the number of quarters with earnings = 0) prior to registration for services
- The percentage of the eight quarters before services in which an individual held multiple jobs
- The length of job tenure (number of quarters out of the most recent eight before application for services) at the most recent employer
- The job turnover rate—i.e., the number of times the main employer in the quarter (the one paying the biggest share of quarterly earnings) changes between quarters in the eight quarters before services were received
- 20 industry categories (using the first two digits of the NAICS codes for employers)

The following predictor variables were defined from data in OSMIS:

- Educational attainment levels (e.g., high school diploma, associate degree, etc.)
- Number of barriers to employment a client faces (e.g., English language ability, status as a single parent, homelessness, status as an exoffender)

- The status of UI claims (e.g., whether an individual was a UI claimant (beneficiary), an exhauster, or a nonclaimant)
- The region of the state the client resides in (one of 16 Michigan Works! areas (MWAs) in the state)
- Whether a client was enrolled in multiple programs
- Status as a veteran
- The number of family members living with the client
- 22 occupational categories (using the first two digits of the ONET codes available for each client, from registration with Wagner-Peysers employment service)⁷

Statistical tests suggest significant differences in means on independent variables across estimation samples for WIOA adults and WIOA dislocated workers (Appendix Table A.1). That is, observable characteristics of participants in the two programs are quite different. Such differences are part of our rationale for developing separate sets of models for WIOA adults and dislocated workers. Among other things, WIOA dislocated workers are older, more educated, and had higher prior earnings than WIOA disadvantaged adults (Appendix Table A.1). Dislocated workers also were more likely to have worked in industries and occupations that paid higher wages and were more likely to claim UI benefits if laid off from work.⁸

⁷ Notes on correcting for missing data before estimation: For variables with multiple categories (e.g., education level), missing values were filled in with the modal category (the most frequently occurring category). For the samples from the Adult and Dislocated Worker programs, missing values were rare for these variables. For binary variables (such as the presence of a barrier), it was frequently the case that a value was only recorded when the variable was applicable to a client (i.e., the value equals 1). Thus, when the variable was not applicable, the client's value for this variable was missing. For the analysis, these missing values were converted to zeros (i.e., the variable was not present). For these variables, the number of missing values tended to be high. However, these missing values were also the easiest to impute. After discussions with subject-matter experts, it was determined that for the work-history variables it would be more accurate to recode missing values as zeros instead of imputing them as the mean or median. Missing values are likely to result from the lack of a work history or because the client worked in another state. Most clients with missing values reside within one of Michigan's counties and are therefore more likely to be missing data because they lack a work history in the eight quarters prior to registration.

⁸ Lachowska, Sorkin, and Woodbury (2022) find that workers who experience layoffs from firms paying higher-than-average wages are more likely to apply for UI benefits.

Estimating Model Parameters Using Data Science

The objective for parameter estimation in Career Explorer models is to best predict outcomes for new WIOA customers at the time of registration for services. Given that context, our prediction models do not account for the effects of reemployment services, because at the time of registration, most clients will not have previously received employment services. And there is a second significant ex ante concern in parameter estimation regarding omitted variable bias: certain demographic characteristics are prohibited from model specification by federal equity guidelines. Recommendations from Career Explorer must be blind about age, gender, race, and ethnicity. However, it is likely that variables included in the models (e.g., variables that measure things like a customer's work history, earnings history, level of educational attainment, or prior employment-program involvement) embody the effects of these omitted demographic variables. Since demographics are not explicitly controlled for, omitted variable bias could be present in the parameters of included variables and therefore model recommendations.⁹

We used data-science methods for improving predictions to determine the final set of variables included in each model.¹⁰ Specifically, a random forest analysis was used to identify which variables were most important in predicting outcomes (i.e., which variables are most predictive of the target variable).

A random forest analysis is based on averaging the results of multiple decision trees, each of which learns from a hierarchy of if/else questions, leading to a decision about a parameter of the model. For example, the decision-tree process in a random forest analysis is like the series of

⁹ Pope and Sydnor (2011) find that remaining parameters in profiling models pick up the effect of prohibited variables for age, race, gender, and ethnicity. That is, not including the variables affects parameter estimates on the remaining variables and therefore model recommendations. Pope and Sydnor's simulations, including prohibited variables and evaluating at means, do not change the ranking of scores but do change the magnitude of scores by an add factor.

¹⁰ Our model specification process followed principles explained by Castle, Qin, and Reed (2009) and overviewed in D4AD (2023).

questions an individual might ask in a game where the goal is to guess an unknown object: Is it an animal? Does it have fur? and so forth. In such a game, some questions will help more than others in arriving at a guess for the unknown object. Similarly, some variables in a model will go further than others in explaining the outcome variable. The importance of variables in this sense is determined by using one of several measures (e.g., information gain, gain ratio, or Gini index). Generally, the bigger the change in one of these measures, the more important the variable.

The primary goal of the modeling performed for the Career Explorer tools is prediction accuracy; of lesser importance is the statistical significance of individual predictor variables in a model. Thus, a machine-learning approach was pursued to generate predictions. Machine learning finds the most accurate models (in terms of accurately predicting outcomes) by dividing the data set into training and testing subsets. We fit the models on the training data set and evaluate the accuracy of their predictions using the testing data set.

For linear regressions, a key strategy affecting prediction accuracy is regularization, which involves reducing the size of the coefficients to reduce *overfitting* (which means a model fits the training data too well to effectively generalize to new data). The optimal amount of regularization is determined by using one or more measures of performance. For example, a receiver operating characteristic (ROC) curve is a graph showing the performance of a classification model at all classification thresholds where the true positive rate (TPR) is plotted vertically and the false positive rate (FPR) is plotted horizontally (Hajian-Tilakim 2013). While this data-science approach improves predictive accuracy, it does make it harder to interpret model parameters as marginal effects of independent variables.

This data-driven approach to quantitative career exploration tools provides an opportunity for annual updates to keep Career Explorer guidance timely and relevant. In principle, models

could be updated by automated systems to create a kind of artificial intelligence (AI) system. Indeed, we could do AI updates by batch processing quarterly, using a rolling set of calendar quarters that balance seasonal factors (Varian 2014). As a new quarter of data is available, it would replace the oldest quarter in the same calendar season.

CAREER EXPLORER TOOLS FOR WORKFORCE PROFESSIONALS

In this paper, we describe the development and uses of five queries that workforce staff could make using Career Explorer when counseling job seekers in career development decisions. The what-if query tools are provided in the User Profile tab of the OSMIS Career Explorer. The first two tools are outlooks related to employment and include the probability of employment within six months and the length of time to find employment without receiving services. The next three tools regard the “benefits of training” and relate to the effect of training on 1) employment, 2) earnings, and 3) the probability of completing training.

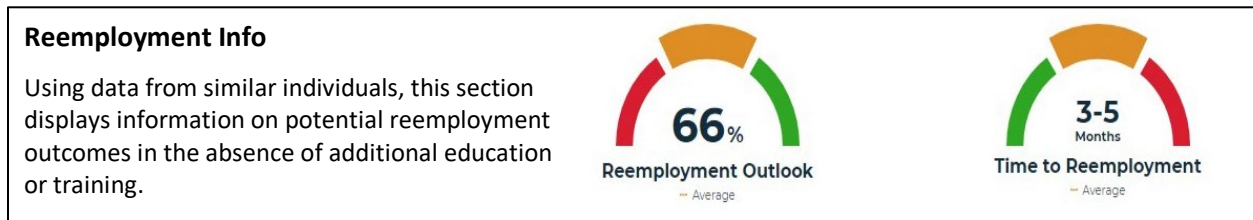
Separate models underlie tools for WIOA adults and WIOA dislocated workers who are considering job skill training.¹¹ Following good practices for systems development, we designed wireframes for the layout of the Career Explorer web pages with input from front-line staff and job seekers.¹² For each of the five tools described here, we list the query in the heading, show display format, and explain how underlying models were estimated. The first two query results from Career Explorer consider the reemployment prospects of an individual client.

¹¹ Michigan Works! staff also use the WIOA adult tools for cash assistance (TANF) applicants in the Michigan Partnership Accountability Training and Hope (PATH) program. The educational profile of the WIOA Adult sample in Appendix Table A.1 is similar in some categories to a recent sample of PATH customers studied by Pepin, O’Leary, and Oberlee (2021). The proportions with high school or GED and associate degree attainment are similar across the two samples.

¹² See Wulf (2012) for an explanation of why wireframes are a great way to start development projects in Internet-based information technology.

The first outcome (the left gauge in Image 1 from the Career Explorer website for staff) is the probability that the client will be employed before the end of the second quarter after registration for services—that is, within the next six months. The statistical model used to compute estimated probabilities for individual customers is a logistic regression estimated on

Image 1 Potential Reemployment Prospects and Time to Reemployment for Individuals without Additional Education or Training



NOTE: The Reemployment Information gauge on the left (“Reemployment Outlook”) gives the probability that the participant will be employed within the next six months in the absence of additional education or training. The Reemployment Information gauge on the right (“Time to Reemployment”) shows the average length of time it will take the participant to become reemployed without services.

SOURCE: PMTC (2023).

variables selected using machine learning techniques.¹³ Machine learning allows the data to select the best set of variables to explain the outcome of interest. We used random forest routines in Python to select the model variables. The estimated parameters of the model are then used to calculate the probability that a client will be employed by the second quarter after registration.¹⁴ This approach provides personalized estimates for each client by multiplying the client’s values

¹³ We estimated parameters of the model in Scikit-learn following the machine learning tradition in which the analytic sample is split into training and validation data sets, and the task is to use least squares principles to choose the “best” model for prediction. From available variables, the routine chooses the best set for predictive accuracy using least squares. After first estimates are produced with the training data, the validation data are used to find the best hyperparameters (most importantly, lambda, which affects how much coefficients are shrunk). Our pipeline found that a large lambda worked best, thereby shrinking coefficient estimates closer to zero. The output for logistic regressions is different from standard procedures because machine learning iterates on coefficients (regularization) to reduce “overfitting” and improve the predictive accuracy of models. Therefore, compared to common least squares logistic regression, the resulting coefficients can be much smaller.

¹⁴ Since we estimate the reemployment model by logistic regression, the probability of employment in the second quarter (Q2), given characteristics X, is: $E(\text{employed in Q2}|X) = \frac{\exp(\text{intercept} + BX)}{1 + \exp(\text{intercept} + BX)}$, where the intercept has the value 6.693. If not transformed, parameter estimates from this equation are marginal effects of the log odds ratio on the employment probability.

for several predictor variables (work history, job location, etc.) by the appropriate estimated coefficients in the model (see Appendix B for the full model).

We estimate the second outcome (the right gauge in Image 1) using an ordinary least squares (OLS) regression model of the number of months to employment on individual characteristics (work history, location, etc.).¹⁵ We included a dummy variable in the model for participation in job training (1) or not participating (0). We computed simulated results by taking the client's values on several variables (work history, location, etc.) and multiplying them by the appropriate coefficients in the model.¹⁶

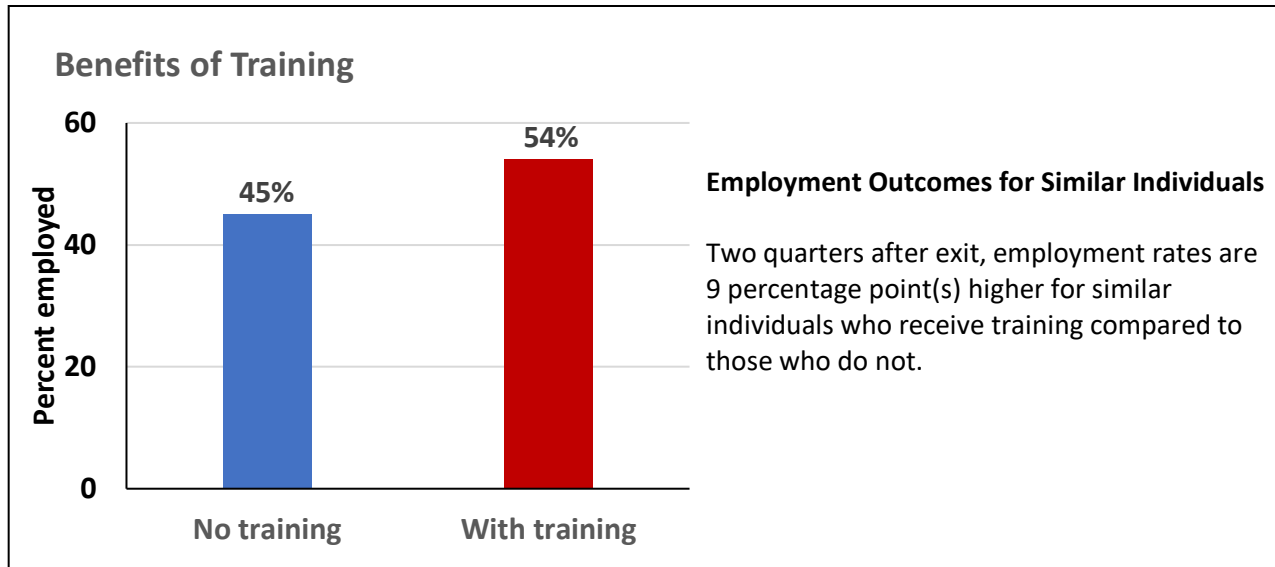
Effect of Training Participation on the Probability of Employment

The statistical model that generates probabilities of employment with and without training is the logistic regression described above, with the outcome of employment within two calendar quarters after program exit. Random forest machine-learning routines selected the best set of variables to explain reemployment. Based on the predicted probability of employment within two quarters after program exit, we group clients into quintiles. For each quintile, we computed the mean probability of employment for individuals who received training and those who did not. Those separate mean estimates are displayed in Career Explorer for a customer, depending on which quintile they fall into, given their predicted reemployment probability based on observable characteristics. An example of the Career Explorer display is given in Image 2.

¹⁵ The OLS models were estimated on normalized variables. That is, for each variable, we subtracted the mean and divided by the standard deviation.

¹⁶ That is, the expected number of months until employment, given characteristics $X = E(\text{months until employment}|X) = BX + 6.780$, where B is a vector of OLS parameter estimates for the model described in the text.

Image 2 Employment Outcomes for Similar Individuals without and with Training



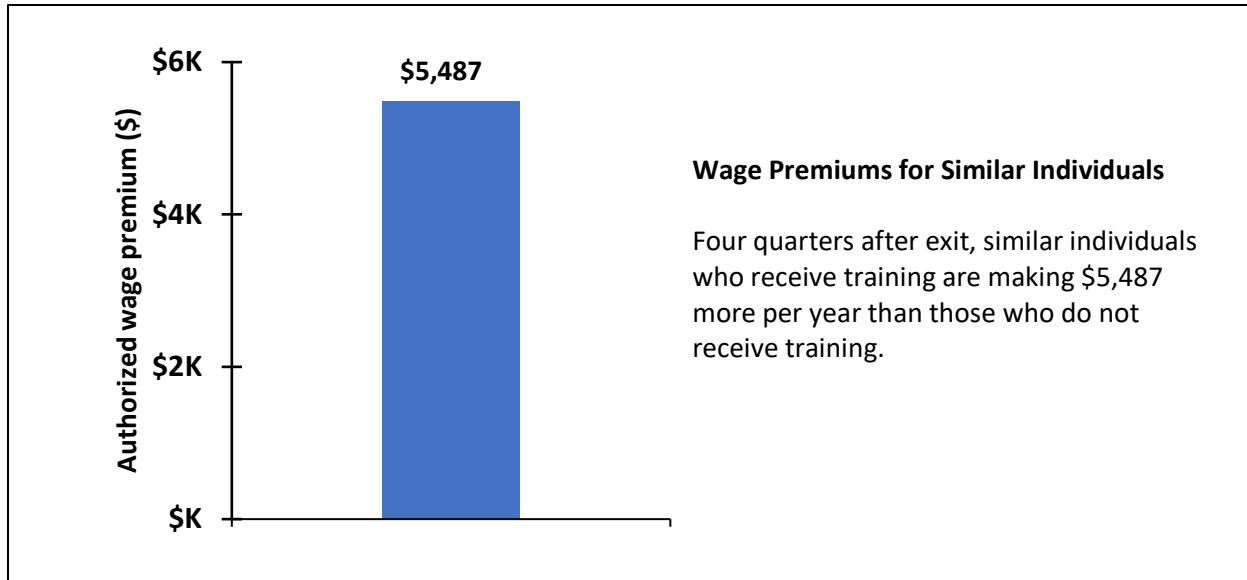
Source: PMTC (2023).

Effect of Training Participation on Annual Earnings

Using the model described above for employment within two quarters after program exit, we calculate the predicted probability of employment for everyone in the estimation sample. For everyone in this sample we also compute total earnings in the four quarters after program exit. Clients are then grouped into quintiles based on their employment probability scores. For each quintile, we computed the mean four-quarter earnings for individuals who received training and those who did not.

We calculated the average wage premium for training for each employment probability quintile by subtracting the mean wage of those in the quintile who received training from the mean wage of those in the quintile who did not get training. An example of the Career Explorer display is given in Image 3. The wage premium produced by Career Explorer is for the quintile corresponding to the client's predicted employment probability.

Image 3 Wage Premium for Training, Four Quarters after Exit

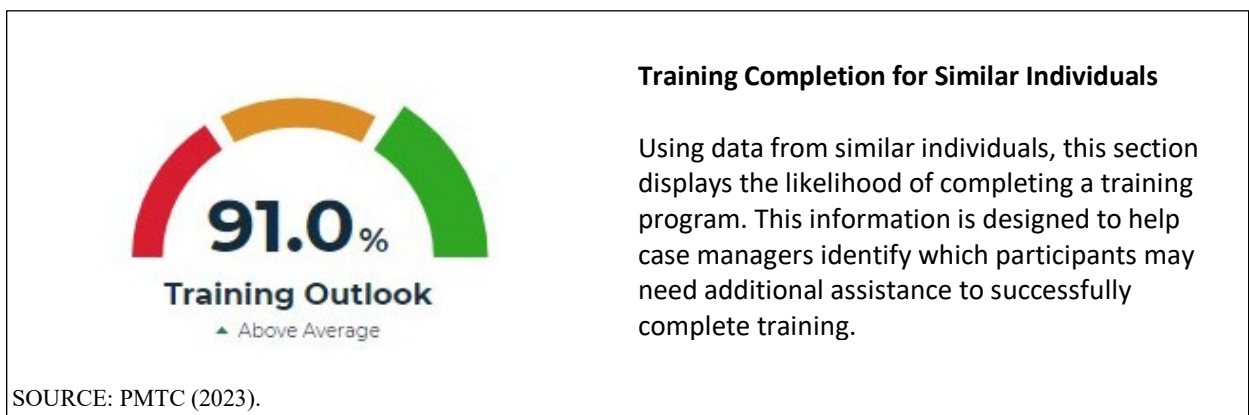


SOURCE: PMTC (2023).

The Probability of Completing Job Training among Those Who Start

As with the other queries, this third measure of the effect of training uses a logistic regression optimized using machine learning techniques, namely a random forest program in Python. The model can then be used to show the probability of completing training for those who have started training. The estimates for each client are personalized by taking the client's values on several variables and multiplying them by the appropriate coefficients. An example is given in Image 4.

Image 4 Training Completion for Similar Individuals



SOURCE: PMTC (2023).

Background Characteristics

For workforce professionals, the first screen in the new OSMIS Career Explorer provides a summary view of customer characteristics, including the following:

- Participant name
- Customer ID
- Date of birth
- Address
- Phone number
- Email
- Workforce region in Michigan (based on customer address)
- Expertise (populates only if participant has existing PMTC account)
- Highest educational attainment
- Veteran status
- Barriers such as disability, English as a second language, etc.

The screen showing all customer characteristics in one view is a handy reference for workforce professionals during the first and any follow-up meetings with the job seeker. This provides a starting point for a discussion about the individual career-development plan.

Staff-Assisted Career Explorer in Action

To understand how Michigan Works! staff decide when to use Career Explorer, we spoke with a career coach, who explained the process of customer selection and referral to the WIOA Adult program. The process begins with a weekly list of all new Michigan Works! customers who register for job search with the Employment Service (ES). When registering with ES, job seekers provide information on personal characteristics and workforce experience. Staff review the weekly intake list to assess who might be eligible for the WIOA Adult program. Since the Adult program is for disadvantaged workers, WIOA eligibility is often granted to those in households receiving SNAP or TANF benefits, or is granted if they have low household income

based on the WIOA income threshold. Notably, someone can be employed full-time and still qualify for the WIOA Adult program, depending on their household configuration. And indeed, 37 percent of the WIOA Adult recipients in the model data were employed at the time of registration. Appendix A provides summary statistics on characteristics of WIOA Adult–eligible applicants in our analysis sample.

After reviewing the weekly list of applicants, staff make telephone calls to potentially eligible individuals for a screening conversation. The career coach said, “It’s like a mini job interview. Just because someone is eligible [for WIOA Adult] doesn’t necessarily mean they are looking for work or training. Our goal is to make sure we help them get full-time, permanent work, whether that’s through an OJT [on-the-job] opportunity or reaching out to an employer or training. We have an up-front conversation about what they want to do.”

Third, after this screening conversation, if an individual wants to work with a career coach, the coach sends that person an email inviting him to a 90-minute in-person orientation session. The email briefly outlines the services available through WIOA: 1) career coaching and job-search assistance; 2) on-the-job training, in which WIOA pays the hiring company half of the individual’s wages for the first few weeks of full-time employment; or 3) classroom vocational training, in which a maximum of \$5,000 can be spent on short-term training through an eligible training provider in a field with high occupational demand.¹⁷

To the orientation, the WIOA Adult applicant must bring a Michigan driver’s license or state ID, her Social Security card, and (for WIOA dislocated workers) evidence that she is receiving or has exhausted Unemployment Insurance (UI). Individuals who qualify under the

¹⁷ The eligible training provider list is available at Michigan Training Connect (MiTC) on the Pure Michigan Talent Connect website (<https://www.mitalent.org/mitc>). Short courses and OJT are typically in the range of four to six weeks, and career coaches can only refer applicants to training and OJT when they have available funding.

WIOA Adult program may also be required to provide proof of income from all household members, and for those receiving SNAP or TANF, a notice of case action letter from DHHS.

This filtering process results in a relatively small number of WIOA enrollees. Of perhaps 300–400 individuals who register for job search with ES in a given Michigan Works! office in a given month, career coaches try to telephone perhaps 60–70 people who are potentially eligible for WIOA Adult or Dislocated Worker services, and maybe 10–15 eventually enter the program, the career coach said.¹⁸

After registration and orientation at a Michigan Works office, individuals are enrolled in WIOA and placed in a career coach’s caseload. At this point, Career Explorer comes into play. The career coach said she uses it with every WIOA adult or dislocated worker. She prefers that individuals come into the service center in person so she can view it together with customers on a big computer screen. In Career Explorer, she uses the user profile screen, which provides basic customer information, and the opportunities screen.

The opportunities screen displays graphs with predicted employment outcomes for similar individuals with or without training. These graphs are based on the occupation and geographic region in Michigan of the individual’s most recent work experience, as entered by the customer at the original ES intake. The coach said she uses the results to show customers where

¹⁸ The WIOA program is not very large. In Program Year 2019 (July 2018–June 2019), a total of 12,140 disadvantaged adults and 2,955 dislocated workers were enrolled in Michigan WIOA programs. Nationwide, the WIOA program garners a significant share of federal funding for active labor programs, but annual participant totals nationwide are not big in absolute terms, and funding is meager. Nationwide in Program Year 2019, WIOA enrolled 640,822 persons in the Adult program and 413,948 in the Dislocated Worker program. Average per-participant expenditures in Fiscal Year 2019 were \$1,319 and \$3,048 in the Adult and Dislocated Worker programs, respectively (USDOL 2020a,b). Holzer (2023) says these funding levels are not sufficient to get meaningful job training—which he pegs at a \$5,000 minimum per customer. He cites computations from the Government Accountability Office that put total federal expenditure on job training (across all programs, including WIOA and others) at less than 0.1 percent of GDP.

they stand at the moment, based on their previous employment, and what they can expect if they are interested in training to upskill and stay in the same industry.

Some customers have experience in many different types of jobs (see examples in Text Box 1, below). If they entered multiple areas of expertise in the original intake—office administration and child care, for example—Career Explorer can display results on separate graphs side by side, showing predictions for employment outcomes in each occupation.

Box 1 Examples of Results for WIOA Adult Disadvantaged Customers from the Staff-Assisted Michigan Career Explorer Tools
<p>Example 1: High probability (79 percent) of being employed within two calendar quarters</p> <p>This customer had a previous job as a computer scientist, worked in the finance industry, lived in Oakland County, was not referred by the UI program RESEA, had a bachelor's degree, had one employer in the eight quarters before registration, and has two family members. Career Explorer suggests a high probability (79 percent) of being employed within two calendar quarters after program exit.</p>
<p>Example 2: Lower probability (50 percent) of being employed within two calendar quarters.</p> <p>This customer had a previous job in transport or shipping, worked in the hospitality industry, lived in the UPWARD talent council area (the upper peninsula of Michigan), was not involved with the UI program, has earned some college credits, had four employers in the eight quarters before registration, and has two family members. Career Explorer suggests a lower probability (50 percent) of being employed within two calendar quarters after program exit.</p>
<p>Example 3: A short (5.03 months) time to reemployment after program registration.</p> <p>This customer had a previous job in office or administrative support, was in the public administration industry, lived in the Detroit area, was not involved with the UI program, has a bachelor's degree, had one employer in the eight quarters before registration, was unemployed in the seven months before registration, and has three family members.</p>
<p>Example 4: A longer (13.31 months) time to reemployment after program registration.</p> <p>This customer had a previous job in health-care support, was in the health-care industry, lived in the Macomb/St. Clair County area, was not involved with the UI program, has had some college and is currently enrolled in school, had two employers in the eight quarters before registration, was unemployed for one month before registration, and has four family members.</p>

NOTE: We show the computations for these examples in Appendix Table B.2.

SOURCE: Computations based on Michigan program administrative data. See computation details in Appendix C.

The career coach emphasized that the staff-mediated version of Career Explorer is valuable because it helps facilitate conversation and decision-making between the career coach and the individual job seeker. In addition to providing economic information, Career Explorer helps create the context for a relationship between the coach and the customer, and it helps the

coach motivate customers. For example, the graphs showing a predicted improvement in employment outcomes after training gets customers' attention "a majority of the time, and in the labor market climate right now, any increase helps out." As the coach said, "It helps me with persuading them about what they want to do...it's a conversation piece!" In other words, the value of a tool like Career Explorer is social and relational as well as informational.

It is important to note that Career Explorer is used in the context of a broader conversation that draws on coaches' knowledge and on other online tools. The career coach described how she discusses the practical aspects of various occupations with customers, especially if they want to change to a new employment sector. For example, if someone says he wants to get a commercial driver's license (CDL), she will talk with him about whether he is prepared for the reality of being away from family and sitting and driving a truck 10 hours a day. She often uses O*NET information available in OSMIS that describes what occupations are like and talks with training-program instructors to get background. She also requires customers to do research on potential courses before they can enroll. The employment predictions available in Career Explorer are just one facet of this conversation.

Finally, the career coach mentioned that some features of Career Explorer definitely need professional mediation. In particular, it can be distracting to have a third screen which shows potential career pathways based on different kinds of job training. For instance, if "certified nursing assistant" (CNA) is entered, the first few occupations are clearly relevant and related to nursing, but lower on the list are occupations that may have an overlap in skills but are not obviously related, such as fire inspectors and lifeguards. The coach said, "The last thing I want to do is add confusion. If I put something in here [specifying] 'CNA' and then these other things pop up, it's like, 'I just took you off focus.'"

SELF-SERVICE CAREER EXPLORER TOOLS ON PMTC

The portion of Career Explorer available for self-service use by the general public on Pure Michigan Talent Connect (PMTTC) does not contain the predictive models available to Michigan Works! staff. Instead, PMTC users are given direct access to customized local labor market information and career exploration–related views of LMI relevant to their own recent work experience and skills.

The self-service Career Explorer tools are based on publicly available Bureau of Labor Statistics (BLS) county-level data on occupational growth rates and wages. Career Explorer provides instant customized views of these LMI data, tailored to a job seeker’s past occupation and geographic location. The system supports simple “what if” queries that display past and future occupational data alongside statewide averages of informative variables such as average earnings. Queries include statements such as “What is the probability that I will lose my current job?” or “What earnings can I expect in Kalamazoo County if I enroll in workforce training?”

When users from the general public access Career Explorer through their PMTC account, they land on the Reemployment Info tab. They are not able to see the User Profile tab, where most of the predictive models are located, or the Reemployment Outlook gauge charts, which are available only to Michigan Works! staff who provide mediated career guidance.

On the Reemployment Info page, self-service users first see a chart of Occupational Wage and Employment Statistics (OEWS) wage data comparing average wages for their most recent occupation to the average of wages across all occupations for the geographic region where they live—as indicated by the home address in their PMTC profile. Users are also presented with long-term regional employment projection data so they can see how compensation in their occupation is expected to perform in coming years. Users can change the occupations and

regions compared in these charts so that they may assess wage outcomes if they were to change occupations or relocate within Michigan.

Elsewhere on the Reemployment Info page, users can view current job postings in their most recent occupation in their home region. Within a given session, users can produce “what if” scenarios for occupation or location changes. Customer changes in the occupation or location will generate new temporary results that are not saved by the system. The system displays three matching job openings, but customers may view more matching job postings through a link on the page.

PMTC users from the general public are also able to see a page of the Career Explorer tool entitled “Pathways.” This page allows users to search for new careers or educational opportunities that might be appealing. For example, if a user is interested in pursuing an apprenticeship to become a plumber, she may search for plumbers on this page and would arrive at a page that shows the same LMI as seen on the Reemployment Info page, along with education or job-training opportunities related to the occupation and current job postings for the occupation.

Through the Pathways page, users are also presented with preselected training opportunities at various levels of education, ranging from short-term training (0–3 months) to bachelor’s degree or higher (4+ years). Originating from Michigan’s Hot Jobs list, approximately five occupations are selected to appear under each level of education. Occupations related to the user’s most recent occupation are emphasized by a bolded font. When a user selects one of the available options, he is presented with the same type of customized LMI data, training/education opportunities, and employment opportunities as are available through the search function of the Pathways page.

EVIDENCE OF CAREER EXPLORER USE AND USEFULNESS

Evidence on the use of the Career Explorer is based on visits to the Google Analytics data-recording Web page and clicks by geographic location and type of access platform (computer, cell phone, or tablet). Subjective evidence on the value of Career Explorer is based on semistructured interviews with workforce professionals and a few customers.

Google Analytics Data on Career Explorer Use

We measure use of Career Explorer since the module became available beginning in July 2021 on both OSMIS and PMTC. At that time, we did not make any provision for evaluating the system, since we were focused only on providing a set of tools for workforce staff and job seekers. Since the system is Web-based, we used Google Analytics to track the number of visits to the various Web pages and features in Career Explorer.¹⁹

Since Career Explorer became fully active, there have been an average of about 515 daily page views. When the tool was first introduced, traffic quickly dropped from a 14-day moving average of about 730 views per day in July 2021 to about 200 daily page views in late October of 2021. The 14-day average of traffic later reached an all-time high of 765 page views in late January of 2022, before settling to an average of 525 views per day in 2022 (Figure 1). In 2023, views per day peaked at 750, again in late January, before trending downward through the present. The January peaks in Career Explorer page views could be paralleling the seasonal pattern of unemployment, which is influenced by seasonal changes in major holidays, weather, and school openings and closings (Tiller, Evans, and Monsell 2023). Average daily page views stand at about 650 views, year-to-date, in 2023. Both the first 60 days and the most recent 60

¹⁹ Data reported in these figures are based on active/engaged users. Google Analytics labels these as “Users” in its product, with additional text tool tips indicating they’re active users. Active users are the unique count of users with engaged sessions.

days show a slight downward trend but maintain similar volumes in daily views, approximately 600 per day (Figure 2).

The overall volume of Career Explorer users is composed mostly of job seekers rather than Michigan Works! case managers. There are an average of less than 10 unique users on any given day on the case manager portion of the application, but job-seeker visitors have averaged around 75 unique users per day over the life of the tool. The number peaked at just under 120 daily job-seeker users when the tool launched in July 2021. We reached this number again in January 2022, and then again in January 2023. User counts are currently trending back down toward the 2021 average of 77 daily job-seeker users (Figure 3).

Averaged by day of the week, users of Career Explorer follow a typical work-week pattern. Daily users peak in the Monday-to-Wednesday period, show declines on Thursday and Friday, and reach their weekly lows on Saturday and Sunday (Figure 4).

While it is not possible to locate exactly Career Explorer users geographically using Google Analytics data, locations can be approximated using IP address–based location estimates. Since the launch of Career Explorer, the largest plurality of daily users had Internet addresses in or near the city of Detroit. On an average day, there are about 9.0 users in the Detroit metro area. Another 3.7 average daily users have Michigan-based IP addresses which Google is not able to assign to a specific city. Chicago and New York are out-of-state cities in the top 15 geographic locations, suggesting Career Explorer is attracting visitors from outside Michigan (Figure 5).²⁰ Outside of Detroit and Grand Rapids, Figure 6 shows there are one or two daily users of Career Explorer in smaller Michigan cities.

²⁰ Ashburn, Virginia, is a data hub. Data on Web page visits were pulled using a Google Analytics product called GA4. The older product was called UA. Google Analytics GA4 fully excludes site visits from bots.

Just over half of all Web traffic since the launch of the Career Explorer tool has been from mobile device users, presenting both an opportunity and a call to improve the tool. Career Explorer has not yet been optimized for use on mobile devices. From July 2021 through April 2023, 50.4 percent of users visited the tool on mobile devices, 47.7 percent on desktop computers, and 1.9 percent on tablets. While desktop users constitute nearly half of all visitors to the site, they appear to be noticeably more engaged than mobile device users. At an average of 208 seconds per visit, engagement time is 1.4 times higher for desktop users than for mobile users. Desktop users also had more engaged sessions per user (1.24 engaged sessions²¹ per user on desktops vs 1.05 for mobile devices). These statistics may reflect the website's desktop-first design and suggest that improving ease-of-use for mobile device users could increase the overall level of engagement with Career Explorer.

Staff Opinions about Career Explorer Tools

The Michigan Center for Data and Analytics (MCDA) study team conducted structured interviews with three Michigan Works! staff based out of Michigan Works! Southwest. The purpose of these interviews was to learn more about their experiences using the Career Explorer tool. Assessments made by Michigan Works! staff inform the future direction of refinements in Career Explorer tools. By revising Career Explorer in staff-recommended ways, we might increase engagement with the tool and ultimately improve efficiency for local and state workforce staff.

All three staff members we interviewed had been involved in the design and testing process for the original Career Explorer tool, so their knowledge of the system might be higher

²¹ Measured as the number of sessions that lasted longer than 10 seconds, or had a conversion event, or had two or more screen or page views (Google.com 2023).

than the average Michigan Works! staff member. All three interviewees had different roles, which we found useful in identifying how different groups/roles use the tool differently. The discussions gathered information on three primary topics: 1) suitability for the needs of a diverse user population, 2) tool visibility, and 3) tool functionality for the various groups of staff and clients.

The primary takeaways from these conversations are the following:

- The user experience could be improved for phone users. Many clients do not have ready access to computers.
- Much of the language shown to clients may need to be simplified for some audiences. Clients with lower literacy levels may need special accommodation.
- The case manager version of Career Explorer is not located in a convenient place on the staff dashboard. Enlarging the link to a client’s Career Explorer profile or making the link more explicit would make the tool more easily accessible and available for Michigan Works! staff.
- The Michigan Works! team works with a diverse group of clients, who differ greatly in education and work experience across the different employment assistance programs. The different customer groups, therefore, have different job search needs. Accounting for the various programs would allow for a more personalized experience—e.g., if a person is enrolled in the PATH program, he may face many barriers to employment, and so showing that person options for careers with bachelor’s degree requirements may be overwhelming).

Customer Opinions about Self-Service Tools

We met with Michigan Works! staff and some of their customers who previously had used the self-service Career Explorer tools on PMTC or were shown the tools with some staff assistance. The following is a sampling of comments from a few customers.

Customer Comments on Self-Service Career Explorer Tools

Here is a general customer reaction to the self-service Career Explorer page on PMTC:

- “This tool was very helpful. It helped me realize I was making the right career choice.”

In reaction to the tools showing training opportunities, one customer said,

- “After I received my truck driver training, was a little discouraged and went back to work in my previous industry. However, after looking at the information provided by Career Explorer, it made me want to give truck driving another try.”

From a case manager who showed four customers how to use Career Explorer on PMTC:

- One customer was looking for work in IT, another was looking for medical transcription work, and two were planning on entering truck driver training.
 - “All four of these folks found it helpful in giving them an overview of what to expect from the field they’re entering.”

From another case manager who walked through the system with a jobseeker:

- “We went through the PMTC Career Explorer together and she felt it was helpful in making a career decision. Her past has been mostly in production, and we went through other occupations she was interested in and found that the medical field had a much brighter outlook. She decided that she was interested in Phlebotomy (which only requires a certificate to start work) and that she might pursue something additional in the medical field down the road.”

SUMMARY AND NEXT STEPS

In the normal course of delivering services to job seekers and employers, workforce agencies in all states accumulate a wealth of information on variables that relate service inputs to labor market outcomes. Career Explorer in the Michigan One-Stop Management Information System uses anonymous program administrative data on recent customers to help workforce professionals inform career choices of new customers. A self-service version of Career Explorer provides customized labor market information directly to job seekers through Pure Michigan Talent Connect.

The Michigan Career Explorer was developed as a demonstration with funding from the U.S. Department of Labor’s Office of Workforce Investment, and the Schmidt Futures program Data for the American Dream. Career Explorer is a model system that all states could implement in their online workforce development administrative systems to be used in every local one-stop center, by all workforce development professionals, and every jobseeker. Our paper provides an

example for state and federal employment policymakers about how to create such a system based on program administrative data, and why it is useful.

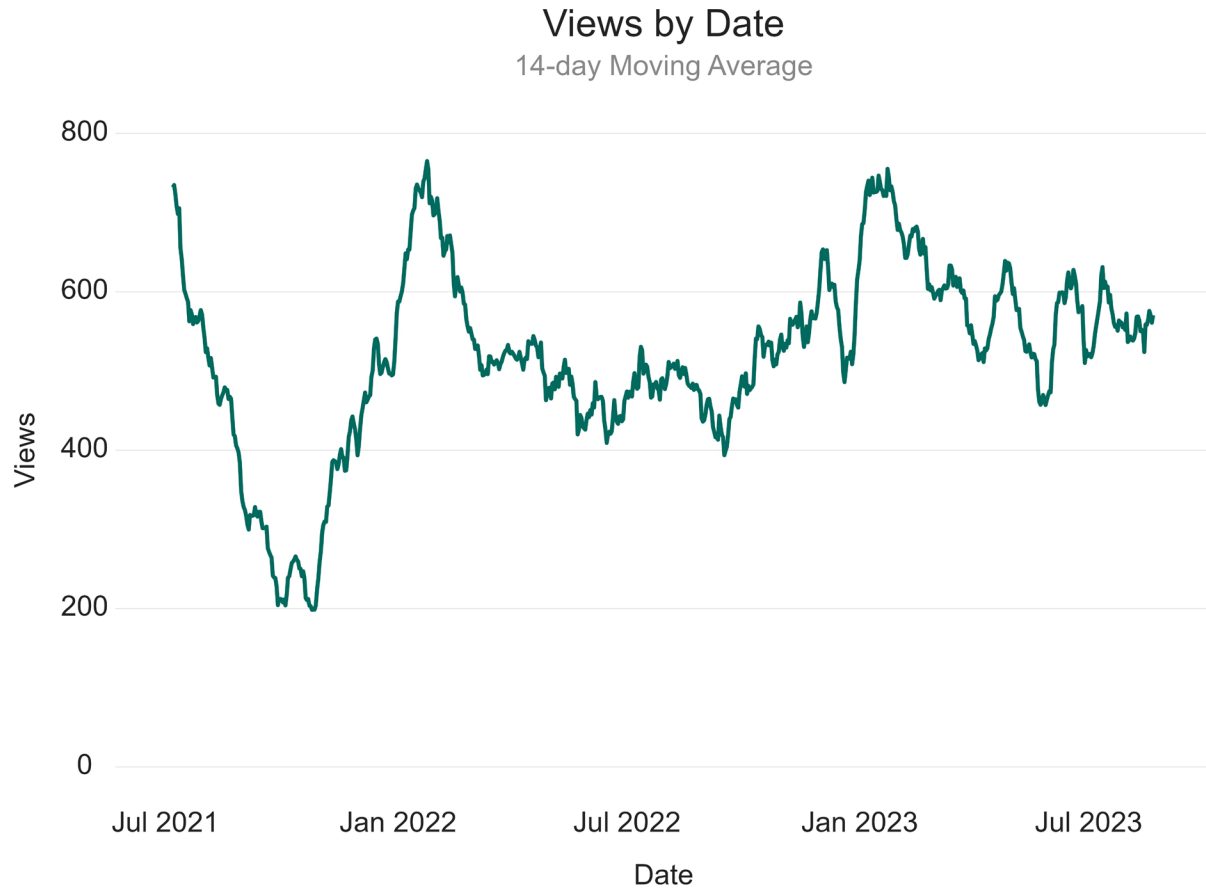
Next steps for the Michigan Career Explorer include refinements of the models for generating guidance and updates of estimation data to keep results timely. The shelf life of Career Explorer algorithms is limited. We are working toward a semiautomated system for predictive analytics. This would involve periodic batching of participant data to keep guidance up to date. Additionally, Career Explorer could lend customized LMI tools to other programs where they are needed. For example, the unemployment insurance (UI) program for Reemployment Services and Eligibility Assessment (RESEA) requires that customized LMI be provided to referrals. Customized views of LMI can be generated in the Pure Michigan Talent Connect self-service version of Career Explorer. Finally, separate Career Explorer-type tools are being planned for other employment programs and customer groups.

REFERENCES

- Behncke, Stefanie, Markus Frölich, and Michael Lechner. 2009. "Targeting Labour Market Programmes—Results from a Randomized Experiment." *Swiss Journal of Economics and Statistics* 145(3): 221–268. <https://doi.org/10.1007/BF03399281>
- Castle, Jennifer L., Xiaochuan Qin, and W. Robert Reed. 2009. "How to Pick the Best Regression Equation: A Review and Comparison of Model Selection Algorithms." Working Paper No. 13/2009. Christchurch, New Zealand: Department of Economics, University of Canterbury. <https://www.researchgate.net/publication/46464688> [How To Pick The Best Regression Equation A Review And Comparison Of Model Selection Algorithms](https://www.researchgate.net/publication/46464688) (accessed October 25, 2023).
- Data for the American Dream (D4AD). 2023. *Strategic Planning Resources: Strategies for Successfully Implementing Jobseeker Tools*. Boulder, CO: Data for the American Dream (D4AD)/NCHEMS. <https://www.d4ad.org/strategic-planning-resources> (accessed October 25, 2023).
- Eberts, Randall W., and Christopher J. O’Leary. 2002. "A Frontline Decision Support System for Georgia Career Centers." Upjohn Institute Working Paper No. 02-84. Kalamazoo, MI: W.E. Upjohn Institute for Employment Research. <https://doi.org/10.17848/wp02-84>
- Frölich, Markus, Michael Lechner, and Heidi Steiger. 2003. "Statistically Assisted Programme Selection—International Experiences and Potential Benefits for Switzerland." *Swiss Journal of Economics and Statistics* 139(3): 311–331. <http://www.sjes.ch/papers/2003-III-4.pdf> (accessed October 25, 2023).
- Google.com. 2023. *[GA4] Analytics Dimensions and Metrics*. Mountain View, CA: Google.com. <https://support.google.com/analytics/answer/9143382?hl=en> (accessed November 10, 2023).
- Hajian-Tilaki, Karimollah. 2013. "Receiver Operating Characteristic (ROC) Curve Analysis for Medical Diagnostic Test Evaluation." *Caspian Journal of Internal Medicine* 4(2): 627–635.
- Holzer, Harry J. 2023. "Should the Federal Government Spend More on Workforce Development?" Commentary. Washington, DC: Brookings Institution. <https://www.brookings.edu/articles/should-the-federal-government-spend-more-on-workforce-development/> (accessed October 25, 2023).
- Lachowska, Marta, Isaac Sorkin, and Stephen A. Woodbury. 2022. "Firms and Unemployment Insurance Take-Up." Upjohn Institute Working Paper 22-369. Kalamazoo, MI: W.E. Upjohn Institute for Employment Research. <https://doi.org/10.17848/wp22-369>

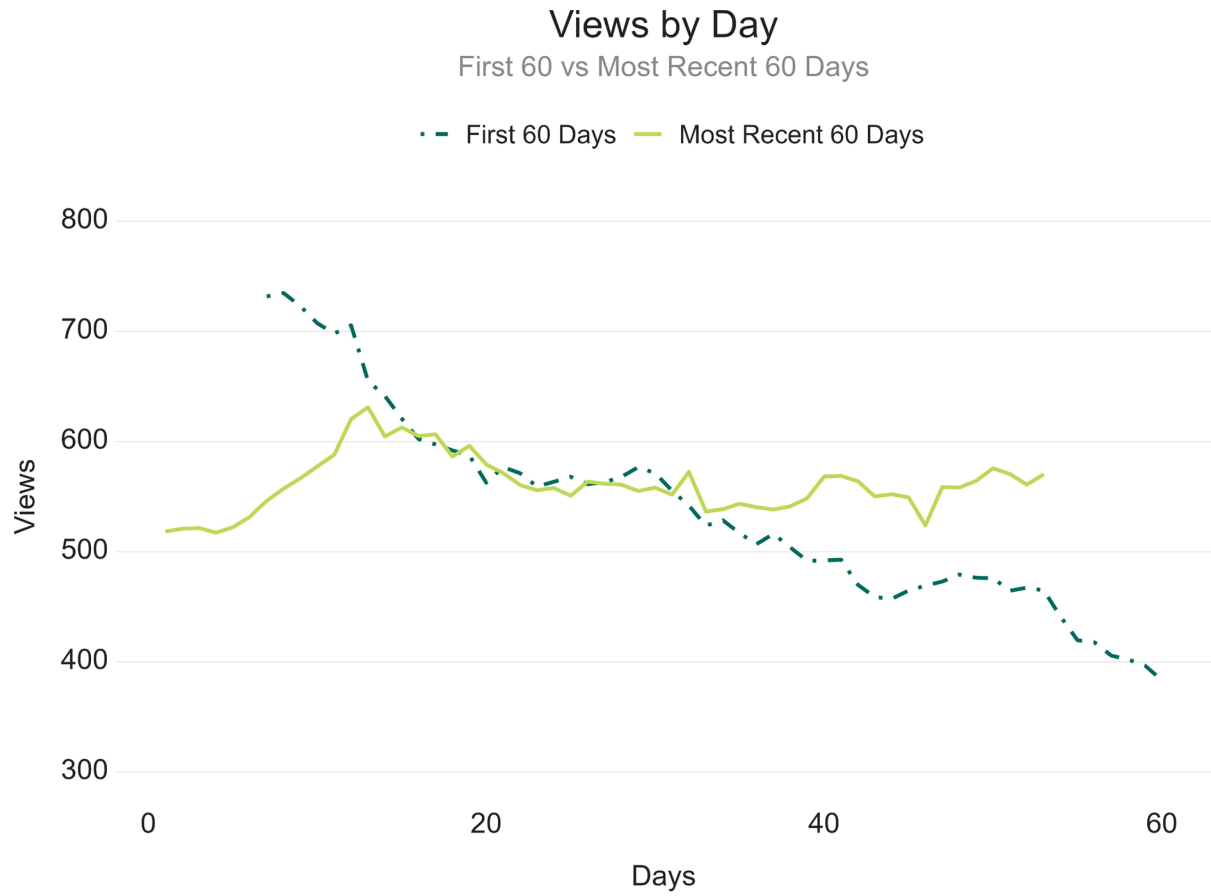
- Pepin, Gabrielle, Christopher J. O’Leary, and Dallas Oberlee. 2021. “Nudges to Increase Completion of Welfare Applications: Experimental Evidence from Michigan.” *Journal of Behavioral Public Administration* 4(2): 1–8. <https://doi.org/10.30636/jbpa.42.237>
- Pope, Devin G., and Justin R. Sydnor. 2011. “Implementing Anti-Discrimination Policies in Statistical Profiling Models.” *American Economic Journal: Economic Policy* 3(3): 206–231. <http://www.aeaweb.org/articles.php?doi=10.1257/pol.3.3.206> (accessed October 25, 2023).
- Pure Michigan Talent Connect (PMTC). 2023. *Career Explorer Tool*. Lansing MI: Pure Michigan Talent Connect. <https://www.mitalent.org/career-exploration> (accessed October 25, 2023).
- Tiller, Richard B., Thomas D. Evans, and Brian C. Monsell. 2023. *Seasonal Adjustment Methodology for National Labor Force Statistics from the Current Population Survey (CPS)*. Washington, DC: Bureau of Labor Statistics, Office of Employment and Unemployment Statistics. <https://www.bls.gov/cps/seasonal-adjustment-methodology.htm> (accessed October 25, 2023).
- U.S. Department of Labor. 2020a. *PY 2018 WIASRD data book*. Social Policy Research (SPR) for the U.S. Department of Labor, Employment and Training Administration, Office of Workforce Investment, Washington, DC: USDOL. <https://www.dol.gov/agencies/eta/performance/results/interactive-data-analysis> (accessed October 25, 2023).
- _____. 2020b. *Budget in Brief, Fiscal Year 2020: Excerpts from Employment and Training Administration (ETA)*. Washington, DC: U.S. Department of Labor. <https://www.dol.gov/agencies/eta/budget/2020> (accessed October 25, 2023).
- Varian, Hal R. 2014. “Big Data: New Tricks for Econometrics.” *Journal of Economic Perspectives* 28(2): 3–28. <http://DOI.org/10.1257/jep.28.2.3>
- Wulf, Andreas. 2012. “Wireframes: A Great Way to Start Development Projects.” *InfoQ: Facilitating the Spread of Knowledge and Innovation in Software Development* (August). <https://www.infoq.com/articles/wireframes-start-development-projects/> (accessed October 25, 2023).

Figure 1 Career Explorer Daily Page Views since Start-Up



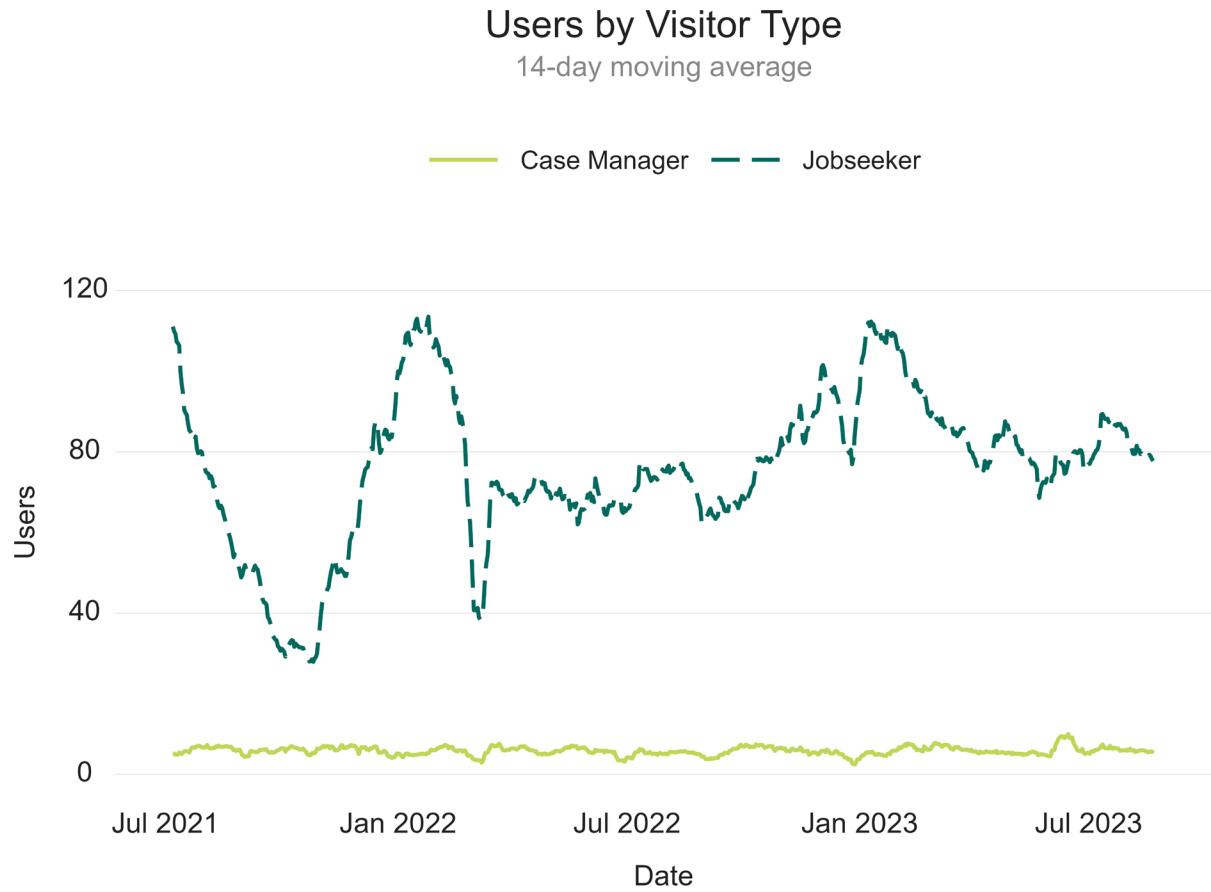
SOURCE: Google Analytics. Retrieved August 29, 2023.

Figure 2 Career Explorer Daily Page Views in the First and Most Recent 60-Day Periods



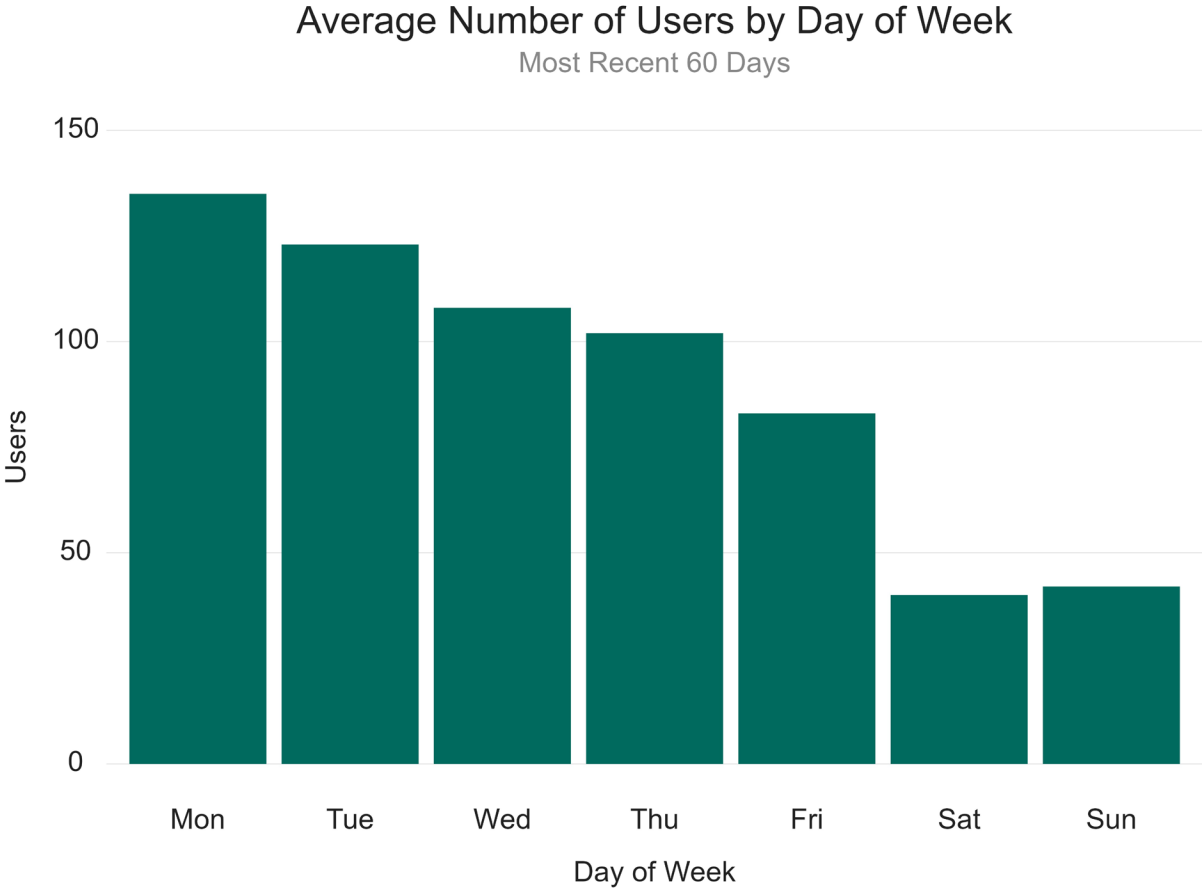
SOURCE: Google Analytics. Retrieved August 29, 2023.

Figure 3 Career Explorer Daily Users by Visitor Type (case manager or job seeker) since Start-Up



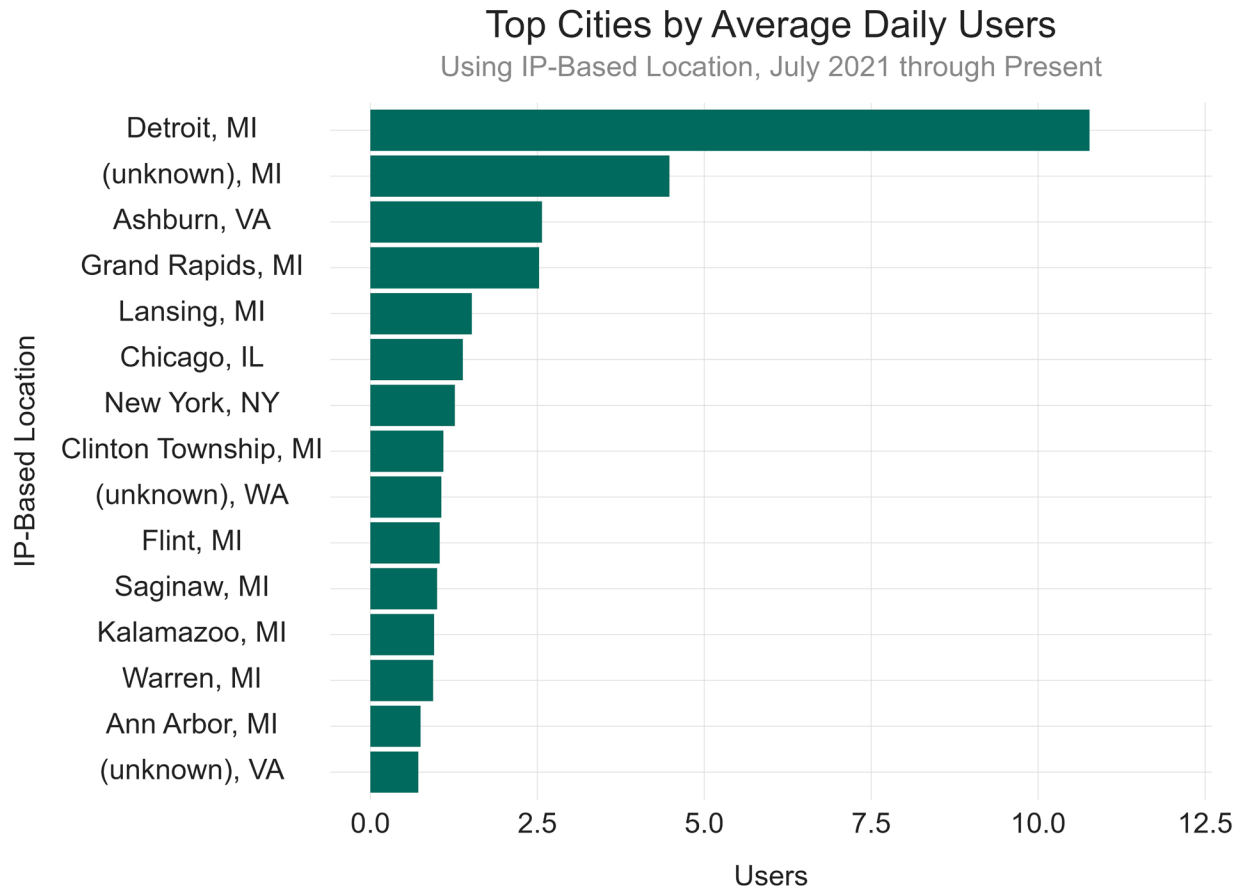
SOURCE: Google Analytics. Retrieved August 29, 2023.

Figure 4 Career Explorer Average Daily Users by Day of the Week since Start-Up



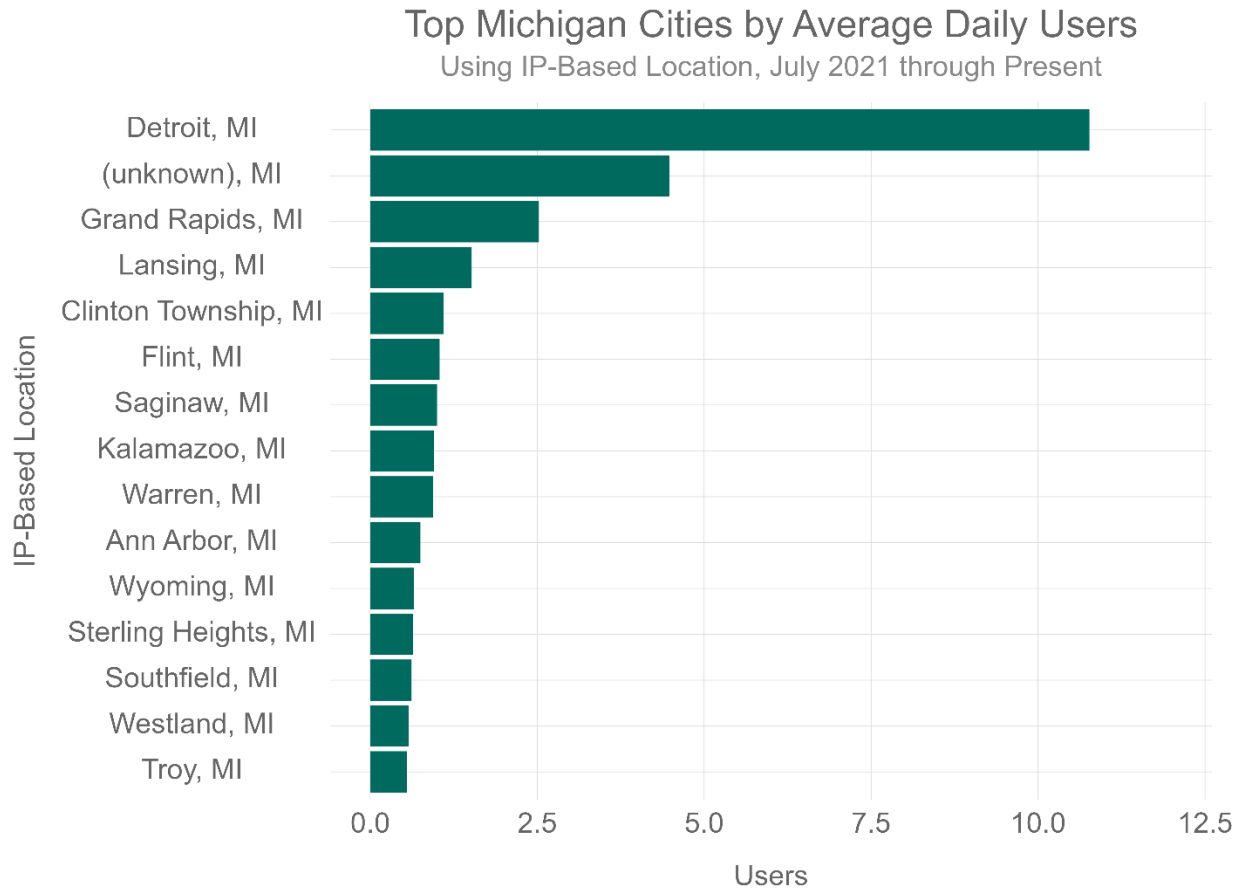
SOURCE: Google Analytics. Retrieved August 29, 2023.

Figure 5 Career Explorer Average Daily Users by Geographic Location since Start-Up



SOURCE: Google Analytics. Retrieved August 29, 2023.

Figure 6 Career Explorer Average Daily Users by Cities in Michigan since Start-Up



SOURCE: Google Analytics. Retrieved August 29, 2023.

Appendix A

Table A.1 Descriptive Statistics for Predictor Variables Used in Models for Mediated Career Explorer Guidance Tools for WIOA Adult and WIOA Dislocated Worker Estimation Samples

Variables	Adult N = 11,852		Dislocated Worker N = 2,509		WIOA Dislocated Worker minus WIOA Adult mean	
	Mean	Std. dev.	Mean	Std. dev.	Difference	t-stat
Prior employment and earnings (7)						
Average quarterly earnings	4,166	4,987	8,726	7,129	4,560	30.50
Variance in quarterly earnings (\$000s)	7,698	298,827	25,917	330,710	18,220	2.55
Proportion of quarters employed ^a	0.502	0.351	0.652	0.300	0.150	22.00
Count of quarters unemployed ^b	1.923	3.180	0.669	2.039	-1.254	-25.03
Proportion qtrs. w/multiple employers	0.132	0.206	0.099	0.175	-0.033	-8.31
Consecutive quarters at same employer	2.782	2.404	4.018	2.289	1.236	24.35
Count of quarters employer changed	1.249	1.218	1.057	0.949	-0.192	-8.73
Educational attainment (7)						
GED	0.117	0.321	0.083	0.276	-0.034	-5.44
Associate degree	0.057	0.232	0.081	0.273	0.024	4.10
Bachelor's degree	0.097	0.296	0.181	0.385	0.084	10.30
High school diploma	0.403	0.491	0.346	0.476	-0.057	-5.42
Other postsecondary degree or cert. certification	0.025	0.156	0.037	0.190	0.012	2.96
Some college	0.246	0.431	0.248	0.432	0.002	0.21
Enrolled in school	0.078	0.269	0.030	0.170	-0.048	-11.43
Occupation of prior employment (22)						
Business and Financial Operations	0.015	0.121	0.040	0.197	0.025	6.12
Computer and Mathematical	0.014	0.119	0.035	0.184	0.021	5.48
Architecture and Engineering	0.015	0.123	0.028	0.165	0.013	3.73
Life, Physical, and Social Science	0.007	0.081	0.008	0.091	0.001	0.51
Community and Social Service	0.007	0.086	0.009	0.095	0.002	0.97
Legal	0.001	0.029	0.004	0.063	0.003	2.33
Educational Instruction and Library	0.013	0.113	0.011	0.105	-0.002	-0.86
Arts, Design, Entertainment, Sports Media	0.008	0.087	0.017	0.128	0.009	3.36
Health-Care Practitioners, Technical	0.023	0.151	0.018	0.133	-0.005	-1.67
Health-Care Support	0.135	0.341	0.044	0.205	-0.091	-17.66
Protective Service	0.018	0.134	0.019	0.136	0.001	0.34
Food Preparation and Serving Related	0.080	0.271	0.025	0.155	-0.055	-13.85
Building, Grounds Cleaning Maintenance	0.049	0.216	0.031	0.174	-0.018	-4.50
Personal Care and Service	0.044	0.205	0.012	0.110	-0.032	-11.06
Sales and Related	0.078	0.269	0.071	0.256	-0.007	-1.23
Office and Administrative Support	0.113	0.316	0.173	0.379	0.060	7.40
Farming, Fishing, and Forestry	0.004	0.064	0.006	0.080	0.002	1.18
Construction and Extraction	0.038	0.191	0.050	0.218	0.012	2.56
Installation, Maintenance, and Repair	0.034	0.182	0.041	0.199	0.007	1.62
Production	0.162	0.368	0.189	0.392	0.027	3.17
Transportation and Material Moving	0.094	0.291	0.071	0.256	-0.023	-3.99
Military Specific	0.002	0.047	0.002	0.040	0.000	0.00
Industry of prior employment (20)						
Accommodation	0.112	0.315	0.043	0.203	-0.069	-13.86
Admin Support	0.162	0.369	0.146	0.353	-0.016	-2.05
Ag_Forest_Fish_Hunting	0.003	0.050	0.004	0.060	0.001	0.78
Arts Entertainment	0.007	0.084	0.010	0.101	0.003	1.39
Construction	0.017	0.128	0.048	0.213	0.031	7.03
Educational	0.016	0.126	0.020	0.140	0.004	1.32
Finance	0.010	0.101	0.035	0.184	0.025	6.60
Health Care	0.156	0.363	0.103	0.304	-0.053	-7.65

Table A1 (Continued)

Variables	Adult N = 11,852		Dislocated Worker N = 2,509		WIOA Dislocated Worker minus WIOA Adult mean	
	Mean	Std. dev.	Mean	Std. dev.	Difference	t-stat
Information	0.006	0.078	0.028	0.164	0.022	6.56
Management	0.003	0.053	0.004	0.063	0.001	0.74
Manufacturing	0.099	0.299	0.193	0.395	0.094	11.26
Mining	0.000	0.021	0.005	0.072	0.005	3.45
Professional	0.025	0.156	0.066	0.248	0.041	7.95
Public Admin	0.016	0.126	0.020	0.138	0.004	1.34
Real Estate	0.008	0.091	0.019	0.137	0.011	3.85
Retail Trade	0.094	0.292	0.102	0.302	0.008	1.21
Transport Warehouse	0.019	0.138	0.023	0.150	0.004	1.23
Unclassifiable	0.001	0.030	0.002	0.049	0.001	0.98
Utilities	0.001	0.030	0.003	0.056	0.002	1.74
Wholesale Trade	0.015	0.122	0.031	0.174	0.016	4.38
Michigan workforce area (15)						
Great Lakes Bay	0.040	0.195	0.078	0.268	0.038	6.73
Berrien/Cass/Van Buren	0.015	0.120	0.029	0.169	0.014	3.94
UPWARD Talent Council	0.036	0.186	0.058	0.233	0.022	4.44
Detroit Empl Solutions	0.441	0.497	0.080	0.272	-0.361	-50.89
GST Michigan Works!	0.102	0.303	0.159	0.366	0.057	7.29
Southwest Michigan Works!	0.015	0.123	0.077	0.266	0.062	11.42
West Central	0.007	0.085	0.011	0.103	0.004	1.82
Capital Area	0.014	0.118	0.053	0.225	0.039	8.44
Macomb / St. Clair	0.053	0.225	0.080	0.271	0.027	4.66
Northeast Michigan Consortium	0.018	0.135	0.014	0.116	-0.004	-1.52
Networks Northwest	0.012	0.107	0.019	0.136	0.007	2.42
Oakland County	0.060	0.238	0.116	0.320	0.056	8.29
Southeast Michigan Consortium	0.054	0.226	0.055	0.228	0.001	0.20
SEMCA	0.027	0.163	0.120	0.325	0.093	13.97
West Michigan Works!	0.093	0.290	0.026	0.159	-0.067	-16.17
Unemployment Insurance (UI) (6)						
Claimant not referred by RESEA	0.053	0.223	0.536	0.499	0.483	47.49
Claimant is RESEA exempt	0.000	0.016	0.000	0.020	0.000	0.00
Claimant referred by RESEA	0.002	0.049	0.066	0.248	0.064	12.87
Beneficiary referred by WPRS	0.006	0.077	0.043	0.202	0.037	9.04
UI exhaustee	0.014	0.117	0.093	0.290	0.079	13.42
Employed at registration	0.367	0.482	0.045	0.208	-0.322	-53.05
Other variables (6)						
Number of barriers	1.463	1.025	1.279	0.979	-0.184	-8.48
County unemployment rate	4.887	1.184	4.940	1.424	0.053	1.74
Days between WP and WIOA registrations	11.941	35.471	34.362	48.534	22.421	21.93
Participated in multiple WIOA programs	0.024	0.153	0.069	0.253	0.045	8.58
Military veteran	0.031	0.173	0.069	0.253	0.038	7.18
Number of family members	2.133	1.497	2.042	1.363	-0.091	-2.98

NOTE: Variables in the first category are based on eight quarters of earnings data prior to program application in most cases, and at least four quarters of earnings data in all cases.

SOURCE: Michigan unemployment insurance (UI) quarterly employer wage record reports on earnings paid.

Appendix B

Table B.1 Parameter Estimates for Outcome Models for WIOA Disadvantaged Adults

Variable	Probability employed within 2Q			Months until employment		
	Coeff. estimate	Standard error	<i>t</i> -stat	Coeff. estimate	Standard error	<i>t</i> -stat
Prior employment and earnings (7)						
Avg. wages for the 8 quarters before registration	0.000141665	0.000004411	32.117	-0.00007	0.00001	-6.83865
Variance of wages for the 8 quarters before registration	0.000000000	0.000000000	-2.215	0.00000	0.00000	1.19839
Proportion of prior 8 quarters employed prior to registration	0.000000017	0.000000775	0.022	-7.75130	0.62210	-12.45989
Number of consecutive quarters unemployed prior to registration	-0.000000096	0.000006855	-0.014	-0.23160	0.02650	-8.73854
Proportion of 8 quarters before registration in which number of employers was > 1	0.000000005	0.000000208	0.026	0.47143	0.19920	2.36663
Number of consecutive quarters at the same employer	0.000000103	0.000003529	0.029	0.78440	0.08733	8.98154
Number of main employer changes in past 8 quarters	0.000000023	0.000002812	0.008	0.38919	0.06447	6.03666
Educational attainment (7)						
GED	-0.000000001	0.000000325	-0.002	0.63350	0.17359	3.64932
Associate degree	0.000000001	0.000000043	0.019	0.51471	0.20266	2.53975
Bachelor's degree	0.000000001	0.000000198	0.006	0.72730	0.19027	3.82236
High school diploma	0.000000006	0.000000901	0.006	0.62338	0.15316	4.07000
Other post HS degree or cert.	0.000000001	0.000000074	0.010	0.68823	0.25748	2.67290
Some college	0.000000004	0.000000450	0.009	1.23044	0.16073	7.65556
Enrolled in school	0.000000002	0.000000047	0.049	1.72926	0.13466	12.84143
Occupation of prior employment (22)						
Business and Financial Operations	0.000000000	—	—	-0.08961	0.31477	-0.28467
Computer and Mathematical	0.000000000	0.000000005	0.012	-0.46094	0.32259	-1.42889
Architecture and Engineering	0.000000000	0.000000006	0.072	-1.46595	0.31431	-4.66408
Life, Physical, and Social Science	0.000000000	0.000000001	0.345	-1.06953	0.43925	-2.43489
Community and Social Service	0.000000000	0.000000039	0.001	-0.07294	0.41770	-0.17463
Legal	0.000000000	0.000000001	-0.057	2.41481	1.15437	2.09188
Educ Instruction and Library	0.000000000	0.000000047	0.006	0.12940	0.33641	0.38464
Arts, Design, Entertainment, Sports, Media	0.000000000	0.000000011	0.002	-0.48050	0.41153	-1.16761
Health-Care Practice and Tech	0.000000001	0.000000020	0.051	0.91237	0.27387	3.33137
Health-Care Support	0.000000004	0.000000238	0.018	-0.00983	0.18861	-0.05214
Protective Service	0.000000000	0.000000037	0.010	0.36231	0.29413	1.23182
Food Prep and Serving Related	0.000000001	0.000000168	0.006	-0.16115	0.20175	-0.79878
Building, Grounds Cleaning, Maintenance	0.000000001	0.000000148	0.004	-0.08119	0.21923	-0.37033
Personal Care and Service	0.000000002	0.000000173	0.009	0.13719	0.22993	0.59664
Sales and Related	0.000000001	0.000000146	0.008	-0.06928	0.20024	-0.34598
Office and Administrative Support	0.000000000	0.000000255	0.001	-0.08778	0.18573	-0.47263
Farming, Fishing, and Forestry	0.000000000	0.000000023	0.000	-0.17976	0.56782	-0.31658
Construction and Extraction	-0.000000001	0.000000076	-0.014	-0.90242	0.23801	-3.79145
Install, Maintain, Repair	0.000000001	0.000000006	0.100	-1.11794	0.23977	-4.66250
Production	0.000000001	0.000000354	0.002	-0.72275	0.17986	-4.01850
Transport and Material Moving	-0.000000001	0.000000228	-0.004	-0.57515	0.19301	-2.97992
Military Specific	0.000000000	0.000000015	-0.002	-0.89787	0.73317	-1.22464
Industry of Prior Employment (20)						
Accommodation	0.000000003	0.000000237	0.013	-0.30960	0.19602	-1.57941
Admin_Support	0.000000002	0.000000498	0.004	-0.34306	0.18588	-1.84555
Ag_Forest_Fish_Hunting	0.000000000	0.000000004	0.031	-1.98819	0.70840	-2.80660
Arts_Entertainment	0.000000000	0.000000016	0.013	-0.36217	0.42504	-0.85209

Table B1 (Continued)

Variable	Probability employed within 2Q			Months until employment		
	Coeff. estimate	Standard error	t-stat	Coeff. estimate	Standard error	t-stat
Construction	0.00000000	0.00000015	0.017	-0.79278	0.31494	-2.51722
Educational	0.00000000	0.00000031	0.013	0.00726	0.31071	0.02338
Finance	0.00000000	0.00000008	0.037	0.17442	0.37562	0.46435
Health_Care	0.00000008	0.00000027	0.034	0.17262	0.19112	0.90320
Information	0.00000000	0.00000005	0.007	-0.27201	0.45713	-0.59503
Management	0.00000000	0.00000017	-0.001	-1.28065	0.64190	-1.99508
Manufacturing	0.00000004	0.00000027	0.136	-0.54500	0.20761	-2.62514
Mining	0.00000000	0.00000010	-0.001	-3.19213	1.63531	-1.95201
Professional	0.00000000	0.00000023	0.013	-0.67346	0.27391	-2.45866
Public_Admin	0.00000000	0.00000008	0.044	-0.45162	0.31230	-1.44610
Real_Estate	0.00000000	0.00000004	0.049	0.11283	0.39769	0.28372
Retail_Trade	0.00000002	0.000000149	0.015	-0.26563	0.20079	-1.32292
Transport_Warehouse	0.00000000	0.00000063	0.001	-0.12020	0.29208	-0.41155
Unclassifiable	0.00000000	0.00000004	-0.005	1.95968	1.10189	1.77846
Utilities	0.00000000	0.00000004	-0.003	-1.57408	1.10353	-1.42640
Wholesale_Trade	0.00000000	0.00000001	0.475	0.15041	0.31854	0.47219
Unemployment Insurance (UI)						
Claimant not referred by RESEA	0.00000001	0.000000205	0.005	0.15868	0.15823	1.00287
Claimant is exempt	0.00000000	0.00000000	-0.015	-0.39433	2.08318	-0.18929
Claimant referred by RESEA	0.00000000	0.00000014	-0.001	-1.58087	0.69589	-2.27171
Beneficiary referred by WPRS	0.00000000	0.000000042	0.001	0.12126	0.43507	0.27870
UI exhaustee	0.00000000	0.000000042	-0.004	0.07448	0.28742	0.25914
Employed at registration	0.00000014	0.000000297	0.048	0.01308	0.07900	0.16553
Michigan Workforce Area (15)						
Great Lakes Bay	0.00000002	0.000000279	0.007	3.09687	0.34562	8.96036
Berrien/Cass/Van Buren	0.00000001	0.000000022	0.028	3.17754	0.41164	7.71914
UPWARD Talent Council	0.00000000	0.000000103	-0.003	2.45783	0.34833	7.05599
Detroit Emp Solutions	-0.00000004	0.000000246	-0.018	0.85053	0.30773	2.76384
GST Michigan Works!	0.00000003	0.000000069	0.048	1.52345	0.31831	4.78611
Southwest Michigan Works!	0.00000000	0.000000081	0.005	0.66121	0.41262	1.60246
West Central	0.00000000	0.000000013	0.022	0.90836	0.49432	1.83758
Capital Area	0.00000000	0.00000000	1.177	2.59278	0.41815	6.20061
Macomb / St. Clair	0.00000001	0.000000365	0.003	2.70324	0.33794	7.99906
Northeast Michigan Consortium	0.00000001	0.000000034	0.019	-0.63572	0.38672	-1.64388
Networks Northwest	0.00000000	0.000000035	0.011	-1.27815	0.43048	-2.96916
Oakland County	0.00000001	0.000000189	0.004	0.80274	0.34296	2.34064
Southeast Michigan Consortium	0.00000002	0.000000098	0.021	-0.14505	0.34139	-0.42489
SEMCA	0.00000000	0.000000196	0.001	1.29676	0.36272	3.57511
West Michigan Works!	0.00000003	0.000000375	0.009	1.04956	0.33218	3.15964
Other variables (6)						
County unemployment rate	0.00000053	0.000009250	0.006	0.29051	0.03415	8.50644
Number of barriers	-0.00000005	0.000004183	-0.001	0.25779	0.03777	6.82539
Days from Wagner-Peyser registration to WIOA registration	0.000000213	0.000544775	0.000	0.00700	0.00097	7.20129
Participated in multiple WIOA programs	0.00000000	0.000000323	0.001	1.30708	0.23759	5.50142
Military veteran	0.00000000	0.000000170	-0.001	-0.00808	0.19698	-0.04100
Number of family members	0.000000028	0.000004233	0.007	0.05612	0.02273	2.46863

NOTE: Parameters for the model probability of “employed within two calendar quarters” can be provided with more precision in scientific notation.

SOURCE: Estimates based on Michigan program administrative data.

Appendix C

Table C.1 Computations of Results from Examples of Outcomes Produced in Mediated Career Explorer for WIOA Disadvantaged Adults

Variables	Probability employed within 2Q			Months until employment		
	Coefficient	Examples		Coefficient	Examples	
		High	Low		Few	Many
Prior employment and earnings						
Average wages for the 8 quarters before registration	4.783E-05	27082.160	134.260	-0.297	21186.930	3235.220
Variance of wages for the 8 quarters before registration	9.945E-11	428351087.610	2489556.810	0.033	19984451.420	3783996.970
Proportion of prior 8 quarters employed prior to registration	1.053E-08	0.500	0.380	-1.987	0.130	0.500
Number of consecutive quarters unemployed prior to registration	-5.598E-08	0.000	0.000	-0.453	7.000	1.000
Proportion of 8 quarters before registration where number of employers was > 1	3.285E-09	0.000	0.130	0.095	0.000	0.000
Number of consecutive quarters at the same employer	6.535E-08	3.000	0.000	1.407	0.000	3.000
Number of main employer changes in past 8 quarters	1.289E-08	1.000	4.000	0.342	1.000	2.000
Educational attainment						
Bachelor's degree	7.988E-10	1.000	0.000	0.250	1.000	0.000
Some college	2.439E-09	0.000	1.000	0.609	0.000	1.000
Enrolled in school	1.489E-09	0.000	0.000	0.434	0.000	1.000
Occupation on prior job						
Computer and mathematical	1.401E-10	1.000	0.000	-0.024	0.000	0.000
Health-care support	2.519E-09	0.000	0.000	0.088	0.000	1.000
Office and admin support	4.329E-10	0.000	0.000	0.000	1.000	0.000
Transport and material moving	-4.352E-10	0.000	1.000	-0.125	0.000	0.000
Industry of prior job						
Accommodation	1.872E-09	0.000	1.000	-0.119	0.000	0.000
Finance	1.817E-10	1.000	0.000	0.009	0.000	0.000
Health care	4.330E-09	0.000	0.000	-0.001	0.000	1.000
Public admin	2.674E-10	0.000	0.000	-0.050	1.000	0.000
Michigan workforce area						
UPWARD Talent Council	-2.652E-10	0.000	1.000	0.369	0.000	0.000
Detroit Empl Solutions	-1.819E-09	0.000	0.000	0.126	1.000	0.000
Macomb / St. Clair	6.600E-10	0.000	0.000	0.416	0.000	1.000
Oakland County	7.021E-10	1.000	0.000	0.244	0.000	0.000
UC involvement						
Claimant not referred by RESEA	6.240E-10	1.000	0.000	0.018	0.000	0.000
Other variables						
County unemployment rate	3.112E-08	3.960	5.080	0.300	3.650	8.710
Number of employment barriers	-2.861E-09	1.000	1.000	0.270	3.000	2.000
Days from WP registration to WIOA registration	1.298E-07	29.900	5.500	0.234	15.350	190.400
In multiple WIOA programs	2.002E-10	1.000	0.000	0.167	0.000	0.000
Military veteran	-1.625E-10	0.000	0.000	-0.006	0.000	0.000
Number of family members	1.662E-08	2.000	2.000	0.061	3.000	4.000
Results for examples		0.790	0.500		5.030	13.310

Table C1 (Continued)

NOTE: Parameter estimates are drawn from Appendix Table B.1. For each of the two outcomes, two examples are given. Computations assign mean values for the selected samples described in the source note for continuous variables, one (1) for dummy variables of characteristics included, and zero (0) for dummy variables of characteristics not included. Assumed values for the example computations are in bold. For the outcome “probability of employment within two quarters after program exit,” examples yield a high and low probability estimate. For the outcome “months until employment after program exit,” examples yield few or many expected months until employment. The variables assigned values of one (1) are listed in the descriptions given for the examples in Text Box 1.

SOURCE: Computations by authors based on Michigan program administrative data. Parameters pulled from full-model estimates reported in Appendix Table B.1. It is not possible to provide data on specific individuals, and thus these data were created by taking the averages for the continuous variables of 10 individuals with high probability of finding employment and 10 individuals with a low probability of finding employment. For the categorical variables, the most common categories among the 2 groups of 10 individuals were selected.